UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

MASTER'S THESIS

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THE IMPACT OF COVID-19 DISEASE ON FINANCIAL MARKETS: EVENT STUDY OF THE WORLD HEALTH ORGANISATION NEWS

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n.d.	no date
ABHAR	Average buy-and-hold abnormal returns
AAR	Average abnormal return
AMEX	American Stock Exchange
APM	Arbitrage pricing model
APT	Arbitrage pricing theory
AR	Abnormal return
BHAR	Buy-and-hold abnormal returns
BMP	Boehmer, Musumeci, and Paulson
CAAR	Cumulative average abnormal returns
CAPM	Capital asset pricing model
COVID-19	The novel coronavirus
EU	European Union
EMH	Efficient market hypothesis
GARCH	Generalized autoregressive conditional heteroskedasticity
GDP	Gross domestic product
IPO	Initial public offering
NASDAQ	National Association for Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
US	United States of America
VIX	S&P 500 volatility index
VXO	S&P 100 volatility index
WHO	World Health Organisation

INTRODUCTION

The novel coronavirus (COVID-19) pandemic outbreak that started in the end of 2019 in China and spread throughout the world, has created an unprecedented shock leading to a multifaceted crisis. The severity and contagiousness of the disease forced governments to enact restrictive measures, preventing the downfall of national healthcare systems (Cimmino, Kroenig, & Pavel, 2020). Preventive measures in the first month after the declaration of global pandemics increased the unemployment rate to more than 10 percent in the United States (hereinafter: US) and gross domestic product (hereinafter: GDP) in the second quarter of 2020 decreased by 30 percent at an annual rate (New Scientist, 2020). In the European Union (hereinafter: EU) GDP fell by 11.1 percent and unemployment rate increased to 14.1 percent (Eurostat, 2021). On the other hand, China experienced a fall in GDP only in the first quarter of 2020, while in the next quarter it already started its recovery and increased GDP to 11.7 percent (OECD, 2020). Nevertheless, all other countries with infectious disease cases and enforced containment measures experienced a fall in GDP and increase in unemployment rate.

The extension of a sudden halt in economic activity led to a short negative investor prospect. Investors in such extreme events are uncertain about event persistence and its magnitude. However, it is known that great events change the stock price movement and increase the risk (Robert, 1988). The methodology of quantitatively assessing investors' response to extreme unexpected exogenous events is known under the name of event studies. Event studies provide a basis for the evaluation of efficient market hypothesis (hereinafter: EMH). In its semi-strong form, EMH assumes immediate impound of relevant new information in stock prices. In addition, the present thesis investigates the geographic proximity of an event and its impact on stock prices and measures investors' fear induced by the coronavirus.

Hence, it is the purpose of this thesis to apply event study methodology to provide an insight into investor reactions to World Health Organisation (hereinafter: WHO) alerts. More specifically, we even carry out a study analysis on US industry portfolios, size-sorted portfolios and two fear indices. The aim of the thesis is to investigate the economic impact of the coronavirus surrounding major events on financial market in the US. It investigates the speed of stock market response following WHO declaration of world pandemic.

For the thesis research part, we define five research questions with which we test if WHO responses on coronavirus lead to negative abnormal returns (hereinafter: AR) and negative cumulative abnormal returns (hereinafter: CAR), where we are interested in the existence of EMH. Secondly, we examine whether WHO alerts had a statistically significant effect on a specific industrial sector. Then we consider the geographic proximity of WHO news effects on US industries and the effect on small versus large companies. Lastly, we examine the investor sentiment on the coronavirus outbreak.

The structure of the master's thesis is as follows; we begin our appraisal with a brief introduction of the theoretical framework and literature review of market efficiency. Firstly, structures of market efficiency and EMH are discussed. We focus on different forms of efficiency, potential market anomalies and investor sentiment where we discuss investors' behaviour during important events and ways of measuring it. Furthermore, we shortly describe the coronavirus outbreak and its impact on global economy and prosperity. Then we turn our attention to the methodology for event study analysis where we discuss each step of the event study. We consider examination period, expected return models, excess return aggregation and significance tests. We conclude the third section with potential issues and biases. In the fourth section we investigate the empirical part of the thesis; firstly, the WHO responses to the coronavirus disease are considered. Our discussion continuous with data analysis. We describe the data used during research and propose research objective. The empirical results of event study are presented next, along with a discussion on each of the research questions. The final section briefly concludes the thesis.

1 MARKET EFFICIENCY

In unpredicted, extreme events the focus in finance is on the market efficiency theory. This chapter starts with an introduction into our research topic, namely market efficiency. Then, the chapter focuses on different forms of market efficiency and presents evidence. Next, we focus on a gap in market efficiency and its potential anomalies. Finally, we conclude with the theoretical background of the investor sentiment by reviewing the literature.

1.1 Description of Market Efficiency

The market is efficient when prices reflect all relevant available information at a certain point of time, which means that if the financial market reflects a certain information set and stock prices change in a relatively short period of time after the arrival of new information to the set, we talk about market efficiency (Fama, 1970). In 1970s the EMH was beginning to be developed by P. Samuelson and E. Fama. Samuelson developed the proposal on the stochastic behaviour of prices, claiming that the unpredictability of the price changes. The stochastic behaviour refers to market efficiency, rather than inefficiency. Malkei's (1992) definition of market efficiency implies that when information set is revealed to all participants, prices are to remain unaffected (Lo, 2007). Thus, if market is efficient no one can consistently earn excess return. Fama focused on empirical research and technical analysis of information market efficiency and defined that the following conditions must be met, for efficient market to exist:

- trading securities is free of transaction costs.
- the information is accessible to all market participants without costs.

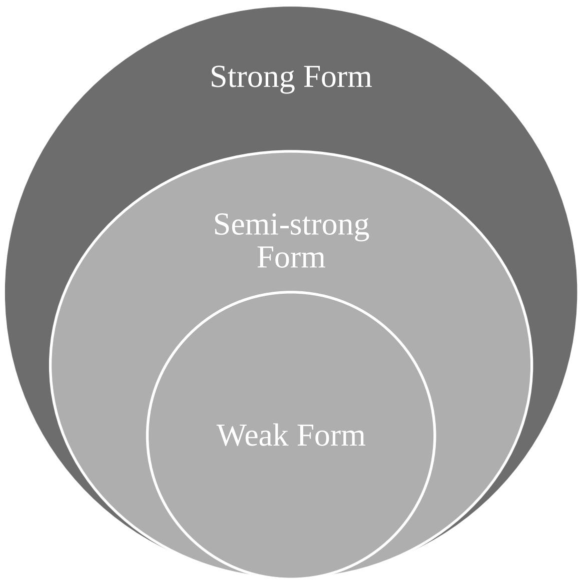
- the investors are rational and participate actively, all information about current and future prices are available all the time.

To test market efficiency, we need an asset pricing model, a model which predicts expected returns without the contamination of exogenous information. Hence, with the EMH test we examine two interconnected hypotheses; whether markets are efficient and whether properties of expected return model are observed in actual returns. Therefore, we might have joint-hypothesis problem, while the test rejection might assume market inefficiency or improper asset pricing model.

1.1.2 Forms of Information Market Efficiency

The trading strategies for testing market efficiency are based on three information subsets (Figure 1); the subset of stock return history (retrieved from past prices), publicly available information (annual reports, initial public offers, stock split, etc.) and any relevant information (besides publicly available information also private information). The weak form, semi-strong form and strong form of market efficiency have been distinguished concerning the above-mentioned information subsets (Fama, 1970).

Figure 1: Forms of market efficiency established according to the information subset



Source: Yalçın (2010).

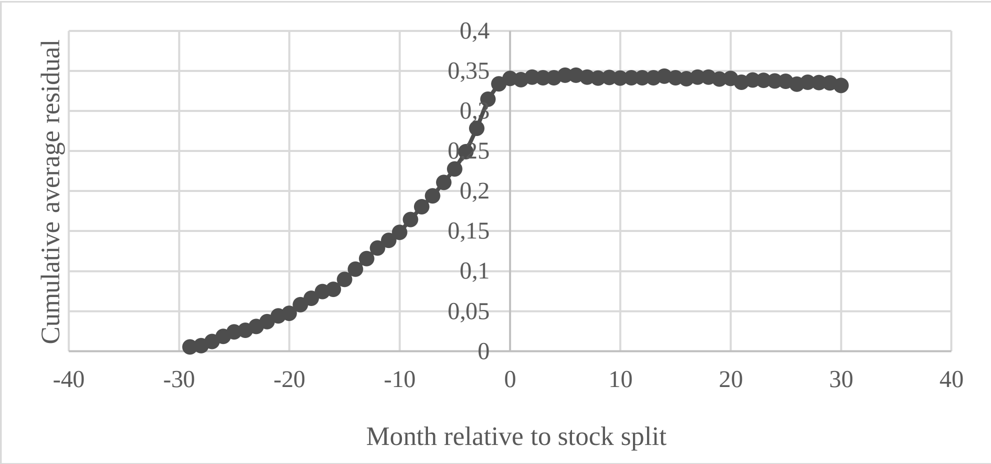
The *Weak form of efficiency* suggests that all historical prices change and trading volume has already been included in current stock prices (Malkiel B. G., 2012). The assertion of weak form is consistent with random walk theory, where price movements are independent. Therefore, a weakly efficient market yields no superior profit with technical analysis (derivation of past prices), thus implying that there is zero correlation between historical stock prices and future stock movements. On the other hand, only by insider trading or fundamental analysis the participants can beat the market (Yalçın, 2010). The weak form efficiency of EMH refuses any price patterns, meaning that if a trader notices low price valuation on Mondays and an increase in price on Fridays, he can consider using this strategy and making some profit. However, if the stock price on Friday does not rise, the market is considered as weak form efficient. Fama (1970) was one of the first who rejected price patterns and predictability tests with random walk theory where the probability of price fall is the same as the probability of price rise.

The *Semi-strong form of efficiency* in addition to past prices encompasses all other information about a certain firm, which will be reflected in stock prices, as visible from Figure 1. Earnings forecasts, stock splits, profit and loss statements, the statement of financial position, quality of management and other fundamental data are inherent in the observed subset. Regarding the weak form efficiency, market participants with technical or fundamental analysis cannot consider excess return from information discussed above, because those will already influence the current prices (Malkiel B. G., 2012). Therefore, only participants with inside data can make excess profit (Yalçın, 2010).

Most of the empirical literature is concerned with semi-strong form tests of market efficiency in which they investigate the speed of price change according to relevant information, i.e., past prices and publicly available information (Fama, 1970). In the empirical analysis of the information about stock split Fama, Fisher, Jensen, and Roll (1969) supported market efficiency. The information about the stock split is not important for a firm's valuation but in most cases stock splits have triggered dividend increase in a short period after the split announcement. In Figure 2 we observe market reaction measured with cumulative average residual which considers the price deviation from the normally expected price. High excessive return is expected in a few months before the announcement and reaches its peak in five months after the event. This price movement is explained by the fact that stock split is publicly known, and market participants anticipate dividend increase, which means that the price rapidly adjusts to the new information and leaves no excess return for new investors. Therefore, this methodology has become a standard for testing semi-strong efficiency.

The *strong form of efficiency* suggests all knowable information embedded in the current stock prices. All information that can be found, represent publicly and privately available information. Therefore, the market assumes zero imperfections and fair prices all the time. Again, investors cannot yield additional return, when inside information are available to all participants without any costs. However, trading on inside information is illegal (Malkiel B. G., 2012).Nevertheless, traders with inside information have received an excess return and rejected the EMH (Titan, 2015).

Figure 2: Cumulative average residuals in the months surrounding a stock split



Source: Fama, Fisher & Jensen (1969).

1.2 Market Anomalies

In the 1980s the concept of market efficiency was highlighted and the validity of EMH was under question. Market efficiency assumes risk-neutral and rational participants. However, investors may overlook important information and might overreact to less important information and underreact to less favorable pieces of information, suggesting irrationality (Malkiel B. G., 2012). Therefore, behavioural finance explains biases in investor decision-making. Not all investors are risk-neutral, they might also be risk takers or risk averse. Due to risk aversion, irrational investors evaluate stock prices according to the noise (irrelevant information for a firm's valuation) leading to security mispricing. The correlation of irrelevant information is known as sentiment, which has the potential power to move stock prices. In other words, sentiment is the price valuation driven by individual's emotions, which prevents perfect rationality (Ackert & Deaves, 2010). In this regard, Baker and Wurgler (2007) pointed out the impact of sentiment on stock prices which is discussed in the next subsection.

Recent empirical evidence has provided conflicting proof of whether EMH exists, implying market inefficiency or irrelevant risk-adjustment model (CAPM etc.). The reason for these inconclusive results stems from market movements that are inconsistent with the theory and are proposed as market anomalies by behavioural finance. The underlying anomalies are the following:

- Volume
- Volatility
- Cash Dividends
- The Equity Premium Puzzle

- Predictability, momentum

The EMH theory assumes trading to be only for liquidity needs or changes in the portfolio, implying a low trading volume. However, we observe millions of transactions on daily basis for various reasons which cannot be explained by EMH. The same can be concluded for volatility, where price movements in efficient market are in the form of new available information. In contrast to the hypothesis, most frequently volatility cannot be explained. Additionally, dividend policy obtained by a firm creates market anomalies due to tax disadvantages. Higher tax rates in cash dividend policy create less income for investors and potential inefficiency. Loss aversion and mental accounting create equity premium puzzle. In other words, despite higher profitability of stock market, irrational investors invest more in government bonds than in stock market (Yalçın, 2010).

Weak form of efficiency and price predictability were rejected by Fama (1970). However, there are significant evidence of predicting future price movements with historical prices and other available information of past performance. The literature regards the higher future performance of low price-earnings ratio firms, low price-to-book ratio firms, medium-term momentum, and reversal effect. In the same manner, other researchers found evidence for lagged reactions of investors to events (earnings announcement), issues of value and growth firms and also the small firm effect (Ackert & Deaves, 2010).

In this regard, the latest financial crisis has brought out market inefficiencies and mistakes of EMH. Most of the researchers blamed the latter theory for the severity of the crisis. However, Malkiel (2012) has argued that the market is relatively efficient rather than perfectly efficient. Considering that at the same time as the information quickly reflects the stock prices, the market gets close to the perfect EMH theory.

1.3 Investor Sentiment

The financial theory assumes rational and unbiased investors. However, great historical events such as the Dot-com bubble in the 1990s, Great Depression in 1929, Black Monday in 1987 and others have severely affected the financial market. Therefore, the assuagement of volatility took some time. The investor sentiment, investigated by the behavioural finance, is observed during those significant events (Baker & Wurgler, 2007).

Limited variations of sentiment measurement were proposed by Baker and Wurgler (2007). Most frequently used method is the investigation of option implied volatility as a potential proxy for investor sentiment. More specifically, if option price increases, the underlying security has higher expected volatility. The Market Volatility Index (hereinafter: VIX) or fear index is implied from the S&P 500 stock index. The VIX is a set of expectations about the future market volatility by financial market participants (Whaley, 2000). Investor behaviour during infectious disease outbreaks has already shown irrational behaviour. Disease-related news during the years 2003 and 2014 have shown positive investor sentiment for the pharmaceutical securities while negative sentiment on the US financial market. In this regard, fear index during the same period has become negative and had a significant impact on reduced portfolio performance, thus implying uncertainty, panic, and anxiety among market participants. Consequently, investors' pessimism induced by infectious disease news can severely affect participants' investment decisions (Donadelli, Kizys, & Riedel, 2017).

However, not only commonly known events but also sports events like FIFA World Cup Games affect investor behaviour and significantly increase liquidity on the financial market (Curatola, Donadell, Kizys, & Riedel, 2016). Additionally, aviation accidents lead to negative sentiment, anxiety, uncertainty, and negative market prices (Kaplanski & Levy, 2010).

The fear during the coronavirus pandemic at the beginning of 2020 has already been explored [1]. Pandemic-induced fear was observed by the number of internet search information about the coronavirus (Costola, Lacopini, & Santagustina, 2020). The constructed index has proposed a significantly negative impact on Chinese stock market returns (Su, Liu, & Fang, 2021) and US indices (Lyocsa, Baumohl, Vyrost, & Molnar, 2020). Also, to observe the impact of the coronavirus pandemic, a global fear index, based on the reported cases of the infected and the dead, has been established. The greatest fear between the global pandemic announcement and the end of April 2020 was observed in Russia, followed by the United States and other European countries. China's market participants did not experience additional fear during this period (Salisu & Akanni, 2020).

2 COVID-19 PANDEMIC IMPACT ON GLOBAL ECONOMY

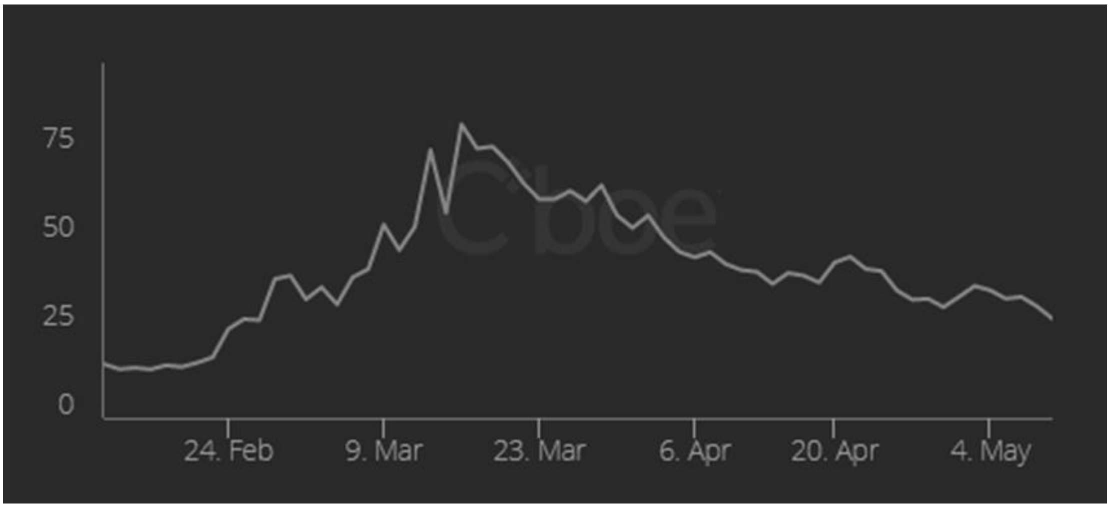
The COVID-19 was first identified in the town Wuhan (China) at the end of December 2019. The mysterious pneumonia rapidly spread through almost all continents. With the increasing number of infected and dead because of the new virus, policy holders responded with social distancing measures. In an attempt to flatten the contagion curve, borders were closed, flights were cancelled, most of the economic activity was halted, normal operation stopped and people were temporarily laid off or had to work from home. Nevertheless, in the beginning of the first wave, China, Spain, and Italy imposed tighter restrictions and closed nonessential businesses (International Monetary Fund, 2020). In this regard, the stock market investors

[1] See also Kose & Jingrui (2021); Mazumder & Saha (2021); Uddin, Chowdhury, Anderson, & Chaudhuri (2021); Fassas (2020); Aguilar, Corinna, Pacce, & Urtasun (2021); Duan, Liu, & Wang, (2021).

reacted to the news about the pandemic with delay, due to bounded rationality, which implies an underestimation of the severity of the coronavirus (Naidu & Ranjeeni, 2021).

The anxiety and fear of the policy holders in addition to preventive measures have shaped the new global economy since March 2020. Figure 3 presents investors' fear with VIX index, where the tendency of rising began after the major pandemic outbreak in Iran on the 24th February 2020.

Figure 3: VIX Index (1.1.2020 – 20.5.2020)



Source: Cboe (n.d.).

The COVID-19 outbreak changed the market participants' behaviour towards better awareness of economic consequences during unpredicted disasters. Ortmann, Pelster, and Wengerek (2020) considered retail investors' behaviour during both outbreaks (spring and autumn 2020) when weekly trading activity was significantly positively correlated with the increasing number of infected. On the financial market, investors established new accounts, new positions and added funds due to the coronavirus. Investors' attention to the new pandemic negatively affected global stock returns during both outbreaks. Increased search for new information about the pandemic from February to mid-March offered more information into financial market and increased volatility (Smales, 2021). Investors' attention to the coronavirus was significant in the week when WHO declared the new virus as a global pandemic (Chundakkadana & Nedumparambilb, 2021).

Policy restrictions during the pandemic have influenced participants' perspective and severely shifted the expectations about the future cash flows, consequently leading to a sharp deterioration in short-term economic prospect. Baker, et. al (2020) observe the importance of newspaper news about the pandemic, which caused the tremendous short-term stock market volatility in the US. Figure 4 presents prices and trading volume of S&P 500 index from February to end of April 2020. The observed index is tracking the performance of 500 large companies, known as the US country market portfolio. Price deterioration and increased trading volume have been observed since the spread of the virus outside China. However, stimulus packages by the regulators impacted positively on market participants (Naidu & Ranjeeni, 2021).

Figure 4: S&P 500 Index price and volume (1.1.2020 - 30.4.2020)

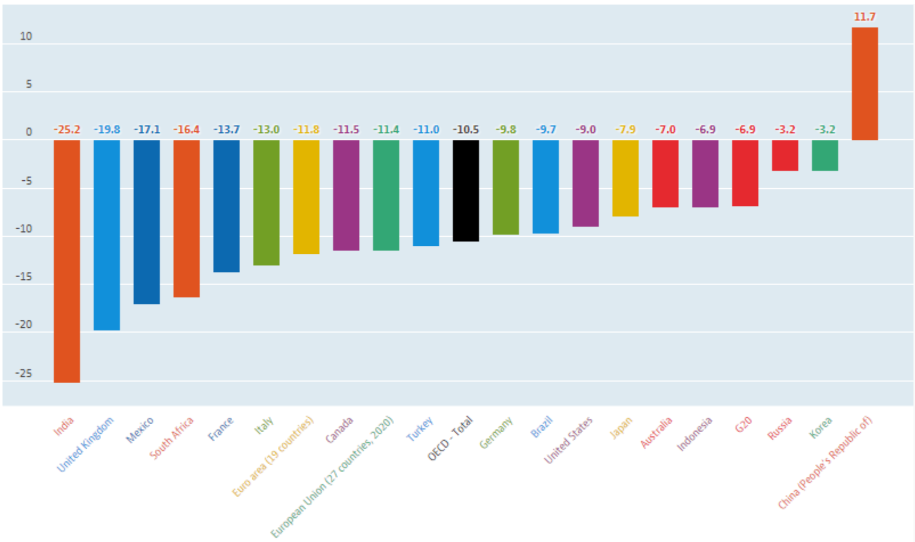
Source: Adapted from Yahoo Finance (2020).

Furthermore, unprecedented shock inflicted by the coronavirus initially led to a sudden pause in the economy and prospect. Therefore, governments tried to mitigate negative effects on economy with stimulus packages, mainly by undertaking different monetary and fiscal measures to support households and businesses. Actions like loan moratoria, direct financial supports, and job retention schemes prevented worse outcomes. Most of the countries financially supported their economy with direct grants to small and medium-sized businesses and low-income households. Nevertheless, reimbursed sick leave has buffered negative effect throughout the lockdown. Additionally, most of the governments funded national health care systems (Siddik, 2020). Inevitably, monetary stimulus and liquidity support offered by central banks have proven significant for increasing economic stability. However, this support policy has led to large public and private debt repayments (International Monetary Fund, 2020).

Most industries suffered from social distancing restrictions and reduced labour supply. Travel bands and closed borders affected tourism industry (Ni & Yin, 2021). The US travel-related firms were affected by new pandemic more, due to the preventive measures taken by the governments. However, larger firms with significant cash reserves, lower leverage and higher market-to-book ratios perform less negative returns (Carter, Mazumder, Simkins, & Sisneros, 2021). Moreover, pharmaceutical and biotechnology sectors have made positive returns during this crisis (Chundakkadana & Nedumparambilb, 2021). In addition to tourism industry, aviation industry also observed significantly negative impacts by the coronavirus outbreak. Unpredicted flight cancellations, travel restrictions, quarantine for passengers, and closed borders immediately stopped cash inflow into the industry. Therefore, most airlines stopped their cargo traffic, yet the transport of food and medicals continued. If we focus on the demand, people adjusted to new restrictions and changed their consumption behaviour. Inevitably, companies had to implement the use of video conferencing platforms (Zoom, MS Teams, WebEx) and households had to delay travelling. Consequently, a longer recovery period is considered for aviation industry (Suau-Sanchez, Voltes-Dorta, & Cugueró-Escofet, 2020).

Hence, OECD in the second quarter of 2020 recorded a significant fall in GDP according to Figure 5, where GDP is observed in G20[2] area. The figure shows a percentage change in GDP from the previous period. According to the studied results, China is the only county with a growth of 11.5 percent, indicating earlier pandemic recovery. Countries with the greatest fall in GDP are India (-25.2%), followed by United Kingdom (-19.8%) and Mexico (-17.1%). In the US GDP fell by 9.0 percentage (OECD, 2020).

Figure 5: GDP in most G20 economies in the second quarter of 2020



Source: OECD (2020).

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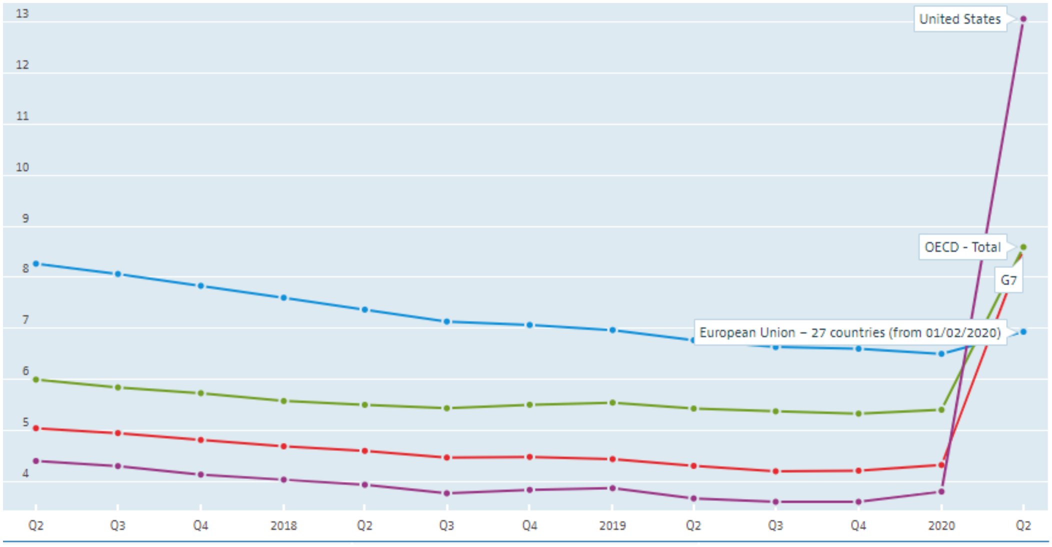
[2] The G20 consists of the following: Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Korea, Mexico, the Russian Federation, Saudi Arabia, South Africa, Turkey, the United Kingdom, the US, and the European Union (OECD, 2020).

In addition to the GDP, preventive measures had a significantly negative impact on labour market. Some of the important industrial sectors were unable to do business and others reduced their workforce. Figure 6 gives an overview of the unemployment rate from 2017 to the second quarter of 2020. In the last quarter, the unemployment rate in the US increased to 13 percent, in the EU to 7 percent and in all OECD countries, it increase to less than 9 percent. The results indicate to the economy reaction to the new pandemic restrictions (OECD, 2021). The developing literature has already examined the impacts of the coronavirus pandemic on stock market, various industries, oil market, firm performance, environment, global supply chain, politics, and other economic participants (Naidu & Ranjeeni, 2021). Additionally, the response in emerging and developing countries has been studied by Harjoto, Rossi, Lee, and Sergi, (2021).

Figure 6: Unemployment rate from Q2 2017 to Q2 2020



Source: OECD (2021).

3 EVENT STUDY METHODOLOGY

In the previous section, we discussed the theory supporting event impact on the financial market, as well as the global deterioration of economy due to the pandemic outbreak. The focus of this section is to present the event study methodology which is applied in this thesis and was established by MacKinlay (1997). Firstly, a brief introduction to the methodology is presented. Then each step is discussed, followed by a choice of timeline and benchmark model. Furthermore, model estimation and cross-sectional aggregation is consider to employ abnormal returns (hereinafter: AR) and cumulative abnormal returns (hereinafter: CAAR). To evaluate the results, different parametric and non-parametric statistical tests are discussed. Additionally, a regression-based event study approach is proposed and potential issues in application are mentioned.

Event studies are statistical techniques for joint testing of the semi-strong EMH and the model of predicted returns. These studies examine the intensity of market price response to specific events or news (IPO, dividend announcement, earnings reports, merger announcements, etc.) (Malkiel B. G., 2012). The response is reflected in the difference between security prices and returns. Additionally, it reveals the impact of events on the stock market with return pattern behaviour. In other words, if there is an efficient market for observed security, the impact of event can be measured by the change in the price around time interval when the event happens, or the information becomes public knowledge. Fama (1970) was one of the first who proposed the methodology for testing capital market efficiency. However, MacKinlay (1997) improved the theoretical foundation made by Fama and provided an event study analysis. While reviewing the literature, Kothari and Warner (2007) considered new methods for measuring abnormal returns and a sophisticated statistical test of significance. Additionally, the long-horizon event window improvement was proposed.

The fundamental type of the event study methodology for the dependent variable uses price returns. However, in modern theory, the application of trading volume and volatilities is also in use as a dependent variable (Eventstudytools, n.d.). The traditional finance literature has taken a particular approach based on statistical tests of the significance of abnormal returns around event day. Brown and Warner (1980) presented different methodologies used in the event studies based on certain events, samples, etc. Additionally, event studies have been used in accounting, management, marketing, law, informatics, and other social sciences. The empirical analysis of the event study has been in use for different events occurring in various firms. Literature studies events, for example earnings announcements, mergers and acquisitions, announcements of new macroeconomic variables and issues of equity (IPO) or debt.

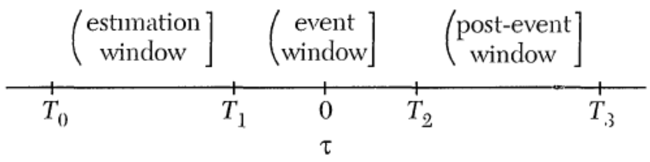
For the analysis, MacKinlay (1997) proposed a general flow of the procedure. First are the determination of the event of interest (the COVID-19 outbreak) and the time frame of the analysis. That is followed by a choice of the appropriate expected performance model, which considers the research question and data availability. The next step is to define the length of the period observation, which is defined by the estimation windows and expected return model. The following step presents an estimation of normal parameters in neutral situations without any significant events. Furthermore, the calculation of abnormal returns and aggregation across firms is considered. Lastly, statistical tests for confirming the validity of event impact are described.

3.1 Determination of the Examination Period

The specification of the observed interval for the estimation window and event window as shown in Figure 7, determine the period of interest. In this regard, time interval from T_0 to

T_1 defines the length of the estimation window, T_{1+1} to T_2 interval represents the event window and 0 the event day. Lastly, T_{2+1} to T_3 defines the post-event window. Respectively, the estimation window is larger than event and post event intervals. Overlapping of the estimation and event windows is not considered due to the event influence on estimated returns. Index τ underneath the timeline represents the price return (MacKinlay, 1997).

Figure 7: Timeline of the even study analysis



Source: MacKinlay (1997).

The choice of the length of estimation and both event and post-event timeframes are individual to researchers. We will use the market model for normal performance, where only estimation and event windows need to be observed. Even though a longer estimation window can perform a greater accuracy, larger set of past returns can lead to biased estimators (important events can occur in the estimation period). Most of the literature suggests 30 to 750 day-long estimation window and a period between 1 and 11 days for the event window. However, the majority implements a 5-day- event window (Eventstudytools, n.d.).

In this regard, we define the timeline for our analysis based on MacKinlay proposition as follows:

- The estimation window will have a length of 252 trading days to achieve accurate results for the benchmark model. With the observed data and ordinary least square (hereinafter: OLS) regression, we will get the parameters for the absence of new pandemic and calculate expected returns. Furthermore, the difference between the observed and expected returns will give abnormal returns, which are expected to be negative.
- The event window with the length of 21 trading days is used, meaning 10 days before and 10 days after the event day, thus considering the abnormal and cumulative rates of returns and the significance tests.
- We will not consider post-event window due to the set limits of the analysis.

3.2 Predicted Return Models

Price performance in the absence of the COVID-19 pandemic can be considered as normal. Therefore, specification of expected return model is necessary for the calculation of ex-ante returns. There is a wide variety of benchmark models in the literature, which I try to present here. In this manner, models are grouped into statistic an economic categories. The first category focuses on the historic stock price returns and statistical assumptions, considering independently identically distributed normal returns. On the other hand, economic models observe investor behaviour. In the following subsections we propose a constant mean return model, market model, market adjusted model and risk adjusted models which have been used in the event studies.

3.2.1 Constant Mean Return Model

The model assumes a constant term for each asset return in the sample. Mean return μ_i for each stock return R_{it} is not considered to be different over time. Constant mean return model is:

$$R_{it} = \mu_i + e_{it} \tag{1}$$

Where e_{it} is the period t disturbance term for asset i with $E(e_{it}) = 0$ and $var\ (e_{it}) = \sigma^2_{e_i}$. Brown and Warner (1980) observe results that are similar to more advanced and precise models for expected return despite the formula's simplicity. Furthermore, abnormal return is:

$$AR_{it} = R_{it} - \mu_i \tag{2}$$

Where R_{it} represents the stock return after the main event. Additionally, the model is consistent with the Asset Pricing Model (hereinafter: APM) under the assumption of a constant expected return for each security (Brown & Warner, 1980).

3.2.2 Market Model

The market model is established on the linear regression model where dependent variable is a market portfolio or market returns. The relationship between security i and market are determined with α_i and β_i coefficients which are used for observation of abnormal returns in the event window. In the regression equation, R_{it} is the period t return for each security i, R_{mt} is the period t market portfolio return. Furthermore, e_{it} is the period t disturbance term, the same as in the previous model. The market model is:

$$R_{it} = \alpha_i + \beta_i R_{mt} + e_{it,} \tag{3}$$

where $E(e_{it}) = 0$ and $var\ (e_{it}) = \sigma^2_{e_i}$, respectively. Furthermore, abnormal return for security i and period t in the event window is:

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt}). \tag{4}$$

Due to the reduction in variance of abnormal returns, the market model shows a development over the constant mean return model. Furthermore, the reduced variance improved the determination of event impact on returns. However, a better model is observed with a higher R^2, therefore a greater reduction in variance (MacKinlay, 1997). The model assumes α to be constant, despite induced risk-free interest rate. Therefore, the market model is in conflict with the assumption of time varying market return.

3.2.3 Market Adjusted Model

The market adjusted model is the simplest expected return model for observing event effects on stock return. The model is used when data availability is limited and it is not feasible to determine the coefficients α_i and β_i in the "normal" market model. The restricted model is consistent with the Capital Asset Pricing Model (hereinafter: CAPM) under the assumptions of no unsystematic risk (α_i = 0) and systematic risk being equal to 1 (β_i = 1). Hence, the estimation window is not observed since the coefficients are predetermined. However, the model should be in use only if necessary, due to potential biases arising from restrictions (MacKinlay, 1997). Therefore, the market adjusted model is represented by a period t market return R_{mt} and abnormal return is as follows:

$$AR_{it} = R_{it} - R_{mt} \tag{5}$$

Comparison period mean adjusted model is the restricted model, based on the average return for security i in ex-ante period $\overline{R}_i = \frac{1}{t_1 - t_0} \sum_{t \in [t_0, t_1]} R_{it}$ (Eventstudytools, n.d.). Therefore, the abnormal return is:

$$AR_{it} = R_{it} - \overline{R}_{it} \tag{6}$$

Additionally, market model with Scholes-Williams beta estimation was developed as a response to the potential biases with daily security returns. Non-synchronous trading of security and market return have an impact on mean and variance estimators. Therefore, with the estimation of β by Scholes-Williams the biases are reduced. However, the significance tests for abnormal performance are the same as in the OLS regression of market model (Brown & Warner, 1985).

3.2.4 Economic Models

MacKinlay (1997) classified CAPM and Arbitrage Pricing Theory (hereinafter: APT) as the main representative economic models. The CAPM model is a single-factor model, considering covariance with market return. The APT model is a multifactor model where, in addition to market risk, other factors which correspond to variation in return are employed. Therefore, the ex-ante return is established as a linear combination of more than one factor and error term. Some of the important APT models are Fama-French 3 Factor Model and Fama-French-Momentum 4 Factor Model. Literature implies a less valuable restriction by CAMP on market model and consequently sensitive results. Therefore, the employment of CAPM became less frequent. Similarly, the popularity of multifactor models declined because of less explanatory power of additional risk factor.

Kothari and Warner (2007) found no flawless expected return model in the event study literature. The proposed models adjusted for systematic risk showed no more power in significance testing than models with no systematic risk adjustments (Brown & Warner, 1980). However, event clustering will increase the variance of abnormal returns which will be consider in the significance tests. Therefore, for the purpose of this thesis, we will employ the most frequently performed model, the market model, which suggests less cross-correlation from residuals than other models (Kolari & Pynnonen, 2011).

3.3 Model Selection and Abnormal Returns Aggregation

The adopted methodology involves an investigation of the correlation between stock returns in the absence of the new virus information and market return. In this regard, we will establish OLS regression of market model in Equation (3) to estimate α and β coefficients in estimation period for each security i (MacKinlay, 1997):

$$\hat{\beta}_i = \frac{\sum_{t=t_{0+1}}^{t_1}(R_{it}-\hat{\mu}_i)(R_{mt}-\hat{\mu}_m)}{\sum_{t=t_{0+1}}^{t_1}(R_{mt}-\hat{\mu}_m)^2}, \tag{7}$$

$$\hat{\alpha}_i = \hat{\mu}_i - \hat{\beta}_i\,\hat{\mu}_m, \tag{8}$$

$$\hat{\sigma}_{e_i}^2 = \frac{1}{L_1-2}\sum_{t=t_{0+1}}^{t_1}\left(R_{it} - \hat{\alpha}_i - \hat{\beta}_i\,R_{mt}\right)^2, \tag{9}$$

where $\hat{\mu}_i = \frac{1}{L_1}\sum_{t=t_{0+1}}^{t_1} R_{it}$ and $\hat{\mu}_m = \frac{1}{L_1}\sum_{t=t_{0+1}}^{t_1} R_{mt}$. Security i return in event period t are observed as R_{it} and R_{mt} as market returns. In the next time interval, we compute the abnormal returns as the difference between returns dependant on an event (in our case new pandemic) and expected returns without the connection to the pandemic outbreak according to the following formula:

$$AR_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i\,R_{mt}. \tag{10}$$

The latter presents an unexpected change or the impact of the event on security price movement. Excess returns are assumed to be normally distributed (conditionally on market portfolio) with zero conditional mean and conditional variance as follows:

$$\sigma^2(AR_{it}) = \sigma_{ei}^2 + \frac{1}{L_1}\left[1 + \frac{(R_{mt}-\hat{\mu}_m)^2}{\hat{\sigma}_m^2}\right], \tag{11}$$

where, σ_{ei}^2 is the error term variance from the market model and the next component is the additional variance due to mistakes in sampling the parameters. Despite the independence of the disturbance term, this error can lead to serial correlation of abnormal returns. Hence, with large estimation window, the second term becomes small (close to zero) and sampling error disappears, which means that the variance of abnormal performance becomes the same as the variance of disturbance term σ_{ei}^2 (MacKinlay, 1997).

To observe the impact of event over longer periods surrounding the event, the abnormal performance had to be aggregated through time or across securities (cross-sectional). For the determination of cumulative abnormal performance, the aggregation of each security i is considered in the event window $T_1 < t_1 \leq t_2 \leq T_2$. The 21-day period, t_1 starts with -10 and ends with t_2 +10 days from the event date as t_0 = 0. The cumulative abnormal returns are observed through the following formula:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it}. \qquad (12)$$

A variance of cumulative abnormal returns is dependent on the length of the estimation window. A short-window variance must be adjusted, but within a longer period, the variance is computed as follows:

$$\sigma_i^2(t_1, t_2) = (t_2 - t_1 + 1)\sigma_{ei}^2 \qquad (13)$$

For multiple events of the same specification or if more than one firm is relating to one event, we can perform an analysis on each firm. However, the informativeness of the analysis is improved by averaging the abnormal returns over a number of securities. In this manner, we consider average abnormal returns computed as follows:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t}\ , \qquad (14)$$

where N is the number of event observations across securities or number of firms in one event case. According to the previous determination, we can aggregate average abnormal returns across time to observe the cumulative average abnormal returns (hereinafter: CAAR) with variance as follows:

$$CAAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AAR_t = \frac{1}{N}\sum_{i=1}^{N} CAR_i(t_1, t_2) \qquad (15)$$

$$var\big(CAAR(t_1, t_2)\big) = \sum_{t=t_1}^{t_2} var(AAR_t) = \frac{1}{N^2}\sum_{i=1}^{N} \sigma_i^2(t_1, t_2) \qquad (16)$$

3.4 Significance Tests

Significance tests are the last step in the event study methodology where we confirm or reject the economic impact of a selected event. Therefore, it is important to apply the event study in such a way that it observes the presence of unusual performance (MacKinlay, 1997). Regarding the type of study, it is important which form of abnormal returns (aggregated or non-aggregated) are considered in the significance testing.

With null hypothesis (i.e., H_0) we reject the existence of abnormal returns in the event window. Therefore, the alternative hypothesis (i.e., H_1) suggests the presence of abnormal returns. The hypotheses for testing abnormal behaviour can be employed in all differently compound abnormal performance measures (AR, CAR, AAR and CAAR), which is written in a formula as (Eventstudytools, n.d.):

$$H_0: \mu = 0,$$
$$H_1: \mu \neq 0.$$

In long-term event studies, buy-and-hold abnormal returns (hereinafter: BHAR) are additionally employed, where we observe average buy-and-hold abnormal returns (hereinafter: ABHAR) with aggregation across securities. The literature appears to divide significance tests into two groups. The first group obtains parametric tests and the second non-parametric ones. The latter are usually used for robustness check and in the case of non-normally distributed abnormal returns (Eventstudytools, n.d.). In this regard, parametric tests are usually reliable for skewed and non-normal distribution of abnormal returns with some sample requirements, due to the central limit theorem (Frost, n.d.). The test statistics for each group and hypothesis are present in Table 1.

Table 1: Test statistics per test level

Null Hypothesis	Parametric test	Non-parametric tests	Test level
$H_0: AR = 0$	AR Test		Individual event
$H_0: AAR = 0$	Cross-Sectional Test, Time-Series Standard Deviation Test, Patell Test, Adjusted Patell Test, Standardized Cross-Sectional Test, Adjusted Standardized Cross-Sectional Test, and Skewness Corrected Test	Generalized Sign Test, Generalized Rank T Test, and Generalized Rank Z Test	Sample of events

(table continues)

Table 1: Test statistics per test level

(continued)

$H_0: CAR = 0$	CAR t-test		Individual Event
$H_0: CAAR = 0$	Cross-Sectional Test, Time-Series Standard Deviation Test, Patell Test, Adjusted Patell Test, Standardized Cross-Sectional Test, Adjusted Standardized Cross-Sectional Test, and Skewness Corrected Test	Generalized Sign Test, Generalized Rank T Test, and Generalized Rank Z Test	Sample of events

Source: Eventstudytools (n.d.).

Inevitably, issues in the development of the "perfect" event study prevent standard t-test to observe all anomalies. The most significant imperfections in event study literature are event clustering or overlapping, which leads to cross-sectional correlation in abnormal returns, event-induced volatility, autocorrelation and non-normally distributed AR. All issues and problems with the methodology are explained in detail in the next section. Consequently, the imperfections lead to biased standard deviation estimate and thus biased t-statistic, leading to rejection of null hypothesis (Eventstudytools, n.d.). Hence, to improve the power of test statistics, most parametric tests are based on standardized abnormal returns (Kolari & Pynnonen, 2011). Non-parametric tests have significantly more power than parametric ones, therefore we decided to use both types of tests in the empirical analysis.

3.4.1 Parametric Tests

Parametric tests assume a normal distribution of observed values, in our case the abnormal performance. However, issues with the event study demanded further development of the methodology. Patell (1976) and Boehmer et al. (1991) proposed standardized returns for the statistic and increased the popularity of the parametric tests. However, Marks and Musumeci (2017) found a powerful BMP test in the case of an event-induced variance and rejected the specification of the Patell test.

Firstly, we observe a commonly used parametric test, t-test. In order to introduce this test, assume that the ARs are independently and identically distributed. The test is easy to perform, but it has issues with cross-sectional correlation and event-induced volatility. The null hypothesis and the test statistic for market model are the following (Eventstudytools, n.d.):

$$H_0: AR_{i,t} = 0,$$

$$t_{AR_{i,t}} = \frac{AR_{i,t}}{SD_{AR_i}} \ , \tag{17}$$

where SD_{AR_i} is the standard deviation of abnormal returns in the estimation period for security i, with the following variance: $SD^2_{AR_i} = \frac{1}{M_i - 1}\sum_{t=t_0}^{t_1}(AR_{i,t})^2$. In this regard, M_i is the number of matched returns. With the aggregation of abnormal performance into AAR, we use a cross-sectional test as follows:

$$H_0\colon AAR_t = 0,$$

$$t_{AAR_t} = \sqrt{N}\frac{AAR_t}{SD_{AAR_t}}, \tag{18}$$

where N stands for the number of observations and SD_{AAR_t} is the standard deviation with a variance: $SD^2_{AAR_t} = \frac{1}{N-1}\sum_{i=1}^{N}(AR_{i,t} - AAR_t)^2$. The cumulative average abnormal returns have the same form of the test as AAR, therefore we skip the equation for CAAR. Additionally, cross-sectional tests are low in power, due to the event-induced volatility.

The Patell Z test or standardized residual test is a very useful parametric test, suggesting immunity of the distribution of abnormal returns. However, it is not immune to event-induced volatility (Marks & Musumeci, 2017). Despite the mistakes of the test, it is commonly employed by the event study researchers. The test is performed on standardized abnormal returns: $SAR_{i,t} = \frac{AR_{i,t}}{SD_{AR_i}}$, where the adjustment term reshapes abnormal returns distribution into a normal bell-shaped form. The forecast-error standard deviation is written as:

$$SD^2_{AR_{i,t}} = SD^2_{AR_i}\left(1 + \frac{1}{M_i} + \frac{(R_{mt} - \overline{R}_m)^2}{\sum_{t=t_0}^{t_1}(R_{mt} - \overline{R}_m)^2}\right). \tag{19}$$

where $\overline{R}_m$ is the mean of the market portfolio in the estimation period. Hence, the distribution of $SAR_{i,t}$ is the same as t statistic with $M_i - 2$ degrees of freedom under the H_0 : $AAR = 0$. The test statistic is the following:

$$z_{Patell,t} = \frac{ASAR_t}{SD_{ASAR_t}}, \tag{20}$$

with $ASAR_t = \sum_{i=1}^{N} SAR_{i,t}$, and the following variance $SD^2_{ASAR_t} = \sum_{i=1}^{N}\frac{M_i - 2}{M_i - 4}$. Similarly, for cumulative abnormal return the test statistic is:

$$z_{Patell,t} = \frac{1}{\sqrt{N}}\sum_{i=1}^{N}\frac{CSAR_i}{SD_{CSAR_i}}. \tag{21}$$

The Patell test statistic is normally distributed under the assumption of cross-sectional independence. Kolari and Pynnonen (2010) modified Patell Z test into the adjusted Pattel Z test due to issues with cross-sectional correlation. In addition to standardized abnormal returns, the adjustment of the average cross-correlation in abnormal returns in the estimation window ($\overline{r}$) is used. The adjusted Patell Z-test statistic and corresponding null hypothesis are the following:

$$H_0: AAR_t = 0,$$

$$z_{Patell,t} = z_{Patell,t}\sqrt{\frac{1}{1+(N-1)\,\overline{r}}}\,. \tag{22}$$

The corresponding test statistic can be considered for CAAR, respectively. When the adjustment term $\overline{r}$ is close to zero, the test statistic is reduced to the "normal" Patell Z test (Eventstudytools, n.d.). Boehmer, Masumeci, and Poulsen (1991) propose a solution for the non-normal distribution of abnormal returns across an event period, event-induced volatility and serial correlation but not for cross-sectional correlation. The null hypothesis and test statistic for the Standardized Cross-Sectional or BMP Test is the following:

$$H_0: AAR_t = 0,$$

$$z_{BMP,t} = \frac{ASAR_t}{\sqrt{N}SD_{ASAR_t}}\,, \tag{23}$$

where the average standardized abnormal returns are defined as in the Patell test, with a variance $SD^2_{ASAR_t} = \frac{1}{N-1}\sum_{i=1}^{N}\left(SAR_{i,t} - \frac{1}{N}\sum_{i=1}^{N} SAR_{i,t}\right)^2$. For CAAR the test statistic and variance are similar, therefore we do not consider it. However, the variance is unique for each expected return model.

Furthermore, Kolari and Pynnonen (2010) modified the BMP test into the adjusted BMP test with consideration of cross-sectional correlation in abnormal performance. Following the adjusted Patell Z test, the adjustment factor is a cross-correlation of abnormal returns in the estimation window, $\overline{r}$. However, standardized abnormal returns remain the same. Null hypothesis and test statistic are as follows:

$$H_0: AAR_t = 0$$

$$z_{BMP,t} = z_{BMP,t}\sqrt{\frac{1-\overline{r}}{1+(N-1)\overline{r}}}. \tag{24}$$

When the adjusted part is zero, the observed test statistic is close to the original BPM test. Equivalently, the same statistic goes for CAAR.

Lamb's parametric test for testing CARs, proposed by Lamb (1995), is not commonly used by researchers, because the employment of the test requires an estimation of specific variance. However, the test allows cross-sectional correlation in an abnormal performance.

3.4.2 Non-parametric Tests

Non-parametric tests are usually employed when we consider small sample sizes and ranked data (Frost, n.d.). The robustness performance does not consider the distribution of observed returns. The most commonly performed non-parametric tests for event studies are the sign test and the rank test (MacKinlay, 1997). However, Kolari and Pynnonen (2010) proposed an improvement for the rank tests with the generalized rank test.

The sign test is performed on abnormal or cumulative abnormal returns with 0.5 expected proportion of positive or negative abnormal returns under the null. The null hypothesis claims equally probable positive or negative performance and independency across securities for AR or CAR. Therefore, null hypothesis is $H_0 = p \leq 0.5$ and its alternative $H_1 = p > 0.5$, where p is the probability of abnormal returns. Under the null, probability of abnormal performance is assumed to be smaller than 0.5, while the alternative suggests the opposite. For the test to be employed, we need the number of abnormal returns with a positive sign (N^+) and total number of abnormal returns (N). Hence, the test statistics follows (MacKinlay, 1997):

$$t_{sign} = \left[\frac{N^+}{N} - 0.5\right]\frac{\sqrt{N}}{0.5} \sim N(0,1). \tag{25}$$

In the case of skewed distributed abnormal returns, the sign test is not suitable. The generalized sign test by Cowan (1992) is the same sign test as described above, however, the bell-shaped distribution of abnormal returns is not required. Corrado's rank test also solves the weakness of the sign test with the ranking of abnormal returns in estimation and event periods into several ranks. Due to the missing values, the standardization of ranks is considered by :

$$K_{i,t} = \frac{rank(AR_{it})}{1+M_i+L_i}, \tag{26}$$

where M_i is the number of non-missing values and L_i is the number of non-missing values in the event period. Therefore, null hypothesis and rank statistics are computed as follows:

$$H_0: AAR = 0,$$

$$t_{rank} = \frac{\overline{K}_t - 0.5}{S_{\overline{K}}}, \tag{27}$$

with $\overline{K}_t = \frac{1}{N_t} K_{i,t}$, variance $S_{\overline{K}}^2 = \frac{1}{L_1+L_2} \sum_{t=t_0}^{t_2} \frac{N_t}{N} (\overline{K}_t - 0.5)^2$ and N as the number of non-missing abnormal returns across securities (Eventstudytools, n.d.).

Generalized Rank T-test and Generalized Rank Z test are non-parametric tests considering cross-correlation of returns, serial correlation, and event-induced volatility. GRANK test assumes an event period as one observation and defines the standardized cumulative abnormal returns for each firm and to account for the induced volatility, the returns are re-standardized by cross-sectional standard deviation. After the generalized standardized AR are defined, the null hypothesis and generalized rank t-statistic is the following:

$$H_0: CAAR = 0,$$

$$t_{grank} = Z \left(\frac{L_1 - 1}{L_1 - Z^2}\right)^2, \tag{28}$$

with $Z = \frac{\overline{K_0}}{S_{\overline{K}}}$. The test statistic has Student t-distribution with $L_1 - 1$ degrees of freedom. Generalized Rank Z test is followed by a standard deviation of $\overline{K_0}$, $S_{\overline{K_0}}^2 = \frac{L_1}{12N(L_1+2)}$ and test statistic:

$$Z_{grank} = \frac{\overline{K_0}}{S_{\overline{K_0}}}. \tag{29}$$

where the null hypothesis assumes that with the increasing number of firms in the sample, the distribution converges quickly to standardized normal distribution. Kolari and Pynnonen (2010) propose a modification to the original rank test, where the missing values in abnormal performance, cross-sectional correlation, and bias-variance are allowed. However, the test is more sensitive to unexpected events than the sign test. Usually, the non-parametric test is performed together with the parametric test and provides a robustness check. In the case of stock daily returns, the non-parametric test provides more accurate conclusions than the parametric test (MacKinlay, 1997).

3.5 Regression Based Event Study

In our research, we investigate one event on multiple securities, considering event clustering or overlapping. This means that the covariance between abnormal returns is not considered to be zero. MacKinlay (1997) proposes two solutions for issues with clustering. First is the aggregation of abnormal returns in the portfolio, where cross-correlation is allowed. Secondly, he proposes an analysis of abnormal returns without aggregation, by using a multivariate regression model. Our solution uses a regression model analysis and applies methodology on equally weighted portfolios.

The methodology discussed above is equivalent to the cross-sectional regression model, which is often in use with multiple-hypothesis testing. Additionally, regression analysis can contain specific characteristics of a firm. Hence, with the latter, we identify the association between the abnormal returns as independent variables and explanatory variables as the dependent variables. The original form is computed as follows:

$$AR_j = \delta_0 + \delta_{1X_{1j}} + \cdots + \delta_{MX_{Mj}} + \mu_j \ , \tag{30}$$

where $E(\mu_j) = 0.\ x_{m,j,m} = 1, \ldots, M,$ are M explanatory variables for j^{th} abnormal return with observed OLS regression coefficients $\delta_{m,}\ m = 0, \ldots M$. Disturbance terms are assumed to be homoscedastic and cross-sectionally uncorrelated (MacKinlay, 1997).

In addition to the traditional methodology, explanatory variables are assumed to be dummy variables with term one during the event period and zero otherwise. However, abnormal returns by observing a single event are usually correlated and variance-biased. Therefore, equal-weighted portfolios are assumed to solve the overlapping problem (Pynnonen, 2005). The regression model is as follows:

$$r_{p,t} = \alpha_p + \beta_p r_{m,t} + \textstyle\sum_{\tau=t_1}^{t_2} \gamma_{p,\tau} D_{\tau,t} + u_{p,}, \tag{31}$$

where $r_{p,t}$ is the average portfolio return of n securities in time t, α_p is the following intercept of regression, β_p is the average coefficient of market return, $\gamma_{p,\tau}$ are the coefficients of abnormal performance of the portfolio for each event period and the u_p is the disturbance term.

Nevertheless, event dummy variables can be replaced by average abnormal returns across the securities to employ aggregated analysis. Apart from additional analysis, another regression method advantage is its additional dependent variables which can be used as control variables. Most control variables employed by researchers of the event studies are lagged returns, dummy variables for days of the week, dummy variables for the first days in the taxation year and for the location, where the event occurs (see, e.g., Ichev and Marinč, 2018; Kaplanski and Levy, 2010). For the investigation of volatility effects in single events, GARCH (1,1) estimation of disturbance term is employed (Pynnonen, 2005).

3.6 Potential Issues and Biases

The literature review presents some difficulties with the specifying event study. The potential problems: event-induce variance, serial correlation, thin trading and cross-sectional dependence or event clustering, can arise from:

- Sampling intervals: With data availability, it is difficult to determine the right time interval of stock returns (daily or monthly). MacKinlay (1997) addresses a better power of tests for daily returns than monthly or weekly returns, concluding that with the reduced intervals, the power of the significance tests increases.

- Using daily stock returns: However, with daily stock returns the assumption of normally distributed returns can be violated. Furthermore, due to the difference in trading intervals (different markets), non-synchronous trading can lead to biased market model parameters. Also, daily returns can exhibit serial and cross-sectional dependence and stationarity of daily variance which influences the variance estimation (Brown & Warner, 1985).
- Event date uncertainty: The identification of the right event date can be difficult due to the appearance of the event of interest in the journal. The observed day can be the day when the news appears in the journal or the day prior to that. We cannot claim which of them is correct with certainty. Therefore, we expand the event window to avoid missing the event.
- Robustness: The formal methodology assumes observed returns to be normally independently and identically distributed. Therefore, for the results to be valid, those assumptions are necessary (MacKinlay, 1997).

4 EMPIRICAL ANALYSIS

The objective of this chapter is to present the observed data, the research objective and the following results. This chapter is organized in the following manner.

First, the research begins with WHO responses to the new COVID-19 pandemic to determine the events employed in the analysis. Furthermore, we describe key areas of interest and research questions. In the following subsection, data sources, used US industry-sorted portfolios and size-sorted portfolios are described, followed by descriptive statistics. The end of this section is concluded with results and their interpretation.

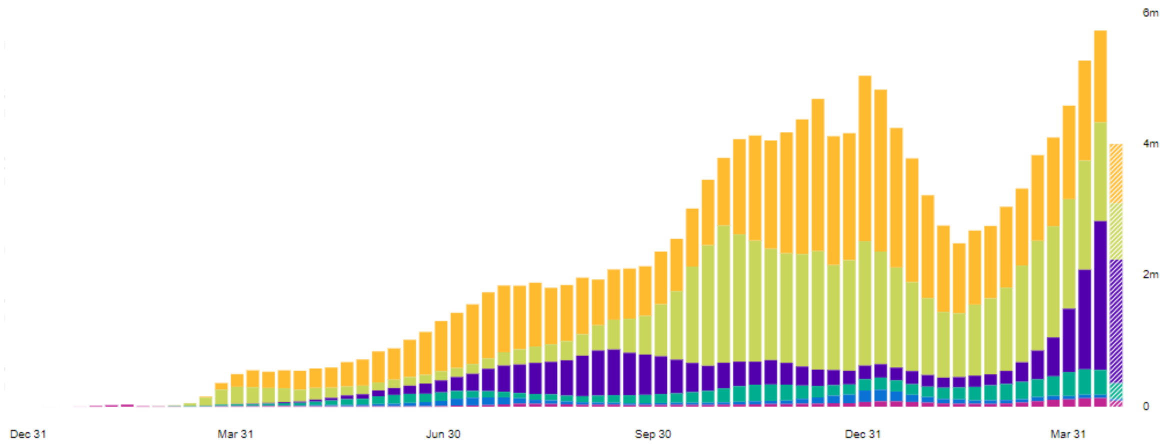
4.1 WHO and Responses to COVID-19 Disease

WHO is an international organisation, active since 1948 and present in 194 countries across six regions, with its headquarters in Switzerland. As a special agency under the United Nations, they endeavour to improve public health and enable people to live better. From the first standardized recommendations on the necessary medications, the organisation provided global standards for air and water. In addition to the recommendations, WHO helped other organisations with providing vaccines and medical supplies. In recent years, their concerns have not been focused on healthy habits like proper meals, exercising or medical check-ups, but mental wellbeing. Since the end of 2019, their main objective concerns the new pandemic (World Health Organization, n.d.).

On the 31st December 2019, WHO publicly issued a statement about new pneumonia for the first time. The latter was observed in a Chinese town, Wuhan. Since then, the organisation updates the number of the infected, the dead and the vaccinated. Additionally, it sends special teams in different countries with cases of COVID-19 to learn more about the new virus and provides recommendations to decrease the number of new cases. Since the first observed case, until the 30th April 2021, there have been 150.110.310 confirmed cases of the infected with the coronavirus with 3.158.792 dead due to the new virus. The concerns around COVID-19 started with the increasing number of newly infected outside China. In this regard, severity increased with a high number of infected cases in Europe, especially in Italy. Figure 8 shows slowly increasing number of COVID-19 infected cases. After Asia, the virus spread towards the west to Europe and after a few weeks to America, Eastern Mediterranean, Africa and Western Pacific. Currently, the most infected regions are America with 61.853.321 confirmed cases and Europe with 51.614.518, respectively (World Health Organization, 2020).

Figure 8: The number of weekly new confirmed cases by WHO Region

The Regions in the figure are observed as follows: yellow- Americas, green- Europe, purple- South-East Asia, light blue- Eastern Mediterranean, Blue – Africa, pink- Western Pacific.

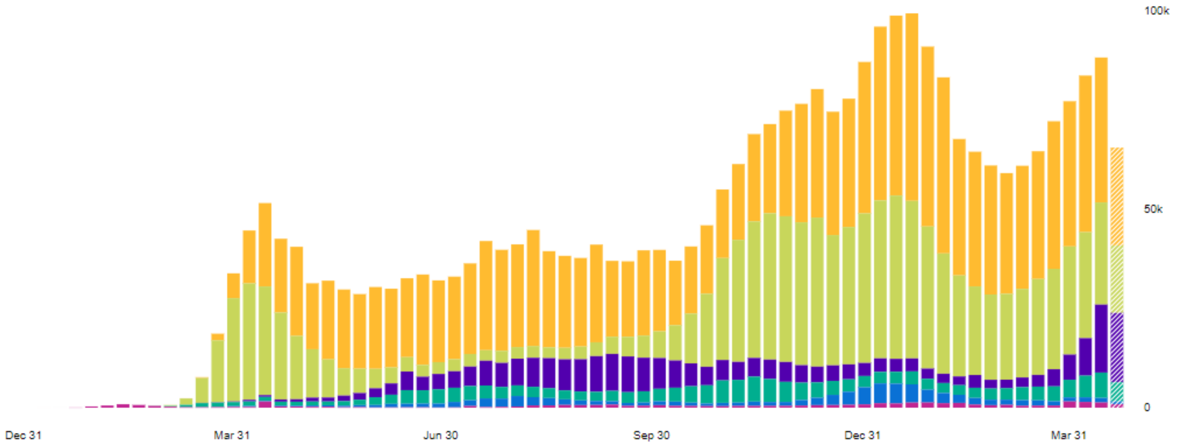


Source: World Health Organisation (2021).

Additionally, Figure 9 gives an overview of the number of deaths due to the coronavirus. Firstly, numbers severely increased in Europe, followed by the United States and other regions. However, at the moment of writing this thesis, the US has recorded the highest number of deaths (1.505.909) by COVID-19. In this regard, our main concern is the stock market in the US. The escalation of the virus forced WHO to declare a world pandemic on the 11th March 2020. Most countries with confirmed cases declared lockdown in the beginning of March to practice social distancing and limit the number of new cases. In December 2020, WHO announced the list of available vaccines and issued a recommendation for suitable vaccinations. Even though the coronavirus pandemic was in the process of discovering the right vaccination, the world was shocked again by the COVID-19 mutations. Until the end of April 2021, some of the most widespread mutations are from United Kingdom, South African Republic, and India (World Health Organization, 2020).

Figure 9: The number of weekly death cases by WHO Region

The Regions in the figure are observed as follows: yellow- Americas, green- Europe, purple- South-East Asia, light blue- Eastern Mediterranean, Blue – Africa, pink- Western Pacific.



Source: World Health Organisation (2021).

4.2 Research Proposal and Limitations

The objective of this part is to introduce the main research questions of the thesis and to provide an insight into market efficiency assumptions in the event study area.

The purpose of the thesis is to quantify how informational efficient are the financial markets in the US. As mentioned above, the US has been among the countries with the most confirmed and death cases (World Health Organization, 2021), the deepest fall in GDP and the highest increase in the unemployment rate. Therefore, our focus in the current thesis is on the US financial market. Nevertheless, WHO news and publications on global health are the most reliable sources of information for media news. The organisation has announced every detail about the coronavirus and provided new information for the financial market. Thus, WHO alerts are used as the exogenous information in the event study methodology to evaluate the economic impact on portfolio returns through the market model. However, for the technical execution of the analysis we use the R program, which includes some limitations. The employment of R package *estudy2* is enabling to observe CAARs only from one event at a time. Meaning, we cannot perform cross-section over events. While we cannot observe multiple events, we perform the event study methodology individually for events within 21 days with no overlapping event period and select the one with the most significant negative abnormal performance, which was the pandemic declaration.

Empirical evidence of the short-term increased volatility by the COVID-19 mentioned in Section 2 are the reason for our interest in market reaction on the employed dataset. We are focused on the speed of reaction and the length of the impact on financial market. Additionally, we are interested in the impact of WHO responses on the selected industries in the US based on the contribution to the country's GDP in the second quarter of 2020 (Aversa, Mataloni, & Pinard, 2020). By following the national data report, political responses to the pandemic and theoretic framework we assume a greater market response in leisure and transport facility sectors. In this regard, we assume a less negative or even positive impact on health care industry. Even though this is a health crisis, households might purchase more medical products and investors might consider this event as a profitable investment. Therefore, positive investor sentiment could increase the future price expectations for the health industry. On the other hand, political restrictive measures (closing nonessential business, closing borders, etc.) have impacted the leisure and transport industries. In this regard, investments in those stocks required higher premiums for additional risk and investors might have expected lower future value due to the escalation and severity of the virus. Both research questions are examined with the even study application on industry and size-sorted portfolio returns, observing the significance of abnormal and cumulative abnormal returns with parametric and non-parametric tests.

We are also interested if the geographic proximity of WHO responses has had an impact on the financial market. Thus, we assume a greater market response to alerts considering the US region and, for the health sector, the announcements from Asia, where the virus originates from, might be significant. Nevertheless, the coronavirus pandemic is first and foremost a health crisis, which also leads to the global economy and social crisis. Since we cannot observe all the events at the same time with the first analysis, we employ the regression analysis with dummy variables for event locations in America, Europe, and Asia. We also focus on the impact of the coronavirus on the size of companies, considering that small agile firms are less stable in exogenous shocks than large robust firms. The literature review on infectious diseases assumes a more negative impact of WHO alerts on small companies rather on large ones. Lastly, we focus on the investor sentiment related to the coronavirus WHO alerts. Behavioural finance finds evidence on negative investor sentiment by exogenous shocks due to recency, irrationality, and risk aversion. Therefore, we analyse the proxy of investor sentiment to observe investor behaviour during the outbreak. In short, the thesis tries to answer the following research questions:

1. Did WHO alerts in response to COVID-19 lead to a short-term negative economic impact around the time of the pandemic declaration on the 11th March 2020?
2. Did WHO alerts about the coronavirus have a longer negative impact on leisure and transport facility industries than on the health care sector in the US? Is the impact on the health care industry positive?

3. Did the geographic proximity of WHO coronavirus announcements affect the industrial sectors in the US?
4. Did WHO alerts in response to the pandemic outbreak have a greater negative impact on small firms than on large firms?
5. Did the market investors experience excessive fear in a short time period (5 trading days) due to WHO alerts in response to COVID-19 (exogenous event)?

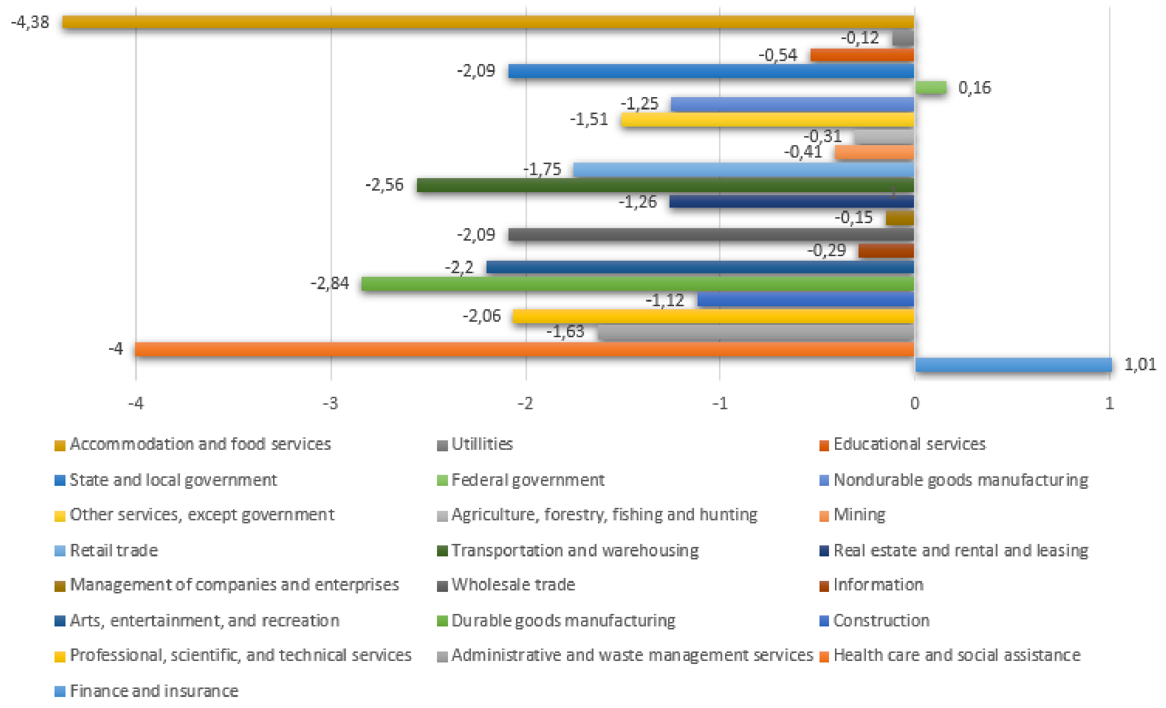
4.3 Data

The preliminary data for event determination is observed on WHO official website. We select WHO responses to the coronavirus in the period between the 31st December 2019 and the 4th April 2020, observing alerts of the first significant infected cases and deaths because of the coronavirus (World Health Organization, n.d.). Appendix 2 contains the list of 20 selected events used in the following analysis in a form of a timeline. Some alerts are followed by specific locations of events, whether they are observed in America, Europe, Africa, Asia or the East. However, the whole dataset of WHO alerts contains information that are irrelevant for our thesis (WHO recommendations for countries, research expeditions in specific regions, etc.). In this regard, we must isolate major events for the US region in the observed period, which have severely changed normal life. The first is the escalation of the virus in America on the 21st January 2020, the second is the political declaration of public health emergency on the 30th January 2020, followed by WHO declaration of the pandemic and the last being the president's declaration of national emergency. For the first part of the analysis, we consider only one announcement, because we would obtain biased results due to overlapping in the case of too many events at the same time. Though for the regression analysis, we select more WHO responses for each region. In this manner, we include 6 additional alerts for Europe and the same number for the American region. All observed responses for Europe and America are present in Appendices 3 and 4. Nevertheless, some of the WHO announcements consider all regions, for example the pandemic declaration, contamination severity and recommendations.

Data for measuring investor sentiment is downloaded from Yahoo Finance (Yahoo Finance, n.d.). Proxies for investor sentiment are considered at around +/- 5 event days to avoid overlapping in the event period. The events are selected by non-overlapping criteria and their contribution to the new health and economic crisis. The event study methodology is also applied to the constructed dataset downloaded from Kenneth R. French's website, where the portfolio returns by different criteria are observed and frequently reconstructed. The securities used in the portfolios are taken from NYSE, AMEX, and NASDAQ stock market (French, n.d.). We observe size-sorted and industry-sorted equally weighted portfolios. Appendix 5 reports all industries in each sector portfolio. Additionally, the analysis takes the market return from the same webpage as the benchmark to be employed in event study methodology.

The US industries have been selected by their negative contribution to the GDP. In Figure 10 all industry groups and their contribution to GDP in the second quarter of 2020 are observed. In the accommodation services and health care sector the GDP decreased for more than 4% from the preceding period, followed by durable goods manufacturing, transportation and warehousing, arts, entertainment, and recreation with more than 2%. Close to a 2% decrease was observed in wholesale trade, professional, scientific, and technical services, and government. Retail trade, real estate, rental and lending, other services and nondurable goods manufacturing recorded approximately 1% drop. The only two sectors that contributed to the increase in GDP are federal government and finance and insurance (Aversa, Mataloni, & Pinard, 2020).

Figure 10: Contributions to percent change in real GDP by US industry group



Source: Aversa, Mataloni & Pinard (2020).

Regarding different industry divisions in the dataset and Figure 10, we use more than one equally-weighted portfolio to observe the same industrial sector. For example, for the health care and social assistance industry, we use health care and medical equipment portfolio in the downloaded data. Overall, we selected 15 different equal-weighted industry portfolios for further analysis. In this regard, Table 2 presents portfolio abbreviations and full industry names. The systematic exclusion of a subset from the overall dataset leads to sample selection bias. In this regard, the estimated parameters in Section 4.4.2 (regression analysis) might be biased.

Table 2: Industry portfolio name

Portfolio abbreviation	Full portfolio name
Fun	Entertainment
Hlth	Healthcare
MedEq	Medical Equipment
FabPr	Fabricated Products
ElcEq	Electrical Equipment
Aero	Aircraft
Ships	Shipbuilding, Railroad Equipment
Telcm	Communications
PerSv	Personal Services
BusSv	Business Services
Trans	Transportation
Whlsl	Wholesale
Meals	Restaurants, Hotels, Motels
RlEst	Real estate
Auto	Automobiles and Trucks

Source: Own work.

The sample consists of 15 industry portfolio returns and 10 size-sorted portfolio returns with 328 observations each. The time frame corresponds to the days between the 26th December 2018 and the 15th April 2020. Table 3 provides an overview of the descriptive statistics of the employed portfolios. The measures of minimum, maximum, mean, median, standard deviation, skewness, kurtosis and sharp ratio are determined for each selected industrial sector. The mean portfolio return is negative or close to zero in all portfolios. The great difference between minimum and maximum returns indicate high volatility in the observed period. All return distributions are highly positively skewed, denoting rather low values. Most of the portfolio returns denote high excess kurtosis, indicating fat distribution tails or more outliers. Additionally, we measure portfolio risk-adjusted returns with the Sharpe ratio. While portfolios are consist of American stocks, the rate of 1-month Treasury bill has been used as the risk-free rate in the Sharp ratio computation. Most of the portfolios report a negative or low Sharp ratio, indicating that the portfolios do not perform well once their risk has been considered.

Table 3: Descriptive statistics of US industry portfolios

Portfolio	Min	Max	Median	Mean	STD	SKEW	KURT	SHARPE
Fun	-19.440	14.810	0.025	-0.046	2.808	-1.408	19.047	-0.1923
Hlth	-16.040	32.220	0.130	0.152	2.804	3.705	55.859	0.0515
MedEq	-10.990	8.120	0.045	0.048	1.836	-0.964	9.386	0.0218
FabPr	-15.320	14.300	-0.070	-0.101	2.521	-0.187	10.068	-0.0432
ElcEq	-13.380	11.420	0.080	0.033	2.123	-1.177	10.961	0.0119
Aero	-14.770	13.000	0.130	0.041	2.561	-0.950	13.678	0.0129
Ships	-13.170	9.510	0.040	-0.118	2.455	-0.722	5.771	-0.0513
Telcm	-11.590	8.630	-0.035	-0.019	1.994	-0.991	11.158	-0.0135
PerSv	-14.770	8.920	0.050	-0.013	2.144	-1.587	15.549	-0.0095
BusSv	-13.590	8.370	0.050	-0.016	1.971	-1.814	15.051	-0.0122
Trans	-11.910	11.850	0.035	-0.048	2.234	-0.900	9.581	-0.025
Whlsl	-11.330	9.130	-0.020	-0.011	1.981	-0.922	11.769	-0.0093
Meals	-19.120	16.760	0.015	-0.036	2.597	-0.503	21.092	-0.0167
RlEst	-14.640	10.520	0.060	-0.007	2.261	-1.407	14.339	-0.0067
Auto	-12.590	10.860	-0,005	0.0004	2.299	-0.7199	8.2417	-0.0032

Source: Own work.

For a better understanding of the size-sorted portfolio returns, we employed the same descriptive statistics for this dataset shown in Table 4. Portfolios of securities are sorted in deciles by their value of capitalization, where deciles are ranked from 1 to 10. Decile 1 presents the smallest 10% of firms in the portfolio and decile 10 presents the largest 10 percent of firms in the portfolio by size.

Table 4: Descriptive statistics of size-sorted portfolios

Portfolio	Min	Max	Median	Mean	STD	SKEW	KURT	SHARPE
Decile 1	-10.490	7.620	0.045	0.042	1.695	-1.529	13.925	0.0200
Decile 2	-13.260	10.680	0.060	-0.009	2.306	-1.053	11.405	-0.0071
Decile 3	-13.950	10.710	0.095	-0.003	2.355	-1.075	12.095	-0.0047
Decile 4	-13.320	10.860	0.095	-0.001	2.271	-0.740	11.337	-0.0039
Decile 5	-13.790	11.810	0.080	0.020	2.252	-0.849	11.966	0.0055
Decile 6	-14.180	11.510	0.130	0.031	2.215	-0.879	12.131	0.0106
Decile 7	-13.120	11.800	0.125	0.027	2.082	-0.857	12.936	0.0091

(table continues)

Table 4: Descriptive statistics of size-sorted portfolios

(continued)

Portfolio	Min	Max	Median	Mean	STD	SKEW	KURT	SHARPE
Decile 8	-12.870	11.870	0.170	0.044	1.997	-0.822	14.376	0.0179
Decile 9	-12.500	11.850	0.150	0.062	1.950	-0.605	14.038	0.0276
Decile 10	-12.350	10.670	0.150	0.068	1.890	-0.642	14.197	0.0318

Source: Own work.

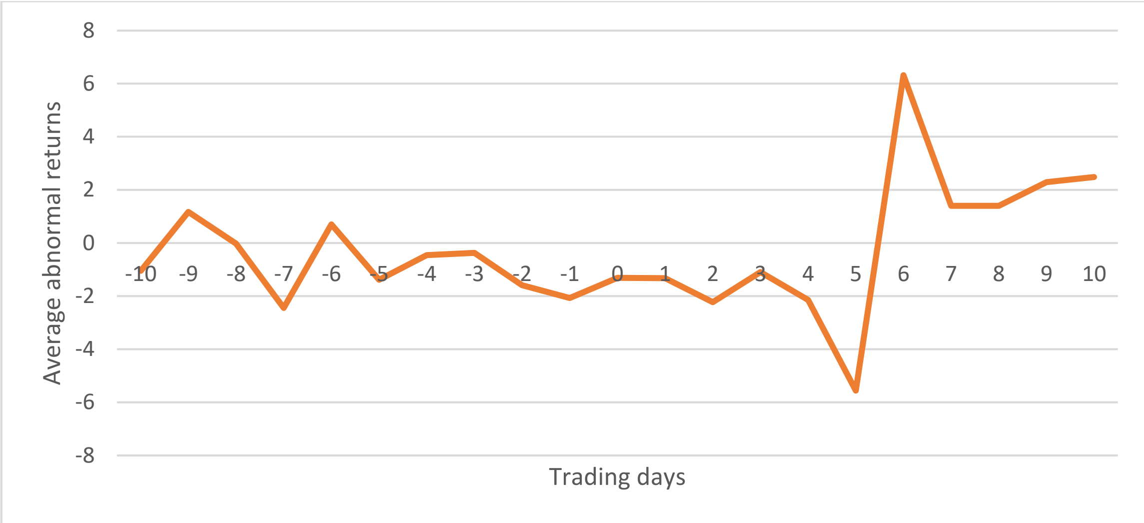
4.4 Results

The following subsection explores the impact of the pandemic related WHO alerts with the event study methodology, described in the previous chapter, on the example of three different datasets. The first two datasets, industry and size-sorted portfolios are united together to perform AARs and CAARs, followed by the results from regression analysis of the same dataset. The investor behaviour proxies are observed independently in the next subsection. The analysis is summarized with the result interpretation.

4.4.1 Event Study Application

We applied the event study methodology with the estimation window of 252 trading days in the selected dataset. The selected timeframe for the estimation window starts on the 2nd January 2019 and ends on the 31st December 2019. The event timeframe starts on the 26th February 2020 and ends on the 25th March 2020 with the global pandemic declaration (the 11th March 2020) as the event day $t = 0$. With the market return model, we estimate parameters for the expected returns and use the difference in observed returns for abnormal performance. With the cross-section of abnormal returns we observe AARs and CAARs, respectively. WHO pandemic declaration as the most significant event in the study was employed to assess a positive or negative impact on portfolio performance. Figure 11 graphically reports abnormal returns cross-sectioned across sectors. The persistence of the event-induced variance is significant, because of the estimated variance of AARs as 5.015 with mean -0.3129. The most negative performance is observed five days after the pandemic declaration and positive the following days, indicating new information. Although graphical reporting of AARs is instructive and suggestive, we support the analysis with statistical tests.

Figure 11: Abnormal performance around the 11th March 2020, [-10, +10]



Source: Own work.

The following Table 5 reports mean values and the estimated parametric and non-parametric significance tests. Large deviations of the AARs from zero indicate abnormal performance. Despite the research limitations, we provide a comprehensive insight regarding the effects of WHO response with three different parametric and two non-parametric tests. The level of significance is denoted by using the asterisk. Nevertheless, the modified rank test by Kolari and Pynnonen (2010) and the generalized sign non-parametric test by Cowan (1992) are used, due to the sensitivity of the parametric tests to extreme outliers. To conclude that the negative AARs may be present, our objective is to reject the null hypothesis of no AARs. Most days in the event period reject the null hypothesis of no abnormal performance. In other words, all significant results in both parametric and non-parametric tests reflect the existence of the negative abnormal performance, indicating high correlation between the coronavirus news and portfolio performance.

Table 5: Abnormal performance parametric and non-parametric tests

Days	Mean	BW_1985	BMP test	Patell Z test	Modified rank	Generalized sign
-10	-1.2504	-2.6271***	-4.1165***	-6.5149***	-1.8514*	-3.2357***
-9	1.2883	2.7067***	3.0914***	5.2249***	1.6735*	3.4812***
-8	0.0514	0.1079	-0.1991	-0.2384	0.0375	0.3813
-7	-3.0324	-6.3710***	-9.0024***	-13.9239***	-2.6562***	-3.7519***
-6	0.7612	1.5993	2.8724**	3.4640***	1.4317	2.4479**
-5	-1.4749	-3.0987***	-5.9647***	-6.9901***	-1.9974**	-2.7186***
-4	-0.6822	-1.4332	-1.8667*	-4.0700***	-0.6171	-0.6519
-3	-0.4270	-0.8971	-1.9401*	-2.1910**	-1.1036	-2.2019**
-2	-1.6831	-3.5361***	-4.1692***	-7.6375***	-2.0098**	-3.2353***
-1	-2.4112	-5.0658***	-5.2928***	-10.4072***	-2.0696**	-3.2353***
0	-1.6403	-3.4462***	-2.9267**	-8.4788***	-1.4830	-1.6852*
1	-1.7582	-3.6939***	-2.5663**	-8.8643***	-1.1745	-2.7186***
2	-2.7562	-5.7910***	-4.1847***	-10.6425***	-1.9835*	-0.6519
3	-1.5620	-3.2816***	-1.7331*	-8.0324***	-0.3377	-2.7186***
4	-3.1338	-6.5839***	-2.9356**	-15.6674***	-1.7903*	-3.7519***
5	-6.5806	-13.8255***	-7.8975***	-30.7673***	-2.8049***	3.9976***
6	6.8019	14.2904***	5.6858***	36.7969***	2.6937***	2.9646***
7	1.4446	3.0351***	2.4654**	7.4364***	1.4942	2.4479**
8	2.0505	4.3079***	3.3111***	9.4679***	1.4830	1.931*
9	3.1803	6.6816***	2.0002*	12.7496***	1.0091	1.4146
10	3.0448	6.3969***	4.0577***	15.9111***	2.1099**	2.9646***

Source: Own work. (*p<0.1, **p<0.05, ***p<0.01)

Figure 12: Cumulative abnormal performance around the 11th March 2020, [-10, +10]

Source: Own work.

The adopted methodology gives an overview of the CAARs in the event period [-10,10] (Figure 12). The observed returns decrease in the period [-5,5] and increase afterwards. The lowest value of CAARs is recorded on the fifth trading day after the 11th March, as previously presented in Figure 11. In this regard, Table 6 reports the CAARs significance, where null hypothesis states that the CAAR is not different from zero. Parametric tests are employed by Brown and Warner (1985) and Lamb. However, the non-parametric test is employed by Cowan (1992). Results are reported at the p-value 0.001 and 0.05, respectively.

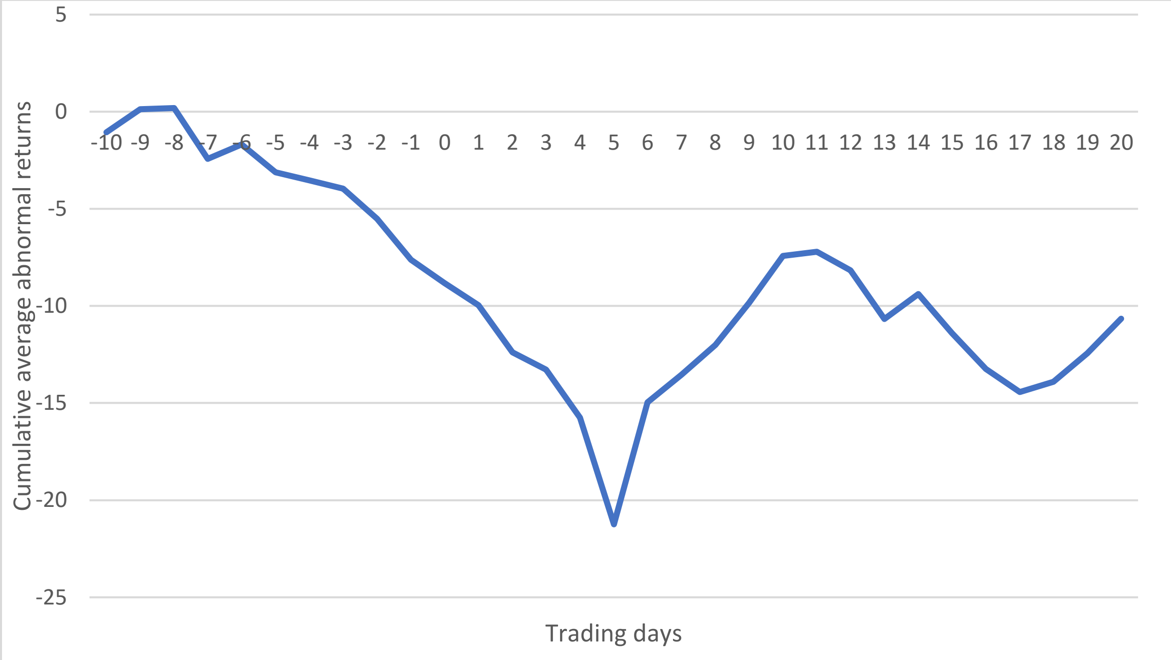
Table 6: CAAR test statistics

Event Window	BW 1985	Lamb test	Cowan test
CAAR [-10, +10]	-4.48***	-3.57***	-2.17***
CAAR [-10, -2]	-4.52***	-4.23***	-2.53**
CAAR [-5, +2]	-9.53***	-8.47***	-4.63***
CAAR [-1, +1]	-7.05***	-6.30***	-2.93***
CAAR [0, +1]	-5.05***	-4.35***	-2.04**
CAAR [0, +5]	-15.0***	-13.1***	-4.07***
CAAR [-5, +5]	**-15.30*** **	**-13.60*** **	**-5.36*** **
CAAR [+5, +10]	**8.596*** **	**8.488*** **	**2.579*** **
CAAR [-10, +20]	**-4.758*** **	**-3.987*** **	**-2.123** **

Source: Own work.

The results indicate an increasing awareness of the consequences following an infectious disease. In this regard, we investigate the economic impact up to 20 days after the pandemic declaration in Figure 13. The event window [-10, +20] yields negative CAARs of 2.123, significant at a 5% level.

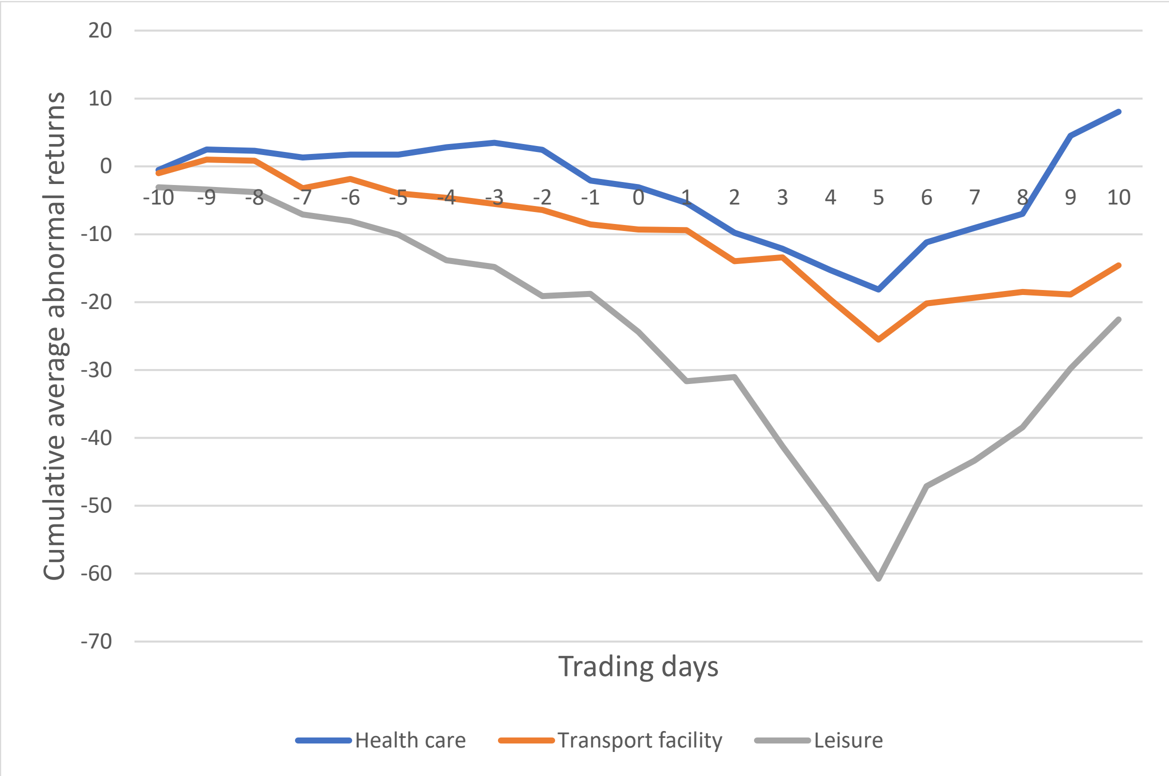
Figure 13: Cumulative abnormal performance around the 11th March 2020, [-10, +20]



Source: Own work.

To answer the question set at the beginning of this section, we observe the event study of specific US industries in connection to the pandemic declaration. Final cumulative abnormal returns of transport facilities, health, and leisure sectors are presented in Figure 14. For the transport facilities, we selected the industry portfolios of aircraft companies, shipbuilding, and car manufacturing. The leisure sector includes entertainment, restaurants, and accommodation portfolios. Lastly, health sector consists of health and medical equipment portfolios. In Figure 14 we observe the excessive negative performance of CAARs in the leisure sector, followed by the transportation facilities. The health sector is the closest to zero value among the selected. Additionally, in the period [-1,8] all the sectors have negative abnormal returns. However, to determine statistically significant results we provide a non-parametric test, following Table 7.

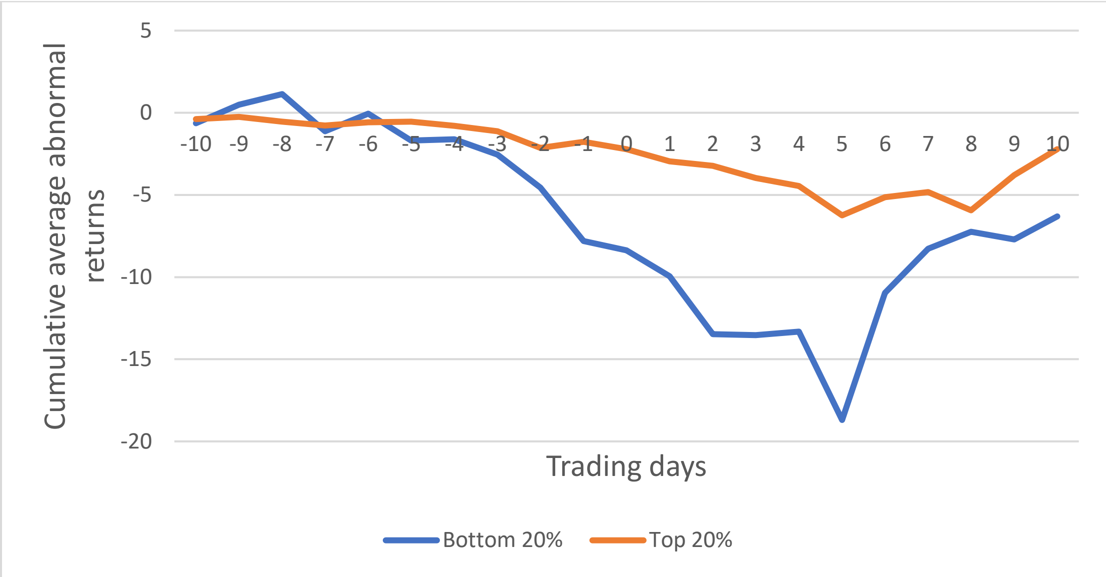
Figure 14: CAARs of health care, transport facility and leisure sector



Source: Own work.

Figure 15 specifically shows the coronavirus impact on 20% of the smallest and 20% of the largest firms by size. In this manner, we observe the discussed methodology on size-sorted portfolios. The bottom 20% of the portfolios with AAR mean of -0.3745 has a variance 5.9614. On the other hand, the top 20% of the portfolios with mean value -0.064 has a variance 0.6777. From Figure 15 we observe the differences in the news impact on both portfolios, proposing a more pronounced event effect for small securities rather than for large securities. Small-sized stocks may experience poor information dissemination in comparison to larger stocks (Tripathi & Pandey, 2021). Additionally, small companies are more influenced by media news. On the other hand, large companies with more employees have better information dissemination and media influence on their stock prices is limited (Ichev & Marinč, 2018). The coronavirus outbreak also influenced large-sized stocks. However, the impact is less severe than on small-sized stocks. For all the selected portfolios, we also performed the non-parametric significance tests by Cowan (1992) in Table 7.

Figure 15: CAARs of smallest and largest portfolios



Source: Own work.

Table 7: Cumulative abnormal performance test statistics for the selected portfolios

Industry	Health	Transport	Leisure	Bottom 20%	Top 20%
CAAR [-10, +10]	-0.8864	-2.324**	-3.141***	-1.143	-2.431**
CAAR [-10, -2]	0.1084	-2.464**	-4.929***	-1.101	-3.051***
CAAR [-5, +2]	**-2.258****	**-3.898*****	**-4.078*****	**-3.807*****	**-2.631****
CAAR [-1, +1]	-2.783***	-1.808*	-2.063***	-2.343**	-1.266
CAAR [0, +1]	-2.014**	-1.177	-3.049***	-1.531	-3.062***
CAAR [0, +5]	-3.919***	-3.260***	-4.317***	-2.224**	-4.368***
CAAR [-5, +5]	**-3.342*****	**-4.520*****	**-5.2618*****	**-4.069*****	**-3.640*****
CAAR [0, +10]	-0.789	-0.700	-0.375	-0.091	-1.433

Source: Own work.

Our results in Figures 14 – 15 and Table 7 indicate significantly negative cumulative average abnormal returns in the observed for leisure and transport facility sectors and both size-sorted portfolios. Among the observed portfolios, health care industry is also negatively affected by the new pandemic, but less than the other portfolios. The potential explanation for the health care industry recovery lies in the increased demand for protective equipment, for example facial masks and disinfectants. The demand for disinfectants soared forcing the manufacturers to increase their production (Evans, 2020). Additionally, the previous pandemics have shown that market participants expect the invention of vaccinations aimed to prevent further spreading of the viruses (Ichev & Marinč, 2018).

The negative effect on the transportation facility and restaurant sectors is consistent with the results by Haroon and Rizvi (2020), who reported higher market volatility caused by the coronavirus panic. Media news contributed to the investment uncertainty and consequently volatility. Together with the pandemic declaration on the 11th March 2020, Donal Trump imposed an entry ban for the citizens of 26 European countries for 30 days. With the travel restriction, the president created more panic and anxiety (Politi & Sevastoputo, 2020). Therefore, new information quickly affected aviation industry and caused a decrease in stock market prices. Carter et. al (2021) explored significant negative abnormal returns on the 16th March 2020, when the European Union closed its borders for the non-citizens. Additionally, our results suggest highly significant negative abnormal returns on the 18th March 2020, which was the day after the Federal Reserve announced financial support for businesses and households through loan moratoria (Federal Reserve System, 2020).

4.4.2 Regression Based Event Study

A multivariate regression model with robust standard errors, corrected for heteroscedasticity, has been used to investigate the relationship of WHO alerts referring to the US, Europe or Asia region and portfolio returns. According to equation (31), the market return variable and dummy variables for the event location are implemented. Additionally, the thesis uses five lagged returns to account for the possible serial correlations as used by Ichev and Marinč (2018).

The regression model is defined as follows:

$$r_{p,t} = \alpha_p + \sum_{j=1}^{5} \gamma_{1,j} r_{i,t-j} + \beta_p r_{m,t} + \sum_{l=1}^{3} \gamma_{2,l} EL_{l,t} + u_p, \quad (32)$$

where $r_{p,t}$ is the rate of return of portfolio i on the day t, α_p is the regression intercept, $r_{i,t-j}$ is the lagged previous-day rate of return, denoting from 1 to 5 days before, $r_{m,t}$ is the market rate of return and $EL_{l,t}$ from 1 to 3 are dummy variables for the locations of events. In this regard, the variable denotes 1 on the event day in a specific region and zero otherwise. The dataset for the regression model consists of 15 industry equal-weighted portfolios from the 3rd January 2019 to the 15th April 2020. Appendix 7 provides the results of the regression model on the size-sorted equal-weighted portfolios.

Table 8: Regression-based event study results

Portfolio	α_i	R_{t-5}	R_{t-4}	R_{t-3}	R_{t-2}	R_{t-1}	β_i	US	ASIA	EUROPE	Adj.R^2
Fun	-0,1070	**-0,1482**	0,0727	-0,0901	-0,0478	**0,2476**	**1,3216**	0,0036	0,3144	-1,1984	0,663
	(-1,138)	(-4,33***)	(0,64)	(-0,82)	(-0,44)	(2,31*)	(11,71***)	(0,01)	(0,69)	(-1,49)	
Hlth	0,0392	-0,1047	-0,0584	0,0743	0,0223	**0,1229**	**1,2719**	0,1639	**0,5369**	-0,2115	0,646
	(0,41)	(-1,46)	(-1,00)	(0,70)	(0,30)	(2,57*)	(5,84***)	(0,55)	(2,09*)	(-0,51)	
MedEq	-0,0668	-0,0873	0,0559	0,0246	**0,1092**	**0,1694**	**0,8499**	0,1454	**0,6284**	0,1960	0,7076
	(-1,20)	(-1,57)	(0,95)	(0,53)	(2,29*)	(3,11**)	(19,28***)	(0,35)	(1,84*)	(0,45)	
FabPr	**-0,1774**	**0,1461**	-0,0750	-0,1090	0,0821	-0,0521	**0,9157**	0,4259	-0,8186	0,065	0,573
	(-2,05*)	(2,25*)	(-1,01)	(-1,72)	(1,09)	(-0,83)	(8,33***)	(0,69)	(-1,54)	(0,06)	
ElcEq	-0,0359	0,0066	0,0350	-0,0269	0,0702	0,0863	**0,9947**	-0,0199	**0,4104**	-0,8322	0,7417
	(-0,59)	(0,10)	(0,54)	(-0,58)	(1,28)	(1,36)	(17,25***)	(-0,06)	(1,71*)	(-1,32)	
Aero	-0,0132	-0,1045	0,1196	-0,0443	-0,0386	**0,2249**	**1,2196**	0,1611	-0,0390	-0,9075	0,6808
	(-0,16)	(-1,39)	(1,42)	(-0,52)	(-0,54)	(3,16**)	(16,85***)	(0,39)	(-0,13)	(-1,34)	
Ships	**-0,1638**	0,0214	-0,0049	**-0,0901**	0,0473	**0,1267**	**1,1139**	-0,2969	0,2526	-0,5254	0,6612
	(-2,11*)	(0,40)	(-0,11)	(-1,85*)	(1,06)	(2,52*)	(23,04***)	(-1,00)	(0,78)	(-1,00)	
Telcm	**-0,0976**	0,0268	-0,0061	-0,0317	**0,0998**	0,0265	**0,9319**	-0,0205	**0,527**	-0,3734	0,783
	(-1,89*)	(0,43)	(-0,10)	(-0,71)	(2,37*)	(0,49)	(18,87***)	(-0,07)	(1,78*)	(-0,88)	
PerSv	-0,0724	0,0241	-0,0094	-0,0907	**0,1295**	0,0562	**0,9884**	0,1570	0,4039	-0,6656	0,7674
	(-1,25)	(0,37)	(-0,15)	(-1,33)	(2,26*)	(0,80)	(17,97***)	(0,40)	(1,31)	(-1,33)	
BusSv	**-0,0918**	0,0068	0,0713	-0,0682	0,0692	**0,1270**	**1,0274**	0,2153	0,1372	-0,2424	0,8668
	(-2,31*)	(0,12)	(1,45)	(-1,14)	(1,72)	(2,40*)	(29,64***)	(0,84)	(0,80)	(-0,74)	
Trans	-0,0936	0,0365	-0,0014	**-0,1344**	-0,0074	**0,0944**	**1,1120**	-0,1698	0,2552	**-0,9605**	0,8001
	(-1,70)	(0,75)	(-0,03)	(-3,02**)	(-0,18)	(2,66**)	(23,80***)	(-0,48)	(0,89)	(-2,00*)	
Whlsl	-0,0821	0,0093	0,0558	**-0,0937**	0,0251	0,0925	**1,0035**	0,2087	0,0753	-0,2751	0,7989
	(-1,68)	(0,15)	(1,12)	(-1,85*)	(0,63)	(1,50)	(24,91***)	(0,65)	(0,29)	(-0,63)	
Meals	-0,1108	-0,1349	0,0355	-0,0816	0,0482	**0,2123**	**1,2107**	-0,0514	0,2826	-0,3763	0,6761
	(-1,35)	(-1,49)	(0,36)	(-0,62)	(0,55)	(2,38*)	(10,36***)	(-0,12)	(0,83)	(-0,61)	
RlEst	-0,0531	0,0109	0,0662	-0,1061	0,0621	0,0785	**1,0963**	-0,3230	0,3664	-0,6073	0,768
	(-0,87)	(0,16)	(1,04)	(-1,59)	(1,21)	(1,02)	(21,40***)	(-0,95)	(1,44)	(-0,96)	
Auto	-0,0784	-0,0205	0,0827	-0,0533	-0,0098	**0,1385**	**1,1059**	0,1005	0,3004	-0,4739	0,7097
	(-1,13)	(-0,42)	(1,45)	(-0,89)	(-0,20)	(2,48*)	(21,10***)	(0,26)	(1,05)	(-0,86)	

Source: Own work. (*p<0.1, **p<0.05, ***p<0.01)

Table 8 gives an overview of the estimated coefficients and adjusted coefficients of determination for each portfolio. The reported coefficients are tested for significance by applying the Student's t-test statistics in comparison to the null hypothesis which states that estimated coefficient is not statistically different from zero. Significance at 10%, 5% and 1% levels are indicated by *, **, ***, respectively.

As far as the industrial sector portfolio is concerned, regression results show quite a good performance for transport and business service portfolios with high adjusted R^2 (around 0.80). The results for fabric products show a relatively poor performance with a lower adjusted R^2. We graphically confirm residual distribution for each model and perform Breusch-Pagan test (1979) for heteroskedasticity and Durbin-Watson test (1971) for serial autocorrelation in residuals. Considering the performance of the tests, we use heteroskedastic robust standard errors. Additionally, F-statistic testing for joint significance of all regressors rejects the null hypothesis. In other words, the hypothesis rejects the claim that the estimated coefficients are equal to zero, thus supporting the validity of the model.

Regarding the results from Table 8, β_i coefficient corresponds to the impact of the market return. The coefficient is positive and statistically significant throughout all portfolios. This implies that the market returns are positively related to the dynamics of the underlying equal-weighted portfolios. The serial correlation coefficient for lag 1, as significantly positive, corresponds to the entertainment, health care, medical equipment, aircraft industry, shipbuilding, business services, transport, accommodation, and car portfolios. The second serial correlation coefficient for lag 2 is positive and significant for medical equipment, telecommunication, and personal services portfolios. The third lagged coefficient concerning shipbuilding, transport and wholesale portfolios is negative and significant. Lastly, the serial correlation coefficient for lag 5 corresponds to the entertainment and fabric products portfolios significantly. The event effect coefficients (corresponding to the event locations: US, Asia and Europe) are significant only for Asia and Europe and even as such noticeable only in a few portfolios. The ASIA coefficient corresponds to the impact of WHO alerts related to the coronavirus originating from Asia, regarding China, Japan, and Taiwan. The coefficient is positive and statistically significant throughout health care, medical equipment, electronic equipment, and telecommunication portfolios. The EUROPE coefficient corresponds to the coronavirus news impact on the European continent. The coefficient is negative and significant for the transport portfolio. Estimated coefficients confirm our expectations, revealing evidence for industry and geographic proximity effect. However, the negative EUROPE coefficient for transport portfolio may be a consequence of Donald Trump's travel ban for the citizens of 26 European countries, declared on the same day as the global pandemic announcement by WHO. The positive effect of Asia-related news regarding the portfolios mentioned above is assumed to be due to increased demand for health care and preventive equipment. Because of the stay-at-home orders, a lot of people worked from home, consequently the demand for computers and other communication devices increased.

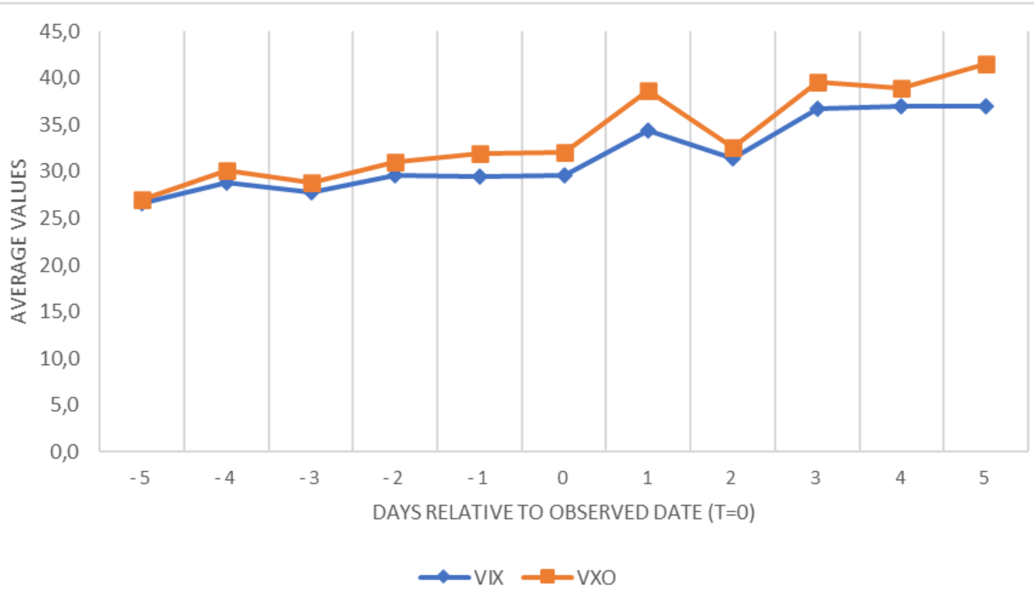
4.4.3 Event Study Application on VIX and VXO Indices

For the investor sentiment proxy, we use implied volatility indices as proposed by Baker and Wurgler (2007). With the event study we test how the coronavirus WHO alerts affect the implied volatility of VIX and VXO indices. We include the following five non-overlapping events from the end of 2019 to April 2020:

- December 31st, 2019 – the first report of WHO on mysterious viral pneumonia in Wuhan, China.
- January 15th, 2020– the first confirmed coronavirus case outside China; in Japan.
- February 21st, 2020 – the first confirmed case of infection with the coronavirus in the US
- March 11th, 2020 – global pandemic announcement by WHO
- April 2nd, 2020 – WHO confirmed virus transmission from person to person before developing symptoms

Furthermore, for the event period, we use -/+ 5 days around the event day and observe the average values of both indices by averaging them across the events. However, for the application, we do not observe the return values before the event period, nor the estimation window. Figure 16 shows the aggregated volatility surrounding the coronavirus alerts. The impact is strong on the event day and is persistent in the following days as well. Table 9 reports the results of the matched pair t-test which measures the significance of volatility pattern by VIX and VXO. In this regard, we compare the average value indices with values before the pandemic outbreak.

Figure 16: VIX and VXO indices average values



Source: Own work.

Table 9: Matched pair t-test for VIX and VXO

Index	Test statistic	p-value
VIX	16.153	$p < 0.0001$
VXO	15.730	$p < 0.0001$

Source: Own work.

The results in Table 9 and Figure 16 indicate a rapid increase in the implied volatility, regarding the negative investor sentiment by the coronavirus outbreak. The results are consistent with Schwert (2003) and Ichev and Marinč (2018) who analysed the impact of the Ebola outbreak on investor mood. However, the increased market volatility may be due to other variables as health and economic world crisis induced by the new pandemic.

4.5 Discussion

Overall, the results obtained in this empirical analysis allow us to make the following conclusions in an attempt to answer the research questions of interest. Working within the scope of the defined methodology by MacKinlay (1997), which was employed for this analysis, we can discuss our research questions in the following subsections.

4.5.1 WHO Alerts and Financial Market

This thesis observes that the overall cumulative average abnormal returns are negative prior and up to ten days after the pandemic declaration. To increase the power of the parametric tests we employ non-parametric tests. A significant negative impact is observed in the period [-5, +5]. The reason for a strong effect of the pandemic on the stock market is the disease severity, quick escalation, and high mortality rate (Baker, et al., 2020). On the 5^{th} day we separately observe the event and perform the event study with the event day on the 18^{th} March 2020 ($t = 0$), where CAAR [0,0] event window yields negative CAAR of 2.84 at 1% level. On the 17^{th} March 2020, the Federal Reserve publicly announced financial help for the population and the next day the European Central Bank announced a massive quantitative easing to mitigate the negative pandemic consequences. The positive CAAR in the event window [+5, +10] might be a result of the investor perception by regulators' financial support and the anticipation of the new information in the set.

The present study is not equipped with the right tools to understand the reasons behind the investor reactions, it can only speculate on possible explanations regarding behavioural finance. Overall, the results indicate biases related to the representativeness issues, pointing to recency. In other words, representativeness means that, in decision-making, investors are too influenced by the latest information in the set and recency specifically implies the importance of recent information. Regarding all information on COVID-19, available in a short period of time, might have had an impact on investors' information processing, implying a confirmation bias. This means that once an investor has some information, he forms his opinion and gathers new information that confirms his opinion (Ackert & Deaves, 2010). Nevertheless, all portfolios yield negative excess returns over the predicted returns. Since we excluded some important events in the proximity and ignored different types of investors, the thesis results are limited.

The results of the event study application on the selected portfolios with the employed CAAR non-parametric test, suggest a significant negative impact on leisure and transport facility industries. The health industry portfolio doesn't confirm positive excess return in the observed period, which is consistent with research by Yunpeng, Qun, & Zhou (2021). Selected industry portfolios have a significantly negative impact on the pandemic declaration. As such, the research question (2) might also get an affirmative reply. However, health industry portfolio does not observe a positive impact in this period. In order to investigate the medical portfolio in detail, with longer time frame we might observe the expected results.

The estimation of the regression model allows drawing the following conclusions. Regressing the industry portfolio returns relating to ASIA, US and EUROPE dependent variables leads to different results depending on the type of the industrial sector. On the one hand, positive significant coefficients of ASIA in health care and medical equipment sectors suggest a positive correlation between portfolio returns and WHO news related to the Asia outbreak, while no other portfolios in the dataset are associated with ASIA news. On the contrary, coefficients for the European outbreak news are negative but not significant. Only the transport industry portfolio is negatively associated with Europe-related WHO news. However, the remaining US coefficient is not significant in any of the portfolios. Because the event location coefficients are significant only in a few industry portfolios, we cannot identify the clear relationship between the portfolios and WHO announcements in the selected sample. Regarding some significant evidence, the research question (3) is neither accepted nor rejected.

The application of the event study methodology indicates that the coronavirus news impact is greater for small companies, rather than large firms. This relatively obvious conclusion was already anticipated by Figure 15, which observes the cumulative average abnormal returns. However, the significance test might be questionable, causing us to doubt whether we adopted the right test or observed a sample too small, in an attempt to get better statistic results. On the other hand, with the regression analysis in Appendix 7 we also observe the impact of the geographic proximity of the coronavirus on the size-sorted portfolios. Despite insignificant results, the coefficients for European event locations are highly negatively associated with firms in the first two deciles. As such, the corresponding values increase with the size of the portfolios. Both adopted methods suggest a negative impact on all portfolio sizes. In this regard, it is not possible to answer the research question (4).

4.5.2 WHO Alerts and Investor Sentiment

The event study methodology with the application of VIX and VXO indices observes investor mood surrounding the coronavirus WHO news related to the event days. A statistically significant increase in volatility on the event day and the persistence in the following days has been observed from the results in Section 4.4.3. Since our research question (5) refers to the short-term impact, we might consider an affirmative answer to it, however the persistence might be longer.

CONCLUSION

The COVID-19 global pandemic with its unprecedented shock has led to one of the worst health and economic crises in modern history. With the restrictive measures taken by the governments to prevent further spreading of the virus, the world economy has experienced a significant economy halt and slow recovery. The restrictive measures focusing on social distancing, prevent normal business operations in some non-essential industries. Because of those measures, the world GDP has fallen and the unemployment rate has increased.

However, the restrictive measures have not only effected macroeconomic indicators but also investor perception of future valuations. People have lost their jobs all of a sudden, they have had to stay at home or work from home. The severity of the virus was underestimated when the cases were present only in China. When Italy and Iran experienced a major outbreak, the uncertainty, anxiety and panic increased along with the governmental restrictive measures. The number of the infected and the dead because of the new virus increased trading volatility on financial market and caused a sudden drop in prices.

While WHO declared the coronavirus pandemic, the US president Donal Trump closed the border for the citizens of 26 European countries. On the other hand, the governments tried to mitigate the negative restrictive measures with monetary and fiscal stimulus, in order to recover investors' trust. Additionally, WHO tried to gather all information about the symptoms and new cases to develop recommendations for the affected countries. The situation in the financial market had stabilized until the second wave in the fall of 2020. Nevertheless, the uncertainty remained because there was still no available vaccine. At the end of 2020, the first vaccinations against the coronavirus were approved by WHO and the age groups most at risk, started receiving the vaccinations. Nevertheless, the uncertainty has increased because of the coronavirus mutations at the beginning of 2021.

This study focuses on the impact of the coronavirus on the financial markets in the US, because it is the country with the highest number of infected cases, it has the highest drop in GPD and the highest increase in unemployment rate, manly in the industry and the size-sorted equal-weighted portfolios, and additionally two fear indices from the end of 2019 to April 2020. We employ the traditionally-based event study methodology, which serves as the basis for measuring the semi-strong EMH. The hypothesis assumes immediate adoption of all relevant information in security prices, thus considering no existence of abnormal performance.

In this study, we investigate the impact of WHO alerts with the event study methodology by MacKinlay (1997). Using the R software program, we first prepared the events of interest for each type of the analysis, as well as the datasets with the total sample including 20 WHO responses, connected to different event locations. For detailed investigation of WHO responses in the US and Europe, where there was the highest number of the infected and the dead by the end of April 2021, we added 6 more WHO alerts for each geographic region. Datasets examine US industry equally-weighted portfolios, size-sorted equally-weighted portfolios and market portfolios by Kenneth R. French website. The VIX and VXO indices were observed from Yahoo Finance.

Despite some research limitations, the empirical results in the first part suggest that WHO responses to the coronavirus negatively impacted the financial market in the US. All tests for CAARs were confirmed at a 1% significance level, leading to the negative CAAR in all event periods. However, CAARs [+5, +10] indicate anticipation of new information. A detailed analysis of the industrial sector revealed a significant negative impact on the leisure, transport, and health care sectors. Furthermore, we adopted the methodology on size-sorted portfolios to observe the impact on small and large-size firms. The results suggest a more negative effect of the coronavirus outbreak for small-sized firms.

Regression analysis for assessing the impact of geographic proximity of WHO alerts was carried out using OLS with robust HC standard errors. In general, the estimated regression coefficients are not statistically significant. On the other hand, the Asian geographic region was positively significant in a few sectors and the European region was negatively associated with the transport industry. Therefore, we cannot confirm the impact of the event locations of WHO alerts on the financial market. We also analysed the investor sentiment by observing fear indices around the event day. Our results provide evidence of rapid increase in implied volatility by WHO responses, suggesting that the investor mood is induced by the COVID-19 outbreak events.

Nevertheless, in the first months of the coronavirus outbreak there were also government restrictive measures alongside WHO news. As such, they might have affected our results, while we tried to avoid event overlapping. Therefore, it is difficult to conclude whether the impact is due only to WHO alerts on the coronavirus. Regarding future research, we recommend carrying out a similar analysis with a greater sample, focusing also on other economies. As such, the investigation of events related to the invention of the first vaccination against the coronavirus and the appearance of new mutations might be intuitive, because new versions of the coronavirus inevitably increase uncertainty. Nevertheless, fear of the new vaccines is increasing, because some of them do not prevent from becoming infected with the new mutations. This research could enable further analysis on the impact of the coronavirus outbreak on the financial markets.

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APPENDICES

Appendix 1: Povzetek (Summary in Slovene Language)

Svetovna pandemija COVID-19 je v začetku leta 2020 pretresla svet in postala povod za največjo zdravstveno, socialno in ekonomsko krizo v moderni dobi. Svetovni voditelji so zaradi vse večjega števila okuženih in umrlih sprejeli preventivne ukrepe, ki niso bili ugodni za gospodarstvo. Posledice ukrepov so bile razvidne v makroekonomskih indikatorjih, predvsem v nižjem bruto domačem proizvodu in rasti stopnje brezposelnosti v začetku leta 2020. Nenaden padec cen na finančnem trgu pa je bil povod za analizo vpliva dogodkov, ki so bili povezani s pandemijo. Zaradi narave krize smo opazovali odzive Svetovne zdravstvene organizacije (WHO), ki je bila v pandemiji ključni vir javno dostopnih informacij.

Empirični del naloge raziskuje vpliv informacij o pandemiji COVID-19 na finančni trg v Združenih državah Amerike. Raziskovalna naloga je opravljena znotraj okvirja, ki je definiran na podlagi obstoječih metod, ki raziskujejo učinkovitost trga. Uporabljena je bila študija dogodkov (angl. event study methodology), ki je bila izpeljana v začetku leta 1970. Analiza v prvem delu vzame v obzir razglasitev svetovne pandemije 11.3.2020 kot dogodek, okoli katerega je postavljena raziskava in razišče njegov vpliv na donose opazovanih portfeljev, ter na racionalno obnašanje investitorjev. V drugem delu pa se osredotoči na izbrane objave zdravstvene organizacije od konca leta 2019, do začetka aprila 2020 z namenom raziskovanja geografske bližine informacij, ki so povezane s korona virusom. Za raziskavo uporabi regresijsko funkcijo, s katero razišče povezanost posameznih portfeljev z izvorom informacij. Rezultati kažejo, da ima razglasitev pandemije pričakovano negativen učinek na finančni trg v Združenih državah Amerike. Najbolj negativni donosi so opazni predvsem v turizmu in sektorju prevoznih sredstev. Kljub majhnemu vzorcu smo zaznali, da so manjša podjetja bolj negativno občutila vpliv informacij o pandemiji kot večja. Z implementacijo analize na indeksu nestanovitnosti smo opazili negotovost in strah s strani investitorjev. Regresijska analiza zaradi pristranskosti pri izbiri vzorca ni zaznala vpliva geografske bližine informacij na donose portfeljev.

Appendix 2 : Disease-related news

The table shows the descriptions of important events observed from December 2019 to April 2020 during the COVID-19 outbreak. Events reported by WHO are sorted by date and event location.

Date	Event location	Short description of the news
December 31st, 2019	Asia	WHO country office reported on cases of a mysterious pneumonia which went viral in Wuhan, China.
January 5th, 2020	Asia	Issue of the first global media news about the disease outbreak by WHO with public health recommendations.
January 11th, 2020	Asia	The novel coronavirus caused its first death.
January 13th, 2020	Asia	The new virus was confirmed in Thailand (outside China)
January 14th, 2020		WHO found no evidence of human-to-human transmission.
January 15th, 2020	Asia	The new virus was confirmed in Japan.
January 19th, 2020		WHO analysis confirmed limited transmission of the virus from human to human.
January 21st, 2020	America	The fist confirmed case of the coronavirus in the US
January 24th, 2020	Europe	The first confirmed cases in France, Europe.
January 29th, 2020	East	The first confirmed case in the United Arab Emirates.
February 11th, 2020		WHO named the novel coronavirus as COVID-19.
February 14th, 2020	Africa	The first confirmed case of infection in Africa.
February 21st, 2020	Europe	The first confirmed case of the coronavirus in Israel.
February 24th 2020	East	Major coronavirus outbreak in Iran.
February 25th, 2020	Africa	The second confirmed case on the African continent.
February 27th, 2020		WHO published recommendations on the use of the protective equipment.
March 9th, 2020		World Bank responded with an 8-billion-dollar financial injection.
March 11th, 2020		WHO declared COVID-19 as a global pandemic. Cases of new virus in Europe stared increasing exponentially.
April 2nd, 2020		Virus transmission from person to person before the infected shows symptoms.
April 4th, 2020		WHO reported more than 1 million confirmed cases of the coronavirus globally.

Source: World Health Organization (2020).

Appendix 3: Disease-related WHO responses on the European outbreak

The table shows the descriptions of important events observed from December 2019 to April 2020 during the COVID-19 outbreak, regarding the European region. Events reported by WHO are sorted by date.

Date	**Short description of the news**
January 24th, 2020	The first three confirmed cases of the new virus in France.
January 31st, 2020	The first cases of the coronavirus in Italy.
February 4th, 2020	The first cases of the coronavirus in Belgium.
February 14th, 2020	WHO recommendations for the ministers of health on quarantine.
February 22nd, 2020	Major coronavirus outbreak in Lombardy, Italy.
February 27th, 2020	The first cases of the coronavirus in Denmark, Estonia, Georgia, Greece, Norway, the Republic of North Macedonia, and Romania.
March 5th. 2020	The first cases of coronavirus in Hungary and Liechtenstein.
March 11th, 2020	WHO announced the coronavirus pandemic.
March 18th, 2020	WHO started the Solidarity Trial in the European region.

Source: WHO (2021).

Appendix 4: Disease-related WHO responses on America's outbreak

The table shows the descriptions of important events observed from December 2019 to April 2020 during the COVID-19 outbreak, regarding the American region. Events reported by WHO are sorted by date.

Date	Short description of the news
January 16th, 2020	Issued recommendations for international travellers, as well as the infection prevention and restriction measures.
January 20th, 2020	14 infected countries reported in the American region. 6 confirmed cases in the United States.
January 25th, 2020	The first confirmed case in Canada.
February 7th, 2020	WHO reports an increasing number of the coronavirus cases in South America. Issuance of recommendations in response to the epidemic.
February 14th, 2020	Recommendations for using PPE.
February 26th, 2020	The first confirmed case in Brazil.
February 28th, 2020	The first confirmed case in Mexico.
March 11th, 2020	WHO announced the coronavirus pandemic.

Source: PAHO/WHO (n.d.).

Appendix 5: US industries selected in the portfolios

US Industry portfolio	Industries	
Fun / Entertainment	Services - motion picture production and distribution Services - motion picture theatres Services - video rental Services - amusement and recreation Services - Misc entertainment	Services - dance studios Services - bands, entertainers Services - bowling centres Services - professional sports Amusement and recreation services
Hlth / Healthcare	Services – health	
MedEq / Medical Equipment	X-ray, electromedical app Surgical, medical, and dental instruments and supplies	Ophthalmic goods
FabPr / Fabricated Products	Fabricated metal, except machinery and trans eq Fabricated plate work Sheet metal work	Metal forgings and stampings Coating, engraving and allied services
ElcEq / Electrical Equipment	Electronic & other electrical equipment Electric transmission and distribution equipment Electrical industrial apparatus Electrical industrial apparatus Electric lighting & wiring equipment Residential electric lighting fixtures Misc electrical machinery, equipment and supplies	Commercial, industrial and institutional electric lighting fixtures Misc lighting equipment Communications equipment Misc electrical machinery and equipment Storage batteries
Aero / Aircraft	Aircraft & parts Aircraft Aircraft engines & engine parts	Aircraft parts Misc aircraft parts & auxiliary equipment
Ships / Shipbuilding, Railroad Equipment	Ship building and repairing	Railroad Equipment
Telcm / Communication	Communications Telephone communications Telegraph and other message communication Radio & TV broadcasters Cable and other pay TV services Communications	Communication services (Comsat) Cable TV operators Telephone interconnect Misc communication services

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PerSv / Personal Services	Rooming and boarding houses Camps and recreational vehicle parks Services - personal Services - laundry, cleaning & garment services Services - diaper service Services - coin-operated cleaners, dry cleaners Services - carpet & upholstery cleaning Services - Misc laundry & garment services Services - photographic studios, portrait Services - Electrical repair shops Services - Radio and TV repair shops Services - Refrigeration and air conditioning service & repair shops Services - Electrical & electronic repair shops Services - Watch, clock and jewelry repair Services - Reupholster & furniture repair Services - Misc repair shops & related services Services - legal Services - educational Services - social services	Services - beauty shops Services - barber shops Services - shoe repair shops & shoeshine parlours Services - funeral service & crematories Services – Misc Services - tax return Services - Misc Services - photofinishing labs (School pictures) Services - auto repair, services & parking Services - automobile parking Services - automotive repair shops Services - automotive services, except repair (car washes) Services - Misc repair services Services - museums, art galleries, botanical and zoological gardens Services - membership organizations Services - private households Services - truck & auto rental and leasing
Meals / Restaurants, Hotels, Motels	Retail - eating places Restaurants, hotels, motels Eating and drinking places Hotels & other lodging places	Hotels & motels Membership hotels and lodging houses Services - linen supply
RlEst / Real Estate	Real estate Real estate operators and lessors Operators - non-resident buildings Operators - apartment buildings Operators - other than apartment Operators - residential mobile home Lessors of railroad & real property	Real estate dealers Title abstract offices Land subdividers & developers Real estate Combined real estate, insurance, etc Real estate agents and managers

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BusSv / Business Services	Commercial printing Signs & advertising specialties Services - industrial launderers Services - business services Services - advertising Services - consumer credit reporting agencies, collection services Services - mailing, reproduction, commercial art & photography Services - services to dwellings & other buildings Services - building cleaning & maintenance Services - Misc equipment rental and leasing Services - medical equipment rental and leasing Services - heavy construction equipment rental and leasing Services - equipment rental and leasing Services - personnel supply services Services - computer processing, data preparation and processing Services - computer facilities management service Services - computer rental and leasing Services - computer maintenance and repair Services - computer related services Services - Misc business services Services - security Services - news syndicates Services - photofinishing labs	Services - telephone interconnect systems Services - Misc business services Services - R&D labs Services - management consulting & P.R. Services - detective and protective (ADT) Services - equipment rental & leasing Services - trading stamp services Services - commercial testing labs Services - business services Services - utility trailer & recreational vehicle rental Services - engineering, accounting, research, management Services - engineering, accounting, surveying Services - accounting, auditing, bookkeeping Services - research, development, testing labs Services - management, public relations, consulting Services - Misc Services - Misc engineering & architect Services - Misc Public warehousing and storage
Whlsl / Wholesale	Wholesale - durable goods	Wholesale - nondurable goods
Autos / Automobiles and Trucks	Tire cord and fabric Automotive trimmings, apparel findings & related products Tires and inner tubes Industrial trucks, tractors, trailers & stackers Vehicular lighting equipment Electrical equipment for internal combustion engines Transportation equipment	Motor vehicle parts & accessories Truck trailers Motor homes Travel trailers and campers Misc transportation equipment Misc transportation equipment Motor vehicles & passenger car bodies Truck & bus bodies Motor vehicles and motor vehicle equipment

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Trans / Transportation	Railroads, line-haul operating Railway express service Local & suburban transit & interurban highway passenger transportation Local & suburban passenger transportation Taxicabs Intercity & rural bus transportation (Greyhound) Bus charter service School buses Motor vehicle terminals & service facilities Misc transit and passenger transportation Trucking & warehousing Trucking & courier services, except air Terminal & joint terminal maintenance	Transportation services Freight forwarding Arrangement of passenger transportation Arrangement of transportation of freight and cargo Rental of railroad cars Misc services incidental to transportation Inspection and weighing services Packing and crating Misc fixed facilities for vehicles Motor vehicle inspection Misc transportation services Transportation Water transport Air transportation Pipelines, except natural gas

Source: French (n.d.).

Appendix 6: Technology setup

To conduct an empirical analysis according to the previously discussed methodology we need an efficient, open-source, commercial, powerful, and user-friendly programming language. Additionally, we need a language with easily accessible and well-written packages for the tasks we require. The R programming statistical language meets all of the requirements. R is a software for statistical computing, providing different statistical methods and allows the implementation of different packages, based on S language (R Core Team, 2021). Computations which are commonly used are linear and nonlinear model building, data analysis, quantitative analysis, and results interpretation with different tools. Rizzo (2019) describes R environment as a system of languages with a runtime environment and graphics, an access to system specific functions, and the ability to store written programs in files. Additionally, the software includes a help system, connected to a comprehensive documentation of packages.

RStudio open-source integrated development environment is a system for an easier interaction with R including a console window, a code editor with a direct support, a graph window and an environment window (RStuido, n.d.). With the RStudio it is easier to run data science experiments, as it allows researchers to write and execute the code simultaneously. Additionally, once the code is written, the user can easily create a so-called package and share it with others by uploading it into the editor console object. However, the RStudio provides a payable version; a licence for organizations with the additional support system.

Since we have already discussed the benefits of using the R programming language for the purpose of the event study application, we can turn our attention to the analysis set-up using the RStudio. Therefore, the main packages we use throughout the empirical part for the event study and the regression application are *estudy2, lmtest, PerformanceAnalytics* and *quantmood*.

The first package provides a convenient way to implement an event study methodology and the corresponding parametric and non-parametric tests. In addition to three different expected return models, with the sophisticated test statistics allows the examination of a the cross-sectional AR and event induced variance (Rudnytskyi, 2020). *Lmtest* is a core package for modelling linear regression models which features various statistical algorithms. It enables an examination of heteroskedasticity, autocorrelation and other biases (Hothorn & Zeileis, 2020). A prime package for econometric modelling with stock returns is *PerformanceAnalytics*. It enables risk analysis of returns with performance indicators (Sharp ratio, Treynor ratio, et.) and other models to perform efficient portfolios (Peterson, 2020). A quantitative modelling framework for easier performance of quantitative analysis is *quantmod* package. It provides data from different sources and is useful for development of statistically-based trading models and data visualization (Ryan, 2020).

For the first section of the event study application, we employ a *estudy2* package on a dataset and perform different parametric and non-parametric tests. In the second stage we use the following two packages *lmtest* and *PerformanceAnalytics* for the regression model. Finally, in the last section we use *quantmod* for the sentiment examination. However, for the employment of the analysis, other less important packages were used, such as *readxsl* for the dataset import. Graphic interpretation has been performed in Excel.

Appendix 7: Regression model on size-sorted portfolios

Portfolio	α_i	R_{t-5}	R_{t-4}	R_{t-3}	R_{t-2}	R_{t-1}	β_i	US	ASIA	EUROPE	Adj.R^2
Decile 1	-0.0384	-0.0431	0.0450	-0.0106	**0.1081**	**0.1806**	**0.8051**	0.1695	0.2243	-0.3671	0.7618
	(-0.84)	(-0.53)	(0.70)	(-0.19)	(1.95*)	(2.54*)	(18.26***)	(0.55)	(0.77)	(-0.88)	
Decile 2	-0.0804	0.0116	0.0362	-0.0792	0.0705	0.0324	**1.1215**	-0.0125	0.2139	-0.4908	0.8082
	(-1.41)	(0.19)	(0.68)	(-1.60)	(1.71)	(0.51)	(25.14***)	(-0.04)	(0.94)	(-1.09)	
Decile 3	-0.0793	0.0019	0.0570	-0.0919	0.0341	0.0446	**1.1896**	-0.0084	0.1598	-0.3703	0.8328
	(-1.45)	(0.03)	(1.03)	(1.78)	(0.81)	(0.74)	(26.39***)	(-0.03)	(0.78)	(-0.90)	
Decile 4	-0.0767	-0.0061	0.0407	-0.0915	0.0018	0.0327	**1.1646**	-0.1062	0.2438	-0.3190	0.8427
	(-1.51)	(-0.12)	(0.77)	(-1.59)	(0.04)	(0.57)	(28.49***)	(-0.36)	(1.18)	(-0.84)	
Decile 5	-0.0590	-0.0019	0.0202	-0.0863	0.0299	0.0550	**1.1761**	-0.0898	0.0962	-0.1119	0.8787
	(-1.33)	(-0.04)	(0.42)	(-1.69)	(0.84)	(1.21)	(30.10***)	(-0.38)	(0.51)	(-0.35)	
Decile 6	-0.0449	-0.0007	0.0100	-0.0828	0.0305	**0.0503**	**1.1712**	-0.0799	0.0895	-0.1496	0.9076
	(-1.19)	(-0.02)	(0.23)	(-1.78)	(0.90)	(1.27*)	(37.83***)	(-0.36)	(0.52)	(-0.50)	
Decile 7	-0.0492	0.0009	0.0248	**-0.0709**	-0.0017	**0.0955**	**1.1330**	0.0047	0.1114	-0.2169	0.9244
	(-1.55)	(0.03)	(0.59)	(-1.72*)	(-0.05)	(2.69**)	(34.09***)	(0.02)	(0.71)	(-0.71)	
Decile 8	-0.0306	-0.0263	0.0054	-0.0620	0.0084	**0.0995**	**1.1047**	-0.0511	0.1052	-0.0941	0.9521
	(-1.22)	(-0.96)	(0.16)	(-1.89)	(0.30)	(3.56***)	(36.22***)	(-0.35)	(0.84)	(-0.41)	
Decile 9	-0.0163	0.0166	-0.0023	**-0.0574**	0.0066	**0.0589**	**1.0739**	-0.0101	0.0790	0.0100	0.9722
	(-0.87)	(0.79)	(-0.10)	(-2.79**)	(0.28)	(2.83**)	(44.70***)	(-0.09)	(0.88)	(0.06)	
Decile 10	-0.0039	0.0081	-0.0232	-0.0215	0.0011	**0.0437**	**1.0447**	0.0178	-0.0116	-0.0649	0.9883
	(-0.32)	(0.49)	(-1.81)	(-1.54)	(0.10)	(2.52*)	(70.61***)	(0.25)	(-0.23)	(-0.75)	

Source: Own work. (*p<0.1, **p<0.05, ***p<0.01)