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The impact of the COVID-19 crisis on companies' market valuations

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Abstract

This thesis focuses on the impact of the COVID-19 crisis on companies' market valuations, both geographically, across industries, and at the firm-level. The period December 31, 2019 - May 31, 2020, referred to as the 'outbreak period', and November 1, 2020 - January 31, 2021, referred to as the 'recovery period', are investigated. The universe consists of companies from the S&P 500 representing the United States; the FTSE 100 representing the United Kingdom; and the FTSE China A 200 index representing China. First, the event study methodology is employed with three event dates associated with the COVID-19 crisis, namely WHO's declaration of Public Health Emergency of International Concern (PHEIC) on January 30, 2020; WHO's declaration of a pandemic on March 11, 2020; and Pfizer-BioNTech's announcement on November 9, 2020, indicating vaccine efficacy above 90%. The results concerning the PHEIC announcement are mixed and not significant when considering cumulative average abnormal returns (CAAR), and it can be concluded that despite the WHO's alarming message indicating a possible global outbreak of the virus, the investigated equity markets do not seem to incorporate the news. In contrast, the CAARs during the pandemic announcement are nearly all negative and significant for different event windows. The entire sample shows a negative return for -1.494% in event window [-1,1] and becomes more pronounced once the event window lengthens, i.e., event window [-5,30] shows a negative return of -7.104%. However, in terms of geographical differences, the sample companies representing China proved to be more resilient to negative abnormal returns than the US and UK companies. As for the Pfizer-BioNTech's announcement, a positive and significant CAAR of 0.936% was found during event window [-1,1]. Second, the panel regression analysis revealed that on average, an increase in the number of COVID-19 cases leads to a decline in market valuations. The stringency index, which represents the containment and closure measures introduced in a country in response to COVID-19, indicates that there may be a pinpoint in the degree of stringency at which the market assesses the introduced policies by a government as "too restrictive" for business operations, which in turn negatively impacts stock returns. By examining pre-COVID firm characteristics, this research found that companies with a larger market capitalization, were less leveraged, had more cash reserves, and were more profitable pre-2020, experienced better stock price reactions during the outbreak period. The recovery period shows similar results, apart from firm size being insignificant and leverage being significant and positive. Finally, while there are various industries in China who show positive returns during the outbreak period, nearly all industries in the UK and US show negative returns. During the recovery period, almost all industries partially, and in some cases completely, recovered from the effects of the pandemic during the outbreak period.

KEY WORDS: COVID-19; PHEIC; pandemic; Pfizer-BioNTech; market valuations; corporate characteristics; financial impact; event study; panel regression analysis

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1. Introduction

COVID-19 has been spreading since late December 2019, where the virus was first detected in Wuhan, Hubei Province of China. On January 13, 2020, the first case of the virus was reported outside of China, in Thailand. Shortly thereafter, on January 30, 2020, the World Health Organisation (WHO) declared the coronavirus as a Public Health Emergency of International Concern (PHEIC), as cases reported in China increased dramatically and the disease spread worldwide. WHO's situation report of January 30, 2020, reported 7,818 confirmed cases worldwide, with the majority in China, and 82 cases in 18 other countries (WHO, 2020). The rapid increase in the number of cases outside of China and the alarming levels of inaction led WHO to announce on March 11, 2020, that the outbreak could be classified as a 'pandemic'. At the time of the pandemic announcement, the virus had resulted to over 100,000 confirmed cases and 4,000 deaths worldwide, covering 110 countries and territories (WHO, 2020). This timeline illustrates the rapid whirlwind that COVID-19 has caused globally in terms of confirmed cases and deaths. In doing so, the virus has not only led to a health crisis, but also has an ongoing impact economically. According to the Organization for Economic Co-operation and Development (OECD), the global real GDP growth witnessed a sharp decline of 4.2% in 2020 (OECD, 2020). Furthermore, COVID-19 caused one of the worst stock market crashes in history, with the Dow Jones Industrial Average and S&P 500 dropping more than 20% in a matter of days in March 2020.

One of the first empirical studies to estimate the impact of the COVID-19 pandemic on market valuations was done by Ngwakwe (2020). The author concludes that the virus had severe impact on global stock markets, by investigating the Shanghai Composite index (China), the Euronext 100 (Europe) and the Dow Jones and S&P 500 (United States), within the early months of the outbreak. While the Shanghai composite index showed to be resilient and experienced significant gain in stock values during the first 50 days into the pandemic, the Dow Jones and Euronext showed significant losses. Research by Khan et al. (2020) also found that the Shanghai Composite Index, which was severely affected at first, showed a recovery over the long event window. The authors conclude that these results can be attributed to the effective measures taken by the Chinese government to contain the spread of the virus, which helped to regain investors' confidence in the stock market. It follows that China ultimately proved to be the safest and most profitable investment destination in the early stages of the pandemic.

In terms of financial impact across industries as a result of the COVID-19 outbreak, Mazur et al. (2020) investigated the U.S. stock market and found that industries such as healthcare, food, and software sectors performed abnormally well generating high returns, while firms operating in real estate, hospitality, and entertainment sectors plummeted. Shen et al. (2020) provide similar evidence by examining Chinese companies from a corporate performance perspective, that being net profit margin on total assets (NROA). Their evidence suggests that industries such as tourism, catering, and transportation experienced a sharp decline in NROA in the first quarter of 2020 due to limitations in production, operation, and sales of these industries. Mazur, Dang and Vega (2020) also concluded that COVID-19 represents a revenue shock to the majority of industries. They argue that the stock market crash in March 2020, by examining the S&P 1500 index, did not occur due to weak economic fundamentals, but because of suppressed consumer spending. Consequently, firms revised downwards their earnings prospects, which led to a reassessment of firm values by the market and a large drop in stock prices. Finally, several studies have analysed the relationship between firm characteristics and COVID-19. Results indicate that firms with stronger financial conditions, that is, more cash, less total debt, and larger profits pre-COVID, experienced better stock price reactions to the virus outbreak than otherwise similar firms. In particular, the importance of liquidity is emphasized, suggesting that firms with sufficient cash and those supported by monetary and governmental interventions are more likely to weather the demanding period of the pandemic, which in turn derives positive market valuation (Ding et al., 2021; OECD, 2020; Ramelli and Wagner, 2020). Regarding leverage and profits, Song et al. (2021) found 'contradictory' evidence, namely a positive and negative moderating effect of leverage and ROA (profits) on stock returns, respectively. However, the authors only investigated the U.S. restaurant industry, while research by Ding et al. (2021) and Ramelli and Wagner (2020) studied the relationship between COVID-19 and firm-level characteristics by assessing global equity markets across the spectrum.

Following existing literature, the purpose of this research is to investigate the impact of COVID-19 on companies' market valuations geographically, across industries, and at firm-level. While most existing literature focuses on the period December 2019 – March 2020, during which major regional stock markets plunged after the first wave of the outbreak, this research will contribute by dividing the impact of COVID-19 in various waves more concretely. This means that the period December 31, 2019 - May 31, 2020, referred to as the 'outbreak period', and November 1, 2020 - January 31, 2021, referred to as the 'recovery period', are investigated, during which several global stock markets fully recovered and even reached all-time highs. The empirical evidence from this study may be used as supportive evidence concerning the decision-making process of shareholders and potential new investors in case of the ongoing COVID-19 pandemic or other unexpected crises to come. The research question that follows from the objective of this study and which will be structurally answered is the following:

What is the impact of COVID-19 on the market valuations of companies since the onset of the pandemic, both geographically and at the industry-level, and does this effect differ between companies with different characteristics?

To provide an overall assessment of market valuations during different stages of the ongoing crisis, the total data span covers August 2019 through January 2021. An event study and a panel regression analysis were conducted using a dataset consisting of nearly 600 publicly listed firms across 3 countries, namely the US, UK, and China. The event study methodology assesses the change (impact) on market valuations around several key developments (events) of interest, and the panel regression analysis studies the time-varying relationship between stock returns and various variables during the previously defined outbreak and recovery period.

The remainder of this study is organized as follow. Chapter 2 provides the theoretical framework followed by an overview of related previous literature regarding: preceding viruses, the impact of COVID-19 on equity markets, the connection between COVID-19 and firm-level characteristics, and finally the 'V-shaped' recovery of stock markets globally since the major crash occurred in the first quarter of 2020. Following the literature review, Chapter 3 outlines how the research methodology is designed and conducted and what data is necessary in order to answer the main research question and provide evidence for the hypotheses of this study. Chapter 4 discusses the empirical analysis, that is, the results and robustness following the event study methodology and panel regression analysis. Finally, Chapter 5 concludes this study by relating the retrieved empirical evidence to the hypotheses of this research and in turn answering the main research question. In addition, Chapter 5 also discusses the limitations of this study, and recommends ideas for further research.

2. Literature review

This thesis is related to the rapidly growing literature on the impact of COVID-19 on the market valuations of companies since the onset of the pandemic. Firstly, the theoretical framework for this topic is derived from the efficient market hypothesis, which implies that capital markets fully and correctly reflect all relevant and available information in determining security prices (Malkiel & Fama, 1970). This research assumes that markets are at least *semi-strong* efficient (the premise), which is necessary in order to perform the event study methodology (Chapter 3) and to capture potential abnormal returns which will immediately be reflected by the event of interest. The semi-strong form of the efficient market hypothesis implies that an investor is not able to structurally earn abnormal returns with information that is provided publicly. Hence, in light of this research, it is expected that there will be a strong relationship between the spread of the COVID-19 pandemic and market valuations during the outbreak period and the recovery period. These periods will be further defined in section 2.5.

Secondly, the theoretical framework is derived from the Modigliani-Miller (M&M) theorem. According to M&M, a firm's financial decision-making does not affect its value. In their initial theorem the authors explain that with well-functioning markets, the market value of a company depends only on the income stream which is generated by its assets and is thus independent of its financial structure (Modigliani and Miller, 1958). Their initial theorem assumed a scenario in which there are no corporate taxes, no bankruptcy cost, no transactions costs, no asymmetric information, and no agency costs. Their paper of 1958 provided insight into a company's capital structure and financing methods with the persuasion that "everything is irrelevant", to precisely identify those factors that are important and relevant in the real-world (Ahmeti & Prenaj, 2015). Subsequently, in order to better reflect real-world conditions, the authors developed a correction to their initial theorem in which they assumed corporate taxes. In this 'corrected' paper the authors conclude that the value of a levered company is greater than the value of an unlevered company due to tax deductibility of interest expense (Modigliani and Miller, 1963). This deductibility positively affects the cashflows of a company, and since the value of the company is determined by its cashflows, the value of a levered company increases. Furthermore, according to Gifford (1998), not only taxes, but all the assumptions of M&M's original theorem reflect a 'controlled' environment, which cannot be observed anywhere in the real world. This frictionless world imagined by M&M is a popular discussion in the field of academics, where researchers are constantly raising the question of how market imperfections affect the value of a company. These imperfections arise not only due to taxes, but also due to managerial self-interest (agency costs), insider's knowledge (information asymmetries), the possibility of bankruptcy (financial distress) and other transaction costs.

In light of this research, taking into account corporate taxes (M&M's corrected theorem), market imperfections due to bankruptcies, transactions, asymmetric information and agency problems, it is assumed that a firms' financial condition (especially pre-pandemic), i.e., cash position, profitability and leverage, will ultimately affect its valuation. Financially flexible firms are expected to weather a period of market collapse caused by COVID-19 better, compared to firms with poor financials (e.g., highly levered companies) which will likely become financially distressed. The definition of financial flexibility is adopted from Fahlenbrach et al. (2020) and refers to the ease with which a firm can fund a cash flow shortfall. A firm that has the highest level of financial flexibility has no difficulty in funding a cash flow shortfall, and a firm is considered more financially flexible if it holds more cash and has less leverage. Thus, if shareholders and investors are somewhat optimistic about the future situation of a firm due to its financial flexibility, the firms' stock return may fall less in response to COVID-19, compared to firms having poor financial conditions. Kahle and Stultz (2013) also showed the importance of financial characteristics of a firm by examining the financial crisis of 2007-2008. They found that the financial structure played an important role in self-financing when cash flows deteriorate due to a crisis.

2.1 Historical evidence

As of September 2021, more than a year and a half after the first case of COVID-19 was detected, the virus has led to more than 200 million confirmed cases and over 4.5 million deaths worldwide (WHO, 2021). The pandemic has not only led to a worldwide health crisis, it also completely disrupted the global economy. In the first two quarters of 2020 the global GDP was 10% lower than at the end of 2019. Resulting policy measures by several countries somewhat cushioned this drop, however according to the OECD Economic Outlook, the global real GDP growth still witnessed a sharp decline of 4.2% in 2020 compared to 2019 (OECD, 2020). According to IMF's Global Financial Stability Report of April 2020, the pandemic triggered the fastest drop of the S&P 500 since the Great Depression of the 1930's. In March 2020, it took the S&P 500 only 16 trading days to drop 20% from its record high reached on February 19, 2020. As COVID-19 spread globally, risky assets and commodities began to fall with unprecedented speed, while the prices of 'safe-haven' assets (e.g., gold and US treasuries) gained, led by investors reassessing the economic impact of the sudden crisis and rushing for safety and liquidity (IMF, 2020).

One of the first empirical studies to estimate the differential effect of the COVID-19 pandemic on market valuations was done by Ngwakwe (2020). The author compares COVID-19 to the 'Black Swan Theory', developed by Taleb (2007). The Black Swan Theory implies a sudden unexpected event, a black swan, that negatively or positively affects the stock market and commercial activities. This theory, to which the author rightly refers, therefore perfectly fits the sudden emergence of the virus in China, which completely overwhelmed the entire global economy given its unique nature. Similar preceding black swans (viruses) have mixed results regarding their effect on equity markets. This includes the disease Severe Acute Respiratory Syndrome (SARS) between 2002-2004. The results on whether or not SARS has had an effect on equity markets remain inconclusive, at least looking from a global perspective. For example, Chen et al. (2018) found that SARS weakened stock markets in the Asian region and concluded that stockholders and policy makers should be concerned about the influence of epidemic diseases on the financial integration of the stock market in Asia. However, Nippani and Washer (2004) who investigated the effect of SARS on 8 countries' stock markets, found no results which suggested a significant effect on the countries' stock markets, except for China and Vietnam. Other researchers have looked at the impact of the outbreak of the Ebola epidemic in Africa (2013-2016) on financial markets from the behavioral finance[1] perspective. Ichev and Marinč (2018) explain that the negative returns in financial markets as a result of Ebola were due to media coverage, which enhanced overall anxiety and pessimism among investors. They find that the geographic proximity of the information to the financial markets increases the importance of the Ebola outbreak and its impact on companies' stock returns. Furthermore, the authors conclude that the Ebola media coverage more pronouncedly affected the stocks of West African Community regions (the epicenter of Ebola) compared to U.S stock markets, which were lightly affected. Their study provided evidence that the closer the media coverage is to the centre of disease occurrence and to stock markets, the more likely the media coverage on the disease will affect the stock market.

An 'epidemic' is defined as the occurrence of cases of an illness in a community or region. In turn, a 'pandemic' emerges when the epidemic spreads over a very wide area, crossing international boundaries and usually affecting a large number of people (Porta, 2014). Although the distinction between an epidemic and pandemic is often blurred in terms of a widely accepted quantitative threshold (Singer et al., 2021), the Centers for Disease Control and Prevention (CDC), the national public health agency of the United States, states that pandemics occur when new influenza viruses emerge that are able to infect people easily and spread from person to person in an efficient and sustained way (CDC, 2020). Moreover, it is clear to say that COVID-19, compared to previous (recent) viruses such as Ebola and SARS, is present on a much larger scale in terms of number of countries, confirmed cases and deaths. This in turn resulted in the closure of boarders, lockdowns, and overall disrupted global supply chains. The COVID-19 outbreak was declared as a Public Health Emergency of International Concern (PHEIC)[2] on January 30, 2020. And unlike a PHEIC, a pandemic is not a defined declaration, and countries have not agreed to take any actions once it is used. This is also reflected in the decision by WHO's Director-

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[1] Behavioral finance theory implies that investor sentiment affects investment decisions and may therefore affect stock pricing. The theory supports that investors are irrational due to the fact that they tend to have psychological and emotional biases, such as overconfidence and overreaction, which lead to this irrationality (Ritter, 2003).

[2] The WHO defines a PHEIC as the following: an event that constitutes to a public health risk to other States through the international spread of disease; and that potentially requires a coordinated international response. The latter implying a situation that: is serious, unusual, or unexpected; carries implications for public health beyond the affected State's national border; and may require immediate international action (WHO, 2005).

General Ghebreyesus, who stated that the decision to classify COVID-19 as a pandemic, as was done on March 11, 2020, was not easy, but resulted from the increasing levels of spread and severity, and by the alarming levels of inaction (WHO, 2020).

The existing literature often includes the comparison between the economic impact of COVID-19 to prior virus outbreaks such as SARS or Ebola, as discussed in the beginning of this section. For instance, the viruses (SARS and COVID-19) are, despite sharing similarities from a medical perspective (both are caused by coronavirus infections), very different. First, by the end of June 2003, SARS had resulted in 8,422 cases and was active in 29 territories, with more than 90% of the cases reported in Asia (WHO, 2003). In contrast, as of September 2021, COVID-19 has led to more than 200 million confirmed cases, is currently active in 223 countries and territories, and is defined by the WHO as the first pandemic caused by a coronavirus (WHO, 2021). Secondly, it took approximately 8 months (November 2002 - July 2003) to bring SARS under control, while COVID-19 is still ongoing as of September 2021 since its first occurrence in December 2019. In addition, as mentioned by Ngwakwe (2020), the stock market and the economic effect of the coronavirus pose bigger threat to stock markets than past epidemics such as the SARS virus, in part because China has grown economically stronger than it was 17 years ago. While the economy of China represented only 4% of the global GDP in 2003, it now accounts for more than 16% of the global economy (MSCI, 2020). Therefore, the author argues that there is more cause for concern when such an economic giant falls sick to a pandemic such as COVID-19. Notwithstanding the fact that developed equity markets today are much more exposed to China and economies have become more intertwined than they were 17 years ago, leaving room for so called 'spillover' effects.

2.2 Early effect of COVID-19 on equity markets

The pronounced effect in the early stage of COVID-19 on equity markets is shown by existing literature, and the results provide compelling evidence that China was more resilient than other financial markets, at least within the early months of the virus outbreak. Ngwakewe (2020) investigated the early impact of COVID-19, that is, 50 days before and 50 days within the pandemic. The author investigated three regional stock markets - China, Europe and the United States with data from their indexes, namely the Shanghai Composite index, the Euronext 100, the DJIA and S&P 500. The author found that the Shanghai composite index showed to be resilient and experienced significant gain in stock values during the first 50 days into the pandemic, whereas the DJIA showed significant losses. The difference in stock values during the pandemic for Euronext 100 and the S&P 500 were not statistically significant, but their mean stock index values showed a reduction in value during the first 50 days. Research by Khan et al. (2020) also found evidence that the Shanghai Composite Index, which was severely affected at first after the announcement of human transmissibility, showed a recovery over the long event window. The authors conclude that these results can be attributed to the effective measures taken by the Chinese government to contain the spread of the virus, which in turn helped to regain the investors' confidence in the stock market. The findings of both papers show stock market participants that China was a safer and more profitable investment destination in the first months of the pandemic.

Mazur et al. (2020) concluded that COVID-19 represents a revenue shock to the majority of industries. They applied the event study methodology in which they assessed the worst daily drops of most global markets by reviewing the following event dates: Black Monday I (9 March, 2020), Black Thursday (12 March, 2020) and Black Monday II (16 March, 2020). They argue that the stock market crash in March 2020, by examining the S&P 1500 index, did not occur due to weak economic fundamentals, but due to suppressed consumer spending. Consequently, firms revised downwards their earnings prospects, which in turn led to a reassessment of firm values by the market and a large drop in stock prices. Industries such as healthcare, food and software sectors performed abnormally well generating high returns, while firms operating in real estate and entertainment sectors plummeted; losing more than 70% of their market capitalizations. Mazur et al. (2020) explain that many sectors are in a position of strength during this crash and that despite this, their values collapse. They continue that a theoretic underpinning for these findings possibly rest on the theory of economic relationships between linked firms, meaning that a 'shock' to one firm affects all associated partners. This shock is between customers and suppliers (Cohen and Frazzini, 2008). Therefore, even for unrelated industries, a revenue shock to one firm may have a negative impact on the revenues of all economically related firms.

2.3 Connection between firm-level characteristics

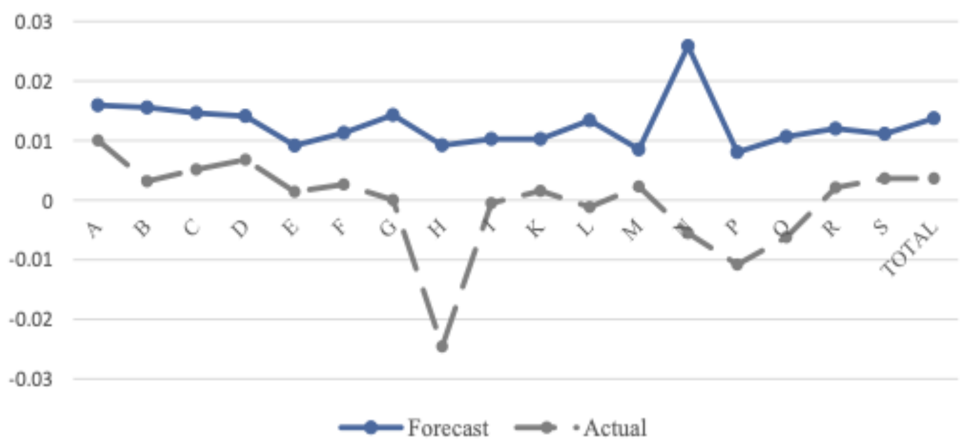
The theoretical underpinning in the aforementioned study by Mazur et al. (2020) is supported by work of Ding et al. (2021), who evaluated the connection between corporate characteristics and the reaction of stock returns to COVID-19 cases using data on more than 6,700 firms across 61 economies. Following a regression analysis, they find that the induced drop in stock prices is larger among firms that are more exposed to the COVID-19 pandemic through their supply chains and customer locations. Furthermore, they conclude that firms with stronger pre-2020 financial conditions, that is, more cash, more unused lines of credit, less total and short-term debt, and larger profits, experienced better stock price reactions to COVID-19 than otherwise similar firms. This is in line with evidence of Ramelli and Wagner (2020), who conclude that investors (and analysts) became concerned about high corporate debt and about the survival chances of firms with little cash as the disease spread. They continue to explain that while cash holdings are expensive for companies in general (i.e., opportunity costs, and because of the potential for agency problems), the emergence of the pandemic highlighted the importance of precautionary cash holdings for firm value.

A study by the OECD (2020) also amplifies the importance of strong financial conditions of a firm pre-COVID, as well as policy interventions. Their key findings imply that without any policy intervention, 20% of the firms in their sample (974,944 unique firms) would run out of liquidity after one month, 30% after two months and 38% after three months. Furthermore, they show that after two months of government interventions, the percentage of illiquid firms would decrease from 30% to 10% compared to the non-policy scenario. Measures to support corporate liquidity include, aside from monetary measures taken by central banks, fiscal interventions such as tax deferrals, wage subsidies, debt moratoria and extension of state loan guarantees. Overall, the stated research suggests that firms with strong financial conditions prior to COVID-19, and those supported by monetary and governmental interventions, are prone to tolerate the demanding period of the pandemic more effectively, which in turn derives positive market valuation.

The aforementioned studies are partially in line with empirical evidence by Song et al. (2021) who examined the effect of COVID-19 on U.S. restaurant firms' stock returns. They studied the relationship between stock returns and pre-pandemic characteristics of firms by employing three firm-level dimensions, i.e., financial conditions, corporate strategies, and ownership structure. Following the financial conditions dimension, they found that restaurant firms with characteristics of larger size and more cash flows, positively affect market valuations. In contrast to the empirical evidence of Ding et al. (2021), they found a positive and negative moderating effect of leverage and ROA on stock returns, respectively. A possible explanation for this contradictory 'leverage-effect' according to the authors, is that when the magnitude of a crisis is unprecedentedly overwhelming like COVID-19, the degree of overall financial distress may have become extremely severe for every restaurant company. Thus, the financial distress caused by a firm's leverage becomes proportionally very marginalized, whereas the tax benefits from leverage (tax shield) still exists. This leverage is possibly seen as extra value for shareholders and investors, which in turn alleviates stock declines. However, this contradictory leverage effect is considered temporary, that is, only under the COVID-19 shock. The actual negative financial impact due to leverage may be yet to come once the situation normalizes to pre-COVID levels and policy support and creditor flexibility disappear. In that case, firms will need to meet their obligations without 'benefiting' from the current relaxations resulting from COVID-19. The authors continue that a possible explanation for their second intriguing finding, referring to a higher ROA pre-pandemic aggravating stock declines, is the gap between pre-pandemic and post-pandemic profitability. They state that from the perspective of shareholders and investors, the impact of COVID-19 shock on future financial performance of a firm may be greater for a firm that was more profitable than its competitors prior to COVID-19. Moreover, in a scenario where unprecedented revenue shortfalls caused by COVID-19 persists, the operations of all restaurant firms will stay stagnant. In that case, the gap between pre- and post-pandemic profitability can be greater for a firm that used to be profitable right before the pandemic, resulting in an even greater decline in that company's stock return.

Among one of the first empirical evidences on the link between the pandemic and firm performance was provided by Shen et al. (2020), who investigated the impact of the COVID-19 crisis on the firm-level performance of listed Chinese companies. They performed a regression analysis and used a Difference-in-Difference model to quantify the impact along high and low affected industries, with NROA 'net profit margin on total assets' representing the company's performance. Financial data of listed Chinese companies from 2013 to 2019 were used to predict corporate performance in t + 1 period (i.e., 2014-2020). From this, they selected data for the first quarter of 2014 to 2020 as the research sample to examine the impact on corporate performance. As shown by the figure below, they found that the COVID-19 outbreak had a significant negative impact on the performance (NROA) of listed Chinese companies through a decrease in investment scales and total revenue. They found an average value for NROA of 0.008, indicating overall profitability is not high or that these companies are on the edge of profitability.

Figure 1. *Forecast and actual value of industry performance in 2020 Q1* [3]



Source: (Shen et al., 2020)

Especially industries such as tourism, catering, and transportation, experienced a sharp decline in corporate performance in the first quarter of 2020, which is reflected in the negative return rate. Furthermore, this negative impact is much more pronounced in high-affected areas, as strict quarantine measures limit consumptions and productions.

[3] The letters represent industry codes; the worst performing industry is that of accommodation and catering (H). The full list of industry codes is provided in the paper.

2.4 V-shaped trajectory

Lastly, to conclude this literature review, it is of importance to shed light on the recovery of COVID-19, as this study will cover both the outbreak period and the 'V-shaped' recovery of financial markets since late March 2020. IMF's Global Financial Stability Report (GFSR) of June 2020 explained that there is a 'disconnect' between rising market valuations and the evolution of the economy, meaning that there is a divergence between the rebound in equity markets after the drop in March 2020 and the steep decline in global economic activity. In the report it is stated that the disconnect was mainly driven due to policy support by central banks and the easing of related lockdown measures which supported the financial condition of firms and boosted overall market sentiment (IMF, 2020). Furthermore, the GFSR of October 2020 suggests that there is a notable differentiation in equity market recovery across countries since the collapse in March 2020 (IMF, 2020). This differentiation is driven by the spread of the virus, the scope of policy support, and sectoral composition. As of October 2020, the stock markets of China and the US showed the fastest recovery since the trough in March, while Latin America showed the slowest recovery. These findings are in line with research by Seven and Yilmaz (2021), who performed a cross-sectional regression model in order to assess the differences in the recovery rates across countries since mid-March to late April 2020. They argue that fiscal stimulus packages are especially effective in supporting equity market recovery during the pandemic, and that countries with larger, more targeted fiscal rescue packages seem to have experienced a stronger recovery than countries offering smaller fiscal rescue packages. Moreover, they show that countries that rely heavily on natural resources and tourism revenues appear to experience a slower recovery. David et al. (2021) also find that stock exchange indices reveal a fast recovery, but that Brazil's index (IBOV) recovering dynamics are poor when compared to other indices. They explain this phenomenon by the fact that, in general, there is larger perception of risk by investors related to countries with larger economic and social fragility.

2.5 Period definition

To examine the impact of COVID-19 on market valuations since the onset of the virus, this research is divided into two sample periods. The first sub-sample is denoted as the 'outbreak period' and covers 31 December 2019 until 31 May 2020. This sample is defined as the outbreak period because it includes several key developments that show the course, and particularly the severity, of the COVID-19 virus. First, on 31 December 2019, Wuhan Municipal Health Commission of China, reported several cases of pneumonia of unknown cause in Wuhan, Hubei Province in China, and a new coronavirus was eventually identified. Secondly, on January 30, 2020, Director-General Ghebreyesus of the international public health agency WHO declared, acting on the advice of the Emergency Committee, that the outbreak of the virus constituted to a Public Health Emergency of International Concern (PHEIC). This was the 6th time the WHO has declared a PHEIC since the International Health Regulations (IHR) came into force in 2005. Previous declared PHEICs were Influenza - Swine flu (2009), Polio (2014), the Ebola outbreak in West Africa (2014), Zika virus (2016), and the Ebola outbreak in the Democratic Republic of the Congo (2019). In addition, WHO's situation report of 30 January 2020, reported 7,818 total confirmed cases worldwide, with the majority of confirmed cases in China, and 82 cases reported in 18 countries outside of China (WHO, 2020). Thirdly, this sample period includes 11 March 2020, when the rapid increase in cases outside of China led the WHO Director-General to announce that the outbreak could be classified as a 'pandemic'. At the end of May 2020, the global number of confirmed cases surpassed the 6,000,000 mark (WHO, 2021).

The second sub-sample is denoted as the 'recovery period' and concerns the period from 1 November 2020 to 31 January 2021. This sample is defined as the recovery period because it includes several positive developments that tackle COVID-19. As of November 2020, the first positive news appeared regarding the effectiveness of vaccines to battle the virus. Namely, on November 9, 2020, Pfizer-BioNTech published a report indicating a vaccine efficacy rate above 90%, and shortly thereafter, on November 16, 2020, Moderna revealed that its experimental vaccine reduced the risk of COVID-19 infection by 94.5% in participants who received it. Subsequently, the first mass vaccination programme in the U.S. began in early December 2020, as the Pfizer-BioNTech and Moderna vaccines were authorized by the U.S. Food and Drug Administration (FDA) on December 11, 2020, and December 18, 2020, respectively. On December 21, 2020, and January 6, 2021, the European Commission of Medicine also granted the first vaccine authorisations of Pfizer-BioNTech and Moderna to be distributed in Europe.

Moreover, given that crisis is not a temporary shock but causes prolonged and continuing damage, both the outbreak and recovery period are considered to be long enough to capture the impact of COVID-19 on companies' market valuations. The defined sample periods form the foundation for both the event study methodology and the panel regression analysis, which will be explained in sections 3.1 and 3.2, respectively.

2.6 Hypotheses development

To contribute to previous academic work on the impact of COVID-19 on companies' market valuations, the objective of this study is to examine the effect of the crisis on global equity markets geographically, across industries, and at the firm-level. This will be done by answering the following research question:

What is the impact of COVID-19 on companies' market valuations since the onset of the crisis, both geographically and at the industry-level, and does this effect differ between companies with different characteristics?

While most existing literature investigates the period December 2019 - March 2020, during which major regional stock markets plunged after the first wave of the outbreak (Ngwakewe, 2020; Khan et al., 2020; Mazur et al., 2020), this research will contribute by dividing the impact of COVID-19 in various waves more concretely. As defined in the previous section, both the outbreak period and the recovery period, during which several global stock markets fully recovered (IMF, 2020; David et al., 2021), will be examined. First, this research will assess the impact on companies' market valuations during the outbreak and recovery period based on three key developments relating to COVID-19, namely: (1) WHO's declaration of a PHEIC on January 30, 2020; (2) WHO's declaration of a pandemic on March 11, 2020; and finally (3) Pfizer-BioNTech's vaccine efficacy announcement on November 9, 2020. The change (impact) in market valuations[4] is measured by the cumulative average abnormal return (CAAR), which serves as a proxy for the overall share price reaction around the key development (event) in question. The PHEIC and pandemic announcement are expected to have a negative impact on market valuations as they indicate the severity of the COVID-19 outbreak. In contrast, the vaccine announcement is expected to have a positive impact on stock returns because it indicates a positive direction to overcome the pandemic. In light of these developments, three hypotheses are formulated that will be assessed using the event study methodology outlined in section 3.1:

[H1]: *Companies' market valuations are negatively impacted, as measured by CAAR, around the announcement of the PHEIC.*

[H2]: *Companies' market valuations are negatively impacted, as measured by CAAR, around the announcement of the pandemic.*

[H3]: *Companies' market valuations are positively impacted, as measured by CAAR, around the Pfizer-BioNTech's vaccine efficacy announcement.*

Given that COVID-19 is not a temporary shock but causes prolonged and continuing damage, a panel regression analysis (discussed in section 3.2) is performed to assess the change in market valuations over a longer period. The panel regression analysis is divided into the two defined sample periods discussed in section 2.5. First, in this context, an increasing number of COVID-19 cases is expected to have a negative impact on companies' market valuations, as an increasing presence of the virus worsens the overall environment to conduct regular business operations, and in turn is expected to damage investors' confidence in companies. This leads to the following hypothesis:

[4] In the continuation of this research the terms "market valuation" and "stock return" are used interchangeably.

[H4]: *Companies' market valuations are negatively impacted by the growth in number of confirmed COVID-19 cases during the outbreak and the recovery period.*

Furthermore, it is expected that companies in countries with tighter restrictions, such as quarantines, business shutdowns and social distancing, will suffer more than companies in countries that have taken less stringent actions. Containment and closure measures lead to greater difficulties in conducting regular business operations, and therefore the following hypothesis is formulated:

[H5]: *A higher level of containment and closure measures introduced by a government to tackle COVID-19 results in a stronger negative impact on market valuations during the outbreak and the recovery period.*

Multiple studies have analyzed the relationship between COVID-19 and firm-level characteristics. The results suggest that firms with stronger financial conditions (e.g., more cash, less total debt, and larger profits) pre-COVID experienced better stock price reactions to the virus outbreak than otherwise similar firms. In particular, the importance of liquidity is emphasized, suggesting that firms with sufficient cash are more likely to weather the demanding period of the pandemic, which in turn derives positive market valuation (Ding et al., 2021; OECD, 2020; Ramelli and Wagner, 2020). Altogether, based on the empirical evidence, the following hypotheses are formulated regarding the relationship between firm characteristics and companies' market valuations:

[H6]: *There is a negative relationship* between a company's size pre-COVID and its stock return during the outbreak period.*

It is expected that there will be a negative relationship between stock returns and firm size during the outbreak period, since larger companies are assumed to have less ability (flexibility) to scale down in terms of fixed costs compared to smaller companies, once operations have come to a halt.

[H6.1]: *There is a positive relationship* between a company's size pre-COVID and its stock return during the recovery period.*

During the recovery period, it is expected that there will be a positive relationship between stock returns and firm size, as larger firms (under normal operational circumstances) are better able to take advantage of economies of scale, and thus benefit from market power, compared to smaller firms.

[H7]: *There is a negative relationship* between a company's leverage pre-COVID and its stock return during the outbreak period.*

During the recovery period, there is expected to be a negative relationship between stock returns and leverage, as highly leveraged firms are assumed to face difficulties when the cash flow stop during the outbreak period, as it lowers their interest coverage ratio and in turn makes them more likely to become financially distressed.

[H7.1]: *There is a positive relationship* between a company's leverage pre-COVID and its stock return during the recovery period.*

It is expected that there will be a positive relationship between stock returns and leverage during the recovery period, since highly leveraged companies are able to benefit from the tax deductibility of interest expense (tax shield) again when the operational environment normalizes to pre-COVID levels.

[H8]: *There is a positive relationship* between a company's cash position pre-COVID and its stock return during the outbreak and recovery period.*

[H9]: *There is a positive relationship* between a company's profitability pre-COVID and its stock return during the outbreak and recovery period.*

During both the outbreak and recovery period, cash and profitability are expected to have a positive relationship with stock returns. Cash reserves and profitability allow a company to be financially flexible, as defined previously in the introduction of the literature review and provide it with the capacity to react and (potentially) be resilient to the ongoing COVID-19 crisis.

Finally, as previously discussed in the beginning of this chapter, empirical evidence from Mazur et al. (2020) and Shen et al. (2020) suggests that there is a significant difference in terms of industry performance during the COVID-19 crisis. Mazur et al. (2020) conclude that many sectors are in a position of strength (pre-pandemic) and yet their values collapse. The authors explain this using the theory of economic relationships between linked firms, where a shock to one firm affects all connected parties. Based on the aforementioned empirical evidence the following hypothesis is formulated:

[H10]: *Industries that can be characterized by direct contact (e.g., construction, recreation, and transportation) experience stronger movements in terms of market valuation during the outbreak and recovery period than those that can operate remotely without breaking their supply chain (e.g., retail and IT).*

3. Methodology and data

This chapter discusses the methodology and data of this research. First, the methodologies used, that is, an event study and panel regression analysis, are discussed. Subsequently, the data and data sources used for this study are explained.

3.1 Event study methodology

An event study is an approach to measure the valuation effects of an 'event', such as a dividend announcement, a merger, or a bankruptcy filing, by assessing stock price reactions around the occurrence of the event (Werner, 2010). According to the efficient market hypothesis (EMH), capital markets fully and correctly reflect all relevant and available information in determining security prices (Malkiel & Fama, 1970). The event study methodology validates to what extend the EMH holds true. In addition, the event is assumed to be unforeseen, which is necessary in order to identify any abnormal stock returns as a measure of the market reaction to the event. Therefore, the developments of COVID-19 can be classified as events, as the unforeseen virus ('a black swan'; see section 2.1), created panic and affected global financial markets simultaneously. The event study methodology is chosen to identify any abnormal returns of the constituent stocks of the chosen indices (section 3.2), during both the defined outbreak and recovery sample of COVID-19. The following dates have been set as event dates, with the first two event days representing the outbreak period and the third event day relating to the recovery period:

1. January 30, 2020: The Director-General of the WHO, T.A. Ghebreyesus, declared that COVID-19 constitutes to a Public Health Emergency of International Concern (PHEIC);
2. March 11, 2020: WHO characterized the COVID-19 outbreak as a pandemic;
3. November 9, 2020: Pfizer-BioNTech's report indicated a vaccine efficacy rate above 90%.

In order to capture the return effects due to the event, the so called event window [t1, t2] is set which includes the event day as illustrated in figure 2. The chosen event windows for each event are: [-1,0], [0,1], [-1,1], [-1,2], [-5,5], [-5,30]. The event windows are chosen to be close to the day of the event, so as to be unaffected by other events in the turbulent periods that are being examined. To improve the robustness of the results, a long event window [-5,30] is also included.

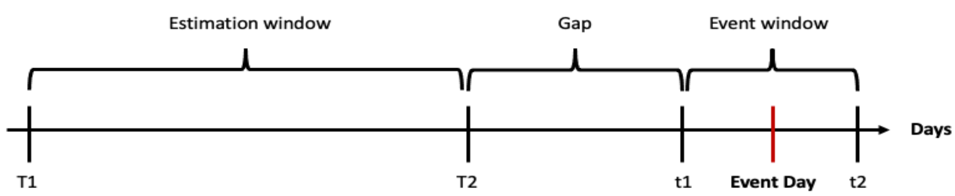


Figure 2. *Timeline around an event*

The estimation window [T1, T2] covers the period prior to the event window [t1, t2], to provide information that is necessary to compute the 'normal returns'. Since the estimation window is before the event window, the stock returns during the estimation period are named normal returns (NR). The estimation window should be long enough to conduct a reliable estimation of these NRs. Research by Armitage (1995) and Park (2004) find that the predicted returns on an event date are not sensitive to varying estimation window lengths, as longs as the window exceeds 100 days. Hence, in this research the estimation period is set from -130 to -30 [T1, T2], i.e., 101 days. As a result of the estimation window, the total data span for the sample periods is extended to August 2019 through May 2020, and May 2020 through January 2021. Furthermore, the 'gap', as illustrated by figure 2, is the period between the end of the estimation window and the beginning of the event window [T2, t1]. This gap ensures that the event has as little impact as possible on the estimation window. For an event study it is important to compare the actual returns with the NR, the latter being the returns that would have been realized if the event did not occur. The following model, known as the 'market model', has been applied to compute the NR:

$$E(R_{i,t}) = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \quad (1)$$

Where, $R_{i,t}$ is the return of stock(i) on day(t), $R_{m,t}$ is the market return on day(t) and $\varepsilon_{i,t}$ is the statistic disturbance. The market return (benchmark) is calculated using the MSCI All Country World Index (ACWI), which covers approximately 85% of the global investable equity opportunity set. The index is weighted approximately 58% towards the United States, 5% towards China, and 4% towards the United Kingdom (MSCI, 2021). These are the countries of interest for this study and will be discussed in section 3.3.

After obtaining the intercept (α_i) and the slope (β_i) of the regression model based on the estimation window, the NRs can be computed. As mentioned, the NRs are calculated using the market model, which is a statistical model that defines abnormal returns as excess returns on the market, adjusted for firm specific risk (MacKinlay, 1997). As previously stated, the market used for this research is the MSCI ACWI. Equation 2 is applied to calculate the abnormal return $AR_{i,t}$:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \qquad (2)$$

Where the parameter $AR_{i,t}$ represents the abnormal return, $R_{i,t}$ the actual return, and $E(R_{i,t})$ the expected return based on the estimations from the market model. The abnormal returns are computed for each stock(i) on day(t), the event date, within the event window. Here, 'i' refers to the total number of observations (number of firms) and 't' refers to the days.

Subsequently, the AR can be accumulated over time to compute the cumulative abnormal return (CAR) as shown by equation (3):

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \quad (3)$$

Finally, by taking the cross-sectional average of the CARs, the cumulative average abnormal return (CAAR) can be obtained:

$$CAAR = \frac{1}{N} \sum_{i=1}^{N} CAR_i \quad (4)$$

3.1.1 Testing abnormal performance

To detect any potential ARs on the event days, usually a parametric t-test is performed which assumes that the individual firm's ARs are normally distributed. This test is designed to determine whether the calculated ARs are significantly different from zero at a certain significance level. While CARs only provide information on whether an individual firm is affected during the relevant event period, the CAAR provides information on the cross-sectional average of all firms that are affected. The null hypothesis states that the CAARs are equal to zero (H_0: $CAAR = 0$), i.e., the expected cumulative price change over the event interval [t1, t2] is zero. The alternative hypothesis states that the CAARs are not equal to zero (H_1: $CAAR \neq 0$), i.e., the expected cumulative price change is significantly different from zero over the event interval. In order to provide evidence for these hypotheses, the most common test statistic is illustrated by equation 5, which concludes whether firms' stock returns jointly deviate from zero:

$$t\ CAAR = \sqrt{N}\ \frac{CAAR}{S} \sim N(0,1) \qquad where,$$

$$s = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (CAR_i - CAAR)^2} \quad (5)$$

The estimator for the standard deviation is computed by taking the sample standard deviation of CAARs. The t-test is then defined by taking the root of the number of observations (number of firms) in the sample and multiplying it by the CAAR, divided by the estimator of sample standard deviation.

To perform this test, among other restrictive assumptions, the independence assumption must be satisfied. The independence assumption implies that all ARs are cross-sectionally uncorrelated. This assumption is valid when the event day is not the same among firms. However, in this research, the ARs are cross-sectionally correlated, since the three chosen event days are the same for all sample firms. As a consequence, the t-statistic will be inflated due to the standard errors being understated, which in turn too often leads to severe over-rejection of the null hypothesis of zero abnormal returns (de Jong & de Goeij, 2011); that is, there is too high a probability of finding evidence in the data even though nothing has actually happened. To overcome cross-sectionally correlated ARs, the ARs of the event window can be scaled (standardized) as was introduced by Patell (1976). The first step, suggested by Patell, is to standardize each AR by its forecast error corrected standard deviation (equation 6):

$$SAR_{i,t} = \frac{AR_{i,t}}{s_i} \qquad \textit{where,}$$

$$s_i = \sqrt{\frac{1}{T1-T2}\sum_{t=T1}^{T2}(AR_{it} - \overline{AR_i})^2} \qquad (6)$$

Where the standardized abnormal returns are denoted by $SAR_{i,t}$, and s_i is the standard deviation of the ARs in the estimation window. As a result of equation 6, the ARs, which are now standardized, can be aggregated to obtain the standardized cumulative abnormal return, SCAR, see equation 7. Following this, the cross-sectional average of the SCARs is taken, that is, the standardized cumulative average abnormal return (SCAAR):

$$SCAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} SAR_{i,t} \qquad (7)$$

$$SCAAR = \frac{1}{N}\sum_{i=1}^{N} SCAR_i \qquad (8)$$

As a result of equation 8, the ARs which are now standardized can be tested appropriately. The null hypothesis states that the SCAARs are equal to zero ($H_0: SCAAR = 0$), and the alternative hypothesis states that the CAARs are not equal to zero ($H_1: SCAAR \neq 0$), as shown by equation 9:

$$t\, SCAAR = \sqrt{N}\, \frac{SCAAR}{S} \sim N(0,1) \qquad \textit{where,}$$

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(SCAR_i - SCAAR)^2} \qquad (9)$$

The purpose of standardization is to ensure that each AR will have the same variance. By dividing a firms' abnormal residual by its standard deviation that is obtained from the estimation window, each residual has an estimation variance of 1 (Patell, 1976). The test statistic under equation 9 is robust against cross-sectional correlation and the SCAARs are again standard normally distributed.

3.1.2 Cross-sectional regression analysis

As explained, the valuation changes of a company can be represented by the cumulative abnormal return (CAR). The CAR is used over an event period as the quantitative representative of the valuation change of a company. In addition to the previous analysis in which the abnormal performance of the cross-sectional average of all firms (SCAAR) is tested, this research will also examine the relationship between the change in the valuation of an individual company and several factors. For this cross-sectional regression analysis, the dependent variable is CAR and the independent variables, which serve as 'control' variables, are the variables, firm size, leverage, cash, and profitability. These variables are explained in more detail in section 3.3. By performing this cross-sectional regression analysis, it is attempted to determine whether the proposed variables have any explanatory power on the magnitude of CARs associated with the event of interest. The regression model is as follows:

$$CAR_i = \alpha_0 + \beta_1 Size_i + \beta_2 Leverage_i + \beta_3 Cash_i + \beta_4 Profitability_i + \varepsilon_i$$

As a result of the standardization of the CARs, as illustrated in the previous section, a continuation of a cross-sectional regression analysis with these standardized CARs is not valid, as it changes the characteristics of the data and therefore the relationship between the CARs and the factors of interest. Hence, the CARs used for the cross-sectional regression analysis are non-standardized. However, there is still the danger of cross-sectional correlation, since the three chosen event days are the same for all firms within the sample. To overcome potential serial correlation in the regression model illustrated above, the standard errors of the CARs are clustered by event date. By clustering the standard errors by the event date, the results are robust to serial correlation and are no longer biased, assuming that errors of different clusters are uncorrelated, but those within a cluster might be correlated.

3.2 Panel regression analysis

The COVID-19 crisis cannot be assigned one or several specific event dates that fully capture a possible adjustment of market valuations, as the crisis has been ongoing since late 2019 with dozens of negative and positive developments. Since the goal of this research is to provide an overall assessment of the market valuations during different stages of the crisis, a panel regression analysis will be the second method of analysis. This method is chosen in order to study the relationship between companies' valuations (stock returns) during the defined outbreak period (December 2019 - May 2020) and the recovery period (November 2020 - January 2021) with various variables. This method will identify the time-varying relationship between the dependent and independent variables.

The following regression model is applied to evaluate how various characteristics shape stock price reactions to COVID-19:

$$RETURN_{i,t} = \alpha_0 + \beta_1 COVID19\_Cases_t + \beta_2 STRINGENCY_t + \beta_3 X'_{i,pre-2020} + \beta_4 COVID19\_Cases_t * X'_{i,pre-2020} + \delta_{i,t} + \varepsilon_{i,t}$$

This regression model is adopted from research by Ding et al. (2021) and Song et al. (2021). In this regression model $RETURN_{i,t}$ represents the weekly stock returns (in percentage) of each firm within a week; $COVID19_{Cases_t}$ represents the weekly growth rate of the number of confirmed COVID-19 cases; $STRINGENCY_t$ represent containment measures introduced by a country in response to the pandemic, and is based on a ordinal scale that runs from 0-100 (with higher values indicating stricter restrictions); $X'_{pre\text{-}2020}$ represent firm characteristics before the COVID-19 outbreak (fiscal year 2019), consisting of a variable for firm size, leverage, cash and profitability; $COVID19\_Cases_t$ * $X'_{pre2020}$ represent the interaction terms that show how firms' stock returns respond to the pandemic as functions of individual corporate characteristics (conditional effect); $\delta_{i,t}$ controls for the industry fixed effects (four-digit code)[5]; $\varepsilon_{i,t}$ is the error term of which *t* and *i* represent time (i.e., week) and firm, respectively.

3.3 Data

To measure the impact of COVID-19 on market valuations, data covering publicly traded companies need to be collected for the samples, that is, the outbreak and the recovery period. The universe consists of companies from the following indices: Standard and Poor's 500 (S&P 500) representing the United States (US); the Financial Times Stock Exchange 100 (FTSE 100) representing the United Kingdom (UK); and the Financial Times Stock Exchange China A 200 (FTSE China A 200) representing China. These three indices are all capitalization-weighted, and thus are a good representation of the equity markets per region in terms of total value. Different indices are chosen to identify possible geographical differences in terms of changes in market valuation due to COVID-19. Stock market information for the indices constituent stocks come from Datastream in Thomson Reuters Eikon. In addition, corporate financials are retrieved from Thomson Reuters Worldscope to assess the relationship between COVID-19 and corporate characteristics on stock returns, with all financial items measured in US dollars.

Explanatory variables that represent COVID-19 are collected from the Centers for Disease Control and Prevention database and Oxford's COVID-19 Government Response Tracker. These databases provide information regarding the number of confirmed COVID-19 cases, as well as policy actions taken by a country in response to the pandemic. The final dataset is a firm-day panel that consists of the constituent

[5] Industry classification is based on four-digit numeric code adopted from Worldscope - Thomson Reuters (Appendix 7).

stocks of the S&P 500, FTSE 100, and FTSE China A 200. Firms operating in the financial sector (banks, insurance companies, public investment trusts), non-profit organizations and governmental enterprises are excluded from the analysis because their balance sheet structure is not readily comparable to that of otherwise similar companies. Besides, a key explanatory variable of interest in this research is leverage, which is hardly comparable between financial and nonfinancial firms (Fama and French, 1992). The remainder of this section outlines the explanatory variables applicable to the applied research methodologies.

3.3.1 Stock returns

After obtaining stock price data of constituent stocks of the S&P 500, FTSE 100, and FTSE China A 200 from Datastream, weekly stock returns are computed as a percentage. Specifically, during the sample periods the dividend-adjusted closing prices of each firm on the last trading day of a week are collected. The difference between the closing price on week(t) and week(t-1) is divided by the price on week(t-1) to compute weekly stock returns (Song et al., 2021; Ramelli and Wagner, 2020). To improve the normality of the weekly stock returns, they are converted to a logarithm.

3.3.2 COVID-19

To capture the effect of COVID-19 on stock returns, one variable has been employed to represent stock return exposure to the crisis. The Centers for Disease Control and Prevention (CDC) database provides, among other indicators, the number of daily confirmed COVID-19 cases, the number of recoveries, and the number of deaths. Although the CDC database is a dashboard, tracking confirmed cases in real time, it provides historical data since January 22, 2020 (CDC, 2021). To establish confirmed cases prior to this date, information on the rest of confirmed cases is collected from the website of the WHO (2021). By focusing on cumulative confirmed COVID-19 cases in the US, UK, and China within the sample periods, growth rates are computed. Since the stock returns are expressed in weekly terms, the variable reflecting COVID-19 is matched with the weekly stock returns of all sampled firms. The weekly growth rate of COVID-19 cases is computed as follows, where one is added to the number of cases to avoid excluding zero values:

$$COVID19\_Cases = \log(1 + cumulative\ cases\ in\ week\ t) - \log(1 + cumulative\ cases\ in\ week\ t-1)$$

The rationale for using a growth-based measure of COVID-19 is adopted from the paper by Ding et al. (2021). The authors explain that using a growth-based measure for COVID-19 follows a typical corporate valuation framework, in which changes in stock valuations (e.g., price-to-earnings multiples) reflect changes in the expected growth rate of future cash flows. The authors continue that changes in the expected growth rate of COVID-19 cases shape changes in the expected growth of future cash flows, and that a higher expected growth rate of COVID-19 would imply a slower growth rate of future cash flows (lower price-to-earnings multiple) and lower stock returns. Hence, in the context of the panel regression analysis, the growth rate of COVID-19 cases functions as a proxy for the market's expectation of the future growth rate of the virus. In addition, by transforming the number of COVID-19 cases to a growth-based measure, the effect of a one unit change on stock returns is substantively meaningful and easy to interpret.

3.3.3 Firm characteristics

Furthermore, this research assesses cross-firm stock price reactions to COVID-19 as functions of several pre-pandemic (fiscal year 2019) corporate characteristics. By examining these characteristics simultaneously as explanatory variables, the independent relationship between each firm characteristic and the responses of stock prices to the crisis can be established. In addition, the variable representing COVID-19 cases is interacted with these pre-2020 corporate characteristics in order to assess how firms' stock returns respond to the pandemic as functions of individual business characteristics. Four factors are examined: firm size, leverage, cash, and profitability. These characteristics serve as key proxies of a firms' financial condition, considering that these variables are used extensively in existing literature examining the effect of firm characteristics on financial performance, especially during the COVID-19 pandemic (Fahlenbrach et al., 2020; Albuquerque et al., 2020; Gerding et al., 2020; Ding et al., 2021; Song et al., 2021).

First, a firm's size, which affects a firm's market power advantage, economies of scale, and overall, its financial performance according to Chauvin and Hirschev (1993), is measured by market capitalization. The market capitalizations are transformed to a logarithm to improve the normality of the data. Secondly, leverage is measured as a ratio of total debt divided by total equity (Debt-to-Equity ratio). Leverage represents the solvability of a firm and is also a factor that influences a firm's financial performance and in turn its valuation given the advantage of a tax shield, that is, tax deductibility of interest expense (Modigliani and Miller, 1963). Thirdly, cash enables a company to be flexible and it predicts a companies' capacity to react and potentially be resilient to COVID-19. This variable equals the total amount of cash and short-term investments divided by total assets. Lastly, similar to cash, profitability may act as a signal that a firm has capacity to endure the COVID-19 shock (Song et al., 2021). Profitability is measured by net income divided by shareholders' equity (ROE). Overall, given the adverse impact of the pandemic on cash flows and liquidity, these variables may shape the response of stock prices to the evolution of COVID-19. It is likely that these characteristics will influence investors' market valuations of a firm in response to the pandemic.

3.3.4 Policy measures

Finally, policy measures introduced by a government to tackle COVID-19 during the ongoing pandemic are taking into account. From Oxfords' COVID-19 Government Response Tracker (OxCGRT) one variable has been employed to represent policy measures, which may provide insight into geographical differences in changes in market valuations. The variable taken from the OxCGRT database is the 'stringency index', which represents the containment and closure measures introduced in a country. This stringency index provides an ordinal scale that runs from 0-100, with higher values indicating stricter restrictions, and is computed based on an aggregate score composed of a combination of the following nine indicators: closings of schools and universities, workplace closing, canceling of public events, limits on private gatherings, closing of public transport, orders to shelter-in-place, restrictions on internal movement between cities and regions, restrictions on international travel, and the presence of public info campaigns urging caution about COVID-19 (Oxford, 2021). According to the authors, the stringency index records the number and strictness of government policies and thus should not be interpreted as 'scoring' the appropriateness or effectiveness of a country, region, or territory's response to the COVID-19 pandemic. Finally, the stringency index data is matched with weekly stock returns of the sampled firms to discover potential effects of lockdown related measures on stock returns.

4. Empirical Results

This chapter presents the results obtained from the event study and the panel regression analysis performed on constituent stocks of the S&P 500 (US), FTSE 100 (UK), and FTSE China A 200 (China). The first section will cover the event study in which three events dates are investigated, and the most pronounced abnormal returns along the different event windows will be evaluated. The second section discusses the panel regression model, which examines the relationship between weekly stock returns and corporate characteristics, a growth-based measure of COVID-19, and finally a stringency index reflecting policy measures introduced by a government.

4.1 Event study

In this section constituent stock returns are analyzed around key events during the onset of the COVID-19 crisis. As mentioned in section 3.1, the following event windows are identified per event date [-1,0], [0,1], [-1,1], [-1,2], [-5,5] and [-5,30]. In the remainder of this section, the different event dates are discussed separately, and in particular the most pronounced CAARs (standardized) will be investigated. In addition, a cross-sectional regression analysis by the event date of interest is conducted to determine whether certain factors, as suggested in section 3.1.2, can explain some of the valuation changes reflected in the CARs (non-standardized).

4.1.1 A Public Health Emergency of International Concern: 30 January, 2020

The first event that is investigated is WHO's declaration on the 30th of January, 2020, stating that the outbreak of the virus constituted to a Public Health Emergency of International Concern (PHEIC). The CAARs over six different event windows are reported in table 1, and the individual abnormal returns (AR) per trading day are reported in Appendix 1.

Table 1. *Event date 1: CAARs surrounding the PHEIC announcement*

		(1) **All**	(2) **China**	(3) **UK**	(4) **US**
CAAR [-1,0]	_cons	.454* (.254)	1.201* (.721)	-1.906*** (.585)	.673** (.284)
CAAR [0,1]	_cons	.407 (.258)	1.312* (.729)	-1.215** (.586)	.437 (.291)
CAAR [-1,1]	_cons	.407 (.258)	1.312* (.729)	-1.215** (.586)	.437 (.291)
CAAR [-1,2]	_cons	-.495* (.274)	-4.591*** (.723)	-1.396** (.581)	.939*** (.297)
CAAR [-5,5]	_cons	-.209 (.288)	-.387 (.867)	-2.827*** (.674)	.345 (.308)
CAAR [-5,30]	_cons	1.016 (.49)	1.478 (.905)	-1.472 (.690)	1.348 (.641)
	Obs.	598	123	76	399

*Robust standard errors are reported in the parentheses. *, **, *** denote 10%, 5% and 1% significance levels, respectively*

As shown by the table, the signs and significance of the CAARs are very different among the countries and event windows. On the event day itself [-1,0] itself, including one day before the PHEIC announcement, the entire sample (column 1) shows a positive return of 0.454% on average, which is counterintuitive. One would expect market participants to react negatively to the WHO statement suggesting the severity of COVID-19 worldwide, and its potential negative impact on business operations. One possible explanation for the positive sign, especially for China, could lie in the praise the WHO had given the Chinese government. Indeed, during this second meeting, the Emergency Committee welcomed the leadership and political commitment of the very highest levels of the Chinese government, particularly their commitment to transparency, and the efforts to investigate and contain the outbreak. Moreover, the immediate response of the Chinese government was accompanied by the rapid development of diagnostic tools. Altogether, this could have been seen as positive news by market participants. The CAARs of event window [0,1] and [-1,1] are identical, implying that the CAAR is not affected one day prior to the announcement of the PHEIC, i.e., there is no information leakage before the official announcement on January 30, 2020. However, examining event window [-1,2], the sign of the CAAR for the entire sample (column 1) changes, which is also the case for the sample representing China. On day 2 the full sample shows a negative CAAR of -0.495%.

Particular is the UK sample, that shows a significant and negative CAAR in nearly all event windows. The negative CAARs may be attributed to the Brexit withdrawal agreement. Since the UK, after 47 years of continued membership, officially left the European Union on 31 January 2020, this may be perceived by investors as unfavorable and uncertain. The event window [-1,2] for China shows a pronounced negative CAAR of -4.591%. This might reflect the concerns about the economic impact of the coronavirus on overall economic growth, as the total number of virus cases in mainland China soared to over 17,000 on 2 February 2020. The US sample has a positive sign in all event windows, suggesting that the US stock market keeps underestimating the spread of the virus, its consequences for the entire economy and therefore also the stock prices for many days after the PHEIC announcement. This result is also found by Vasileiou (2021), who concluded that the S&P 500 index seemed to underestimate the PHEIC for 3 weeks after it was announced. Up to February 21, 2020, the index does not show any cause for concern, as the returns are positive relative to the pre-PHEIC period.

Overall, it can be concluded that despite the WHO's alarming message to countries, indicating a possible global outbreak of the virus, equity markets do not seem to incorporate the news, as shown by the mixed results in table 1. One may expect that the PHEIC announcement should immediately lead to an overall market decline, as a result of potential economic slowdown, increased risk aversion, and due to lower future growth expectations among investors. But here might also lie the explanation for the mixed results regarding the CAARs. As the PHEIC declaration was made early into the COVID-19 crisis, the development of the number of confirmed COVID-19 cases, global spread, and potential imposed business restrictions, were still very unclear. Consequently, market participants were unsure how to respond to the development of the crisis. In addition, Appendix 4 shows the CAARs of the entire sample by industry (as categorised in Appendix 7) over the event window [-5,5]. As shown by the table (column 1), the most negative returns are realized in the industries: Apparel (-7.996%), Oil, gas, coal, & related (-6.272%), and the Electrical industry (-5.468%), which are all statically significant at the 5% level.

4.1.1.1 Cross-sectional regression analysis

This section summarizes the results of the cross-sectional regression analysis of the model proposed in section 3.1.2. The objective of this analysis is to determine whether the proposed variables have any explanatory power on the magnitude of the CARs associated with the PHEIC announcement on January 30, 2020. The CARs of event window [-1,1] are chosen as the main dependent variable since these CARs are closest to the announcement of the PHEIC and are less likely to be affected by other market events. To improve the robustness of the results, the CARs of the event windows [-1,2], [-5,5] and [-5,30] are included as dependent variables. Note that the CARs are non-standardized, as previously elaborated in section 3.1.2.

***Table 2**. Cross-sectional regression analysis: PHEIC*

	[-1,1] CAR	[-1,2] CAR	[-5,5] CAR	[-5,30] CAR
CASH	.065	.076	.104*	.330***
	(.054)	(.052)	(.055)	(.056)
ROE	.0002	.0002***	.0002***	.0005***
	(.001)	(0)	(0)	(0)
LEV	0	0	0	0
	(0)	(0)	(0)	(0)
SIZE	-.004	-.003	-.002	-.012
	(.005)	(.005)	(.005)	(.010)
_cons	.123	-.013	.041	.145
	(.088)	(.092)	(.1)	(.179)
Observations	598	598	598	598
R-squared	.10	.192	.135	.233
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

*Robust standard errors are reported in the parentheses. *, **, *** denote 10%, 5% and 1% significance levels, respectively*

Table 2 shows that the control variables are all insignificant in event window [-1,1], implying that the variables have no explanatory on the magnitude of the CARs. However, once the event window is expanded to [-1,2], the variable ROE becomes statistically significant at the 1% level, and in the longer event windows [-5,5] and [-5,30], the variable CASH also becomes statistically significant at the 10% and 1% level, respectively. Firstly, ROE has a positive relation with CAR, implying that firms with a higher ROE prior to the announcement, that is, firms with a higher profitability ratio pre-2020, experienced higher abnormal returns around the PHEIC announcement, than otherwise similar firms. Furthermore, CASH also shows a positive relation with CAR in event windows [-5,5] and [-5,30], implying that firms with more cash prior to the announcement, that is more cash reserves pre-2020, experienced higher abnormal returns around the PHEIC announcement. Economically the signs for CASH and ROE makes sense, as cash reserves and profitability allow a company to be flexible and provide it with the capacity to react and (potentially) be resilient to the COVID-19 crisis. The table suggest that the explanatory power (R-squared) of the control variables is highest in event window [-5,30], i.e., in this event window the control variables explain most of the variation in the CARs. However, as mentioned earlier, the significance and signs of the CAARs are mixed (Section 4.1.1) and the market does not seem to respond to the PHEIC's announcement, so the event cannot be directly related to the control variables.

4.1.2 Declaration of the pandemic: 11 March, 2020

The next event that is being examined is the announcement made by the WHO on the 11th of March 2020, stating that the COVID-19 outbreak could be characterized as a pandemic (WHO, 2021). The CAARs over the different event windows are reported in table 3, and Appendix 2 reports the abnormal returns for each trading day individually.

***Table 3**. Event date 2: CAARs surrounding the pandemic announcement*

		(1) **All**	(2) **China**	(3) **UK**	(4) **US**
CAAR [-1,0]	_cons	-1.019*** (.273)	0.847 (.738)	-4.664*** (.577)	-.9*** (.308)
CAAR [0,1]	_cons	-1.494*** (.301)	1.283* (.762)	-5.34*** (.634)	-1.617*** (.347)
CAAR [-1,1]	_cons	-1.494*** (.301)	1.283* (.762)	-5.34*** (.634)	-1.617*** (.347)
CAAR [-1,2]	_cons	-2.341*** (.309)	1.767** (.82)	-6.881*** (.671)	-2.742*** (.334)
CAAR [-5,5]	_cons	-4.917*** (.348)	1.953*** (.745)	-9.241*** (.747)	-6.211*** (.388)
CAAR [-5,30]	_cons	-7.104*** (.417)	.109 (.561)	-11.843*** (.1304)	-8.425*** (.517)
	Obs.	598	123	76	399

*Robust standard errors are reported in the parentheses. *, **, *** denote 10%, 5% and 1% significance levels, respectively*

Table 3 displays a summary of the CAARs and shows that nearly all are significant at the 1% level for different event windows. On the event day itself [-1,0], including one day before the pandemic announcement, the entire sample shows a negative return of -1.019% on average. As shown by the table, the CAARs of event window [0,1] and [-1,1] are identical, implying that the CAAR is not affected one day prior to the announcement of the pandemic, i.e., there is no information leakage before the official announcement on March 11, 2020. Furthermore, column 1 of table 3 indicates that the negative CAAR becomes more pronounced once the event window is extended. This is also the case when the ARs per individual trading day are considered, as shown by Appendix 2. In the event windows [-5,5] and [-5,30] the entire sample shows a negative CAAR of -4.917% and -7.104%, respectively, indicating that the abnormal returns were not only concentrated on the event day itself, but also on the days following the announcement. Thus, it can be concluded that equity markets did not immediately react fully to the public statement but needed some time to digest the negative news from the WHO. The differences between countries in terms of the sign of CAARs are striking. While stocks in the US and the UK showed negative returns in response to the pandemic announcement (in all event windows), stocks in China showed positive returns. The positive CAARs for China can be attributed to the fact that the Chinese government immediately adopted an aggressive strategy to quarantine the centre of an outbreak of COVID-19, as evidenced for example by the lockdown of Wuhan on 23 January 2020, and which is also evidenced by the rapidly rising stringency index shown in Appendix 6. Their strategy also seemed to be successful in terms of the trend in cumulative COVID-19 cases as shown by Appendix 6, which is substantially lower compared to the US and the UK. Hence, as shown by the different event windows, the market viewed China as a safer and more profitable investment opportunity (destination) compared to the US and the UK, which is consistent with previous research by Ngwakewe (2020) and Khan et al. (2020). Furthermore, Appendix 4 shows the CAARs of the entire sample per industry over the event window [-5,5]. As shown by the table (column 2), the most negative returns are realized in the sectors: Oil, gas, coal, & related (-10.116%), Apparel (-8.26%), and the Tobacco industry (-7.182%), which are all statically significant at the 1% level.

4.1.2.1 Cross-sectional regression analysis

This section provides an overview of the results obtained from the cross-sectional regression analysis during the pandemic announcement. The CARs of the event window [-1,1] are chosen as the main dependent variable, as these CARs are closest to the announcement of the pandemic. To improve the robustness of the results, the CARs of the event windows [-1,2], [-5,5] and [-5,30] are included as dependent variables, particularly since the negative effect of the abnormal returns becomes stronger once the event window lengthens.

Table 4. *Cross-sectional regression analysis: Pandemic*

	[-1,1] CAR	[-1,2] CAR	[-5,5] CAR	[-5,30] CAR
CASH	.144***	.119***	.163***	.256***
	(.051)	(.049)	(.056)	(.056)
ROE	.0004***	.0004***	.001***	.001***
	(0)	(0)	(0)	(0)
LEV	0	0	0	0
	(0)	(0)	(0)	(0)
SIZE	-.005	-.004	-.001	.056***
	(.007)	(.006)	(.007)	(.007)
_cons	.068	.059	.004	-1.318***
	(.111)	(.106)	(.121)	(.121)
Observations	598	598	598	598
R-squared	.173	.235	.301	.355
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

*Robust standard errors are reported in the parentheses. *, **, *** denote 10%, 5% and 1% significance levels, respectively*

Table 4 shows that the variables CASH and ROE are statistically significant in all event windows at the 1% level. Firstly, CASH has a positive relation with CAR, implying that firms with more cash reserves pre-2020 experienced higher abnormal returns around the pandemic announcement. Furthermore, ROE shows a positive relation with CAR, implying that firms with a higher ROE, that is a higher profitability ratio pre-2020, experienced higher abnormal returns around the pandemic announcement, than otherwise similar firms. The signs and significance levels of CASH and ROE are somewhat similar during PHEIC announcement, at least in event window [-5,5], and economically the signs make sense. As previously explained, cash reserves and profitability allow a company to be flexible and better withstand the COVID-19 shock. Noteworthy, the variable SIZE is positive and significant in the event window [-5.30], i.e., firms with a larger market capitalization pre-2020 experienced higher abnormal returns. This implies that larger firms in the longer event window are perceived as more save, likely to endure the ongoing COVID-19 crisis better than smaller firms. Finally, the explanatory power (R-squared) of the model increases as the "event window" lengthens. This suggests that more variation in CARs is explained by the control variables once the "event window" is extended.

4.1.3 Vaccine effectiveness: November 9, 2020

The final event that will be investigated is the announcement regarding the Pfizer-BioNTech vaccine on November 9, 2020, which indicated a vaccine efficacy rate above 90% against the coronavirus. The CAARs over different event windows are reported in table 5, and the abnormal returns for each trading day individually are reported in Appendix 3.

***Table 5**. Event date 3: CAARs surrounding the Pfizer-BioNTech announcement*

		(1) **All**	(2) **China**	(3) **UK**	(4) **US**
CAAR [-1,0]	_cons	.868*** (.229)	2.748*** (.593)	.694* (.801)	.306* (.24)
CAAR [0,1]	_cons	.936*** (.231)	2.037*** (.583)	1.574* (.868)	.466* (.242)
CAAR [-1,1]	_cons	.936*** (.231)	2.037*** (.583)	1.574* (.868)	.466* (.242)
CAAR [-1,2]	_cons	.587*** (.221)	.967* (.574)	1.674** (.822)	.261 (.231)
CAAR [-5,5]	_cons	.784*** (.249)	1.203* (.659)	1.322 (.923)	.55** (.257)
CAAR [-5,30]	_cons	0.527 (.344)	-.155 (.869)	1.553 (1.213)	.549 (.375)
	Obs.	598	123	76	399

*Robust standard errors are reported in the parentheses. *, **, *** denote 10%, 5% and 1% significance levels, respectively*

The table above summarizes the CAARs and shows that nearly all values are statistically significant. On the event day itself [-1,0], including one day before the Pfizer-BioNTech vaccine announcement, the entire sample shows a positive return of 0.868% on average. As shown by the table, the CAARs of event window [0,1] and [-1,1] are identical, implying that the CAAR is not affected one day prior to the announcement of the vaccine announcement, i.e., there is no information leakage before the official announcement on November 9, 2020. Looking at the CAARs of event window [-1,1], it seems that the market reaction to the vaccine was not only concentrated on November 9, 2020, but also one day after the event. This is consistent with the individual ARs, as shown in Appendix 3. On day 1 of the event window [-1,1], the entire sample shows a positive CAAR of 0.936%, and all underlying countries are positive and statistically significant. Research by Kucher et al. (2021) also finds that COVID-19 vaccine news positively effects stock returns. They find that firms' expected future cash flows increase and the expected future discount rate decreases in response to positive news about vaccines, which in turn causes positive stock price reactions. The CAARs, especially for the China sample, may be inflated due to the declaration on 7 November 2020 that Joe Biden won the US election, as investors viewed Biden's victory as positive for trade and technology policy, especially as the relations between Donald Trump and China deteriorated during his four-year tenure. In addition, Appendix 4 shows the CAARs of the entire sample per industry over the event window [-5,5]. As shown by the table (column 3), only the industry Apparel is statistically significant at the 10% level, which shows a negative return of -10.65%. The industries Aerospace and Oil, gas, coal, & related show a positive return around the vaccine announcement of 5.46% and 1.39%, respectively, but these are not statistically significant.

4.1.3.1 Cross-sectional regression analysis

This section provides an overview of the results obtained from the cross-sectional regression analysis. The CARs of the event window [-1,1] are chosen as the dependent variable, as these CARs are closest to the announcement of the Pfizer-BioNTech vaccine effectiveness. CARs induced by the vaccine announcement are assumed to be concentrated in event window [-1,1], given that the sign of the individual AR (Appendix 3) all turn negative once the event window lengthens. However, to improve the robustness of the results, the CARs of the event windows [-1,2], [-5,5] and [-5,30] are included as dependent variables.

Table 6. *Cross-sectional regression analysis: Pfizer-BioNTech*

	[-1,1] CAR	[-1,2] CAR	[-5,5] CAR	[-5,30] CAR
CASH	-.027	-.017	-.025	-.12
	(.044)	(.043)	(.047)	(.057)
ROE	.0002	.0002	.0003	.0004
	(.0003)	(.0003)	(.0003)	(.0005)
LEV	-.0005***	-.0004***	-.0004***	-.0004***
	(.0001)	(.0001)	(.0001)	(.0001)
SIZE	-.012**	-.008**	-.013**	-.021**
	(.006)	(.005)	(.006)	(.007)
_cons	.351	.242	.374	.470
	(.164)	(.15)	(.161)	(.204)
Observations	598	598	598	598
R-squared	.132	.122	.13	.19
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

*Robust standard errors are reported in the parentheses. *, **, *** denote 10%, 5% and 1% significance levels, respectively*

Table 6 shows that the variables LEV and SIZE are negative and statistically significant at the 1% and 5% level, respectively, in all event windows. First, note that during the PHEIC and pandemic announcement both CASH and ROE were positive and statistically significant, while they do not appear to be significant during the vaccine announcement. One explanation for these findings could be that during the period under consideration, namely around November 9, 2020, COVID-19's hold on the world is weakening, as evidenced by the declining average of COVID-19 cases recorded in Appendix 9. The insignificance for both variables CASH and ROE could be attributed to the fact that investors have positive expectations about the future development of the crisis. As a result, investors are demanding less cash reserves and profitability buffers from companies, as it is expected that companies are able to operate under normal circumstances again, i.e., similar to the period pre-COVID. In other words, the less pronounced the COVID-19 shock (impact) on business operations, the less demanding market participants are on firms' cash reserves and profitability.

Secondly, while the variables LEV and SIZE were insignificant in most event windows during the PHEIC and pandemic announcement, they appear to be significant during the vaccine announcement. LEV has a negative relation with CAR, implying that firms who were more leveraged prior to the vaccine announcement, that is, higher leveraged firms pre-2020, experienced lower abnormal returns around the event of interest. A possible explanation for the sign and significance of LEV could be that high leverage restrict companies to effectively recuperate once the operational environment returns to normal levels again. Put differently, highly levered companies are less financially flexible than otherwise similar companies, which leads to a greater difficulty in conducting regular business operations. Furthermore, SIZE shows a negative relation with CAR, implying that firms with a larger market capitalization pre-2020 experienced lower abnormal returns. The SIZE effect can be explained by the fact that larger companies have less operating flexibility that smaller firms in terms of costs (especially fixed costs) once operations come to a halt. Smaller companies tend to have less fixed cost (are more flexible in that sense) and are therefore better able to scale down. Despite positive developments regarding the COVID-19 crisis during the period under consideration, investors may have been more reluctant towards bigger companies because of their lack of operating flexibility. These mixed results compared to the other investigated events could be attributed to the ongoing uncertainty regarding future developments of the crisis. Finally, the table suggest that the explanatory power (R-squared) of the control variables is similar among the event windows, apart from the longer event window [-5,30].

4.2 Panel regression analysis

This second part of the chapter discusses the results of the regression model as specified below. In order to evaluate how proxies of COVID-19 development, imposed government restrictions, and corporate characteristics shape stock price reactions, weekly stock returns are regressed on various variables. In addition, this panel data analysis examines weekly stock returns across geographies and industries in order to potentially detect any notable differences in terms of stock price reactions. The following model is applied in order to provide an overall assessment of market valuations during different stages of the crisis:

$$RETURN_{i,t} = \alpha_0 + \beta_1 COVID19\_Cases_t + \beta_2 STRINGENCY_t + \beta_3 X'_{i,pre-2020} + \beta_4 COVID19\_Cases_t * X'_{i,pre-2020} + \delta_{i,t} + \varepsilon_{i,t}$$

4.2.1 Descriptive statistics

First, the descriptive statistics of the variables in the research model are presented in table 7 and table 8, that is, the outbreak and the recovery period, respectively. The descriptive statistics provide the background and basic understanding of the samples of this study and will allow for a better interpretation of the significance of the empirical result that will be discussed in the next section. The variables LEV, CASH, and ROE have been winsorized at 1% and 99% to delete the outliers from the sample and to improve the normality of the variables. Winsorizing ensures that the values at the tails of the distribution are not removed but are recoded to less extreme values. Hence, the 1 percent of the lowest values are recoded to the value of the 1st percentile, and the 1 percent of the highest values are recoded to the value of the 99th percentile.

Table 7. *Summary of descriptive statistics: Outbreak period (December 31, 2019 - May 31, 2020)*

Variables	N	Mean	Std. Dev.	Min	Max	p25	p75
RETURN	13481	-.015	.11	-1.033	.679	-.058	.040
COVID19_Cases	13481	.608	.737	0	2.6	.001	1.221
STRINGENCY	13481	43.588	33.502	0	81.94	5.56	72.69
SIZE	13481	17.12	1.032	14.371	21.536	16.380	17.634
LEV	13481	1.154	1.113	0	4.107	.416	1.495
CASH	13481	.157	.132	.01	.498	.055	.22
ROE	13481	.177	.206	-.169	.712	.067	.259

Table 8. *Summary of descriptive statistics: Recovery period (November 1, 2020 - January 31, 2021)*

Variables	N	Mean	Std. Dev.	Min	Max	p25	p75
RETURN	7956	.016	.068	-.252	.427	-.024	.046
COVID19_Cases	7956	.067	.038	.002	.154	.049	.096
STRINGENCY	7956	72.652	5.596	62.5	87.96	71.76	75.46
SIZE	7956	17.12	1.032	14.371	21.536	16.380	17.634
LEV	7956	1.154	1.113	0	4.107	.416	1.495
CASH	7956	.157	.132	.01	.498	.055	.22
ROE	7956	.177	.206	-.169	.712	.067	.259

Note: RETURN represents the weekly stock returns (in percentage) of each firm within a week, with a year consisting of 52 weeks; COVID19_Cases represents the weekly growth rate of the cumulative number of confirmed cases; STRINGENCY represents containment measures introduced by a country in response to the crisis; SIZE represents firm size measured by market capitalization; LEV represents Debt-to-Equity ratio of each firm; CASH represent cash and short-term investments divided by total assets; and ROE represents profitability, and is measured by net income divided by shareholders' equity. In addition, note that the summary statistics of the four corporate characteristics (size, leverage, cash, and profitability) are identical in both sample periods. That is, both sample periods refer to pre-COVID characteristics of firms (fiscal year 2019), which is assumed to be the latest data shareholders and investors were able to access and utilize in evaluating a firms' financial condition in reaction to COVID-19. This allows for an understanding of how pre-2020 corporate characteristics shape stock price reactions during the ongoing pandemic.

Next, the summary statistics of the variables presented in table 7 and table 8 will be discussed. RETURN (in percent), the dependent variable, has a mean of -0.015 and a standard deviation of 0.11 in the outbreak period, and a mean of 0.016 and a standard deviation of 0.068 in the recovery period. Converting RETURN to normal returns[6] results in a mean RETURN in the outbreak period of -3.39%, while the mean RETURN in the recovery period is 3.75%. The weekly growth rate of COVID-19 cases ranges from 0 to 2.6 along with a mean of 0.608 in the outbreak period, and from 0.02 to 0.154 along with a mean of 0.067 in the recovery period. This implies that the weekly growth rate of COVID-19 cases was more than 60% in the outbreak period, with a maximum growth rate of 260%. In contrast, the weekly growth rate of COVID-19 cases during the recovery period was 6.7%, with a maximum of 154%. Overall, the significant difference in weekly growth rate of COVID-19 cases between the samples reveals the positive development with regard to the spread of the virus. STRINGENCY has a mean of 43.588 with a maximum of 81.94 during the outbreak period, and a mean of 72.652 with a maximum of 87.96 during the recovery period. The stringency index is an ordinal scale which ranges from 0 to 100, with higher values indicating stricter restrictions in response to COVID-19. Hence, the results follow that the strictness is greater, on average, during the recovery period compared to the outbreak period. SIZE, the logarithm of a firms' market capitalization, has a mean of 17.12, a minimum of 14.371, and a maximum of 21.536. Leverage (Debt-to-Equity ratio) shows a mean of 1.154, with a minimum and maximum of 0 and 4.107, respectively. That is, the sampled firms, on average, have 115.4% the level of debt relative to their total equity. CASH shows a minimum value of 0.01 and a maximum value of 0.498, along a mean of 0.157. This implies that the sampled firms, on average, have 15.7% cash and short-term investments relative to their total assets. Finally, the profitability ratio, measured by ROE, has an average value of 0.177, ranging from -0.169 to 0.712. This suggests that the sampled firms had an average return, measured by net income, of 17.7% on their shareholders' equity, with the lowest return being -16.7%, and the highest 71.2%.

Table 9 and table 10 show the results of Pearson's correlation analyses among the variables. As expected, there is a negative and significant correlation between COVID19_Cases and RETURN during the

[6]As explained in section 3.3.1 RETURN is transformed to a logarithm to improve the normality of the weekly stock returns. To covert this value into weekly 'normal' returns, the following formula can be applied: 10^log, where log is the value shown in table 7 and 8.

outbreak period. Note that during the recovery period, there appears to be an inverse relationship between the growth rate of COVID19_Cases and RETURN compared to the outbreak period. This has to do with the fact that the mean growth rate of COVID19_Cases significantly decreases during the recovery period, while the mean growth rate increases during the outbreak period, as shown in Appendix 5. Moreover, nearly all pre-pandemic firm characteristics are significantly correlated with COVID19_Cases and STRINGENCY, except for ROE. Noteworthy is the positive correlation between STRINGENCY and RETURN in the outbreak period, and the negative correlation in the recovery period. These opposing effects are also found by Aggarwal et al. (2021), who argue that on the one hand investors feel safer the more stringent the lockdown process is (behavioral), and on the other hand, that stringency negatively affects the overall returns by impacting growth estimates (rational). The authors however do not provide a clear explanation for these mixed results. From the perspective of a rational investor, one would indeed expect that containment and closure measures negatively affect stock returns, as it leads to a greater difficulty in conducting regular business operations.

Table 9. *Pearson correlation: Outbreak period*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) RETURN	1.000						
(2) COVID19_Cases	-0.175***	1.000					
(3) STRINGENCY	0.241***	-0.118***	1.000				
(4) SIZE	0.045***	0.019**	-0.041***	1.000			
(5) LEV	-0.048***	0.017*	-0.062***	0.009	1.000		
(6) CASH	0.060***	-0.023***	0.097***	0.114***	-0.238***	1.000	
(7) ROE	0.075***	0.003	-0.003	0.218***	0.228***	0.196***	1.000

Table 10. *Pearson correlation: Recovery period*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) RETURN	1.000						
(2) COVID19_Cases	0.067***	1.000					
(3) STRINGENCY	-0.249***	-0.118***	1.000				
(4) SIZE	-0.021*	0.077***	-0.105***	1.000			
(5) LEV	0.004	0.183***	-0.068***	0.013	1.000		
(6) CASH	0.038***	-0.306***	0.094***	0.115***	-0.242***	1.000	
(7) ROE	-0.039***	0.006	-0.012	0.220***	0.235***	0.187***	1.000

*Robust standard errors are reported in the parentheses. *, **, *** denote 10%, 5% and 1% significance levels, respectively*

In light of this study, the mixed correlations could be due to the level of stringency, which has a mean of 43.59 during the outbreak period, while the mean is 72.65 during the recovery period. Hence, there might be a pinpoint in the level of stringency at which the market evaluates the lockdown related policies from positive to negative, leading to negatively affected stock returns. Finally, among the pre-pandemic firm characteristics, nearly all variables are either positively or negatively correlated with RETURN (except for leverage) and correlated with each other, that is, during both the outbreak and recovery period.

4.2.2 Regression analysis: Outbreak period

This section presents the regression results of the research model by examining the outbreak period that ranges from December 31, 2019 to May 31, 2020. Table 11 reports the regression results, that is, the relationship between the moderating role of firm characteristics, the development of COVID-19, and imposed government restrictions on weekly stock returns, while controlling for country and industry fixed effects.

Table 11. *Regression results: Outbreak period*

Variables	(1) RETURN	(2) RETURN
COVID19_Cases	-.022***	-.065***
	(.001)	(.021)
STRINGENCY	.001***	.001***
	(0)	(0)
SIZE	.003***	.002
	(.001)	(.001)
LEV	-.004***	-.001
	(.001)	(.001)
CASH	.003	-.011
	(.008)	(.01)
ROE	.033***	.022***
	(.005)	(.007)
COVID19xSIZE		.002**
		(.001)
COVID19xLEV		-.006***
		(.001)
COVID19xCASH		.025**
		(.01)
COVID19xROE		.018***
		(.007)
_cons	-.094***	-.067***
	(.02)	(.024)
Observations	13481	13481
R-squared	.094	.097
country FE	Yes	Yes
industry FE	Yes	Yes

*Robust standard errors are reported in the parentheses. *, **, *** denote 10%, 5% and 1% significance levels, respectively*

First, the results of column 1 without interactions terms will be discussed, of which nearly all variables are statistically significant at the 1% level, with the exception of CASH which is insignificant. The growth rate of COVID19_Cases shows a negative impact on weekly stock returns. In economic terms, the data shows that a one percent increase in COVID19_Cases, on average, results in -0.022% decrease in RETURN, ceteris paribus. In addition, STRINGENCY, which records the strictness of 'lockdown' policies introduced by government that primarily restrict people's behavior, has a positive relationship on weekly stock returns. Economically, the research model shows that a one percent increase in

STRINGENCY is, on average, associated with approximately 0.1% increase in RETURN, ceteris paribus. This implies that government policies, such as the closure of workplaces, non-essential businesses, and restrictions on gatherings, had a positive impact on stock returns during the outbreak period. The following economic relationships, on average, are found between a one percent increase in the statistically significant pre-pandemic firm characteristic of interest and RETURN, holding all else fixed: SIZE leads to a 0.003% increase; LEV leads to a -0.4% decrease; and ROE leads to a 3.3% increase in RETURN. Overall, this implies that firms who had a larger market capitalization, were less leveraged, and were more profitable pre-2020, experienced better stock price reactions compared to otherwise similar firms during the outbreak period.

Column 2 of table 11 includes the interaction terms that show how firms' stock returns respond to the pandemic as functions of individual corporate characteristics. By including these interaction terms, the effects of the variables SIZE, LEV, CASH, and ROE are not the main effects on RETURN anymore but become 'conditional effects'. Put differently, the effect of the proposed variables SIZE, LEV, CASH, and ROE that form the interactions depend on the level of the other variable in the interaction, namely COVID19_Cases. As a result of the interaction terms, it is possible to interpret the moderating effect of the corporate characteristics on the relationship between COVID-19 and stock market returns, i.e., to show which corporate characteristics mitigate or aggravate the negative effect of COVID19_Cases on RETURN during the outbreak period. As illustrated in table 11, the interaction term (COVID19xSIZE) shows a positive impact on weekly stock returns. The coefficient suggests that the negative impact of growth in confirmed cases on stock market returns weakens when companies had a larger market capitalization pre-2020, i.e., SIZE has a positive moderating effect on the relationship between COVID19_Cases and RETURN. In addition, firms who were less leveraged (COVID19xLEV), had more cash reserves (COVID19xCASH), and had higher profitability (COVID19xROE) pre-2020, were less likely to experience negative stock returns in response to COVID-19.

Specifically, consider two similar firms: one with SIZE at the 25th percentile (16.38) and another at the 75th percentile (17.634). Holding all other factors fixed, the estimations in column 2 show that a 'smaller' firm (25th percentile) would experience an 8.4%[7] greater decline in stock returns than a larger firm (75th percentile) in response to COVID19_Cases. In a similar vein, firms at the 75th percentile that were: more leveraged (1.495), held more cash (0.22), and had higher profitability (0.259) pre-2020, would experience (8.8%), 6.9%, and 5.7% (more) less stock return decline in response to COVID-19, respectively, compared to those in the 25th percentile (LEV of 0.416, CASH of 0.055 and ROE of 0.067).

[7] Computed as follows: (−0.065+0.002*16.38) / (−0.065+0.002*17.634) − 1); adopted from Ding et al. (2021).

4.2.2.1 Geographical differences

Table 12 presents the same regression analysis as was done in the previous section, but now specified per country. Striking is the difference in magnitude of the development of COVID19_Cases on RETURNS among the countries. In economic terms, the first three columns of table 12 show that a one percent increase in COVID19_Cases, leads, on average, to a -0.013%, -0.06% and -0.032% decrease in RETURNS, for China, UK and the US, respectively. Furthermore, STRINGENCY has a negative effect on RETURN in China (-0.1%), while it has a positive effect on RETURN in the UK and the US (0.1%). This could be explained by the fact that the Chinese government responded immediately with strong movement restrictions starting in January 2020, while restrictions in the UK and US were introduced more gradually up to March 2020. It is only from March 2020, around the date when the pandemic is announced (March 11, 2020), that the restrictions introduced for the UK and the US also increase sharply, as shown in Appendix 6. The immediate restrictions imposed by China may have been too restrictive on business operations, leading to a negative view from market participants and in turn negatively affecting stock returns. With respect to SIZE there are some notable differences: it has a negative effect on returns in China, while it has a positive effect in UK (though insignificant) and the US. As for the other corporate characteristics, the signs and values are somewhat similar across countries, except for some significance levels for SIZE and LEV. The variable CASH is found to be insignificant for all countries, which is consistent with the full sample as discussed in the previous section.

Table 12. *Regression results: Outbreak period by country*

Variables	**(1) China**	**(2) UK**	**(3) US**	**(4) China**	**(5) UK**	**(6) US**
COVID19_Cases	-.013***	-.06***	-.032***	-.028***	-.236***	-.115***
	(.002)	(.004)	(.002)	(.038)	(.069)	(.028)
STRINGENCY	-.001***	.001***	.001***	-.001***	.001***	.001***
	(0)	(0)	(0)	(0)	(0)	(0)
SIZE	-.003*	.004	.005***	-.004*	-.002	.001
	(.002)	(.003)	(.001)	(.002)	(.003)	(.002)
LEV	-.006***	-.003	-.005***	-.006***	0	-.002
	(.002)	(.002)	(.001)	(.002)	(.003)	(.001)
CASH	.013	.006	-.002	.008	.018	.027*
	(.011)	(.024)	(.01)	(.013)	(.032)	(.014)
ROE	.037***	.034***	.042***	.049***	-.002	.027***
	(.011)	(.013)	(.006)	(.013)	(.017)	(.008)
COVID19xSIZE				.001	.011***	.005***
				(.002)	(.004)	(.002)
COVID19xLEV				-.001	-.005	-.004***
				(.002)	(.004)	(.002)
COVID19xCASH				.01	-.021	.045***
				(.013)	(.038)	(.015)
COVID19xROE				-.023*	.062***	.024***
				(.013)	(.02)	(.008)
_cons	.098***	-.112**	-.116***	.106***	-.013***	-.062***
	(.032)	(.043)	(.02)	(.038)	(.057)	(.027)
Obs.,	3212	1694	8575	3212	1694	8575
R-squared	.054	.261	.12	.055	.268	.123
industry FE	Yes	Yes	Yes	Yes	Yes	Yes

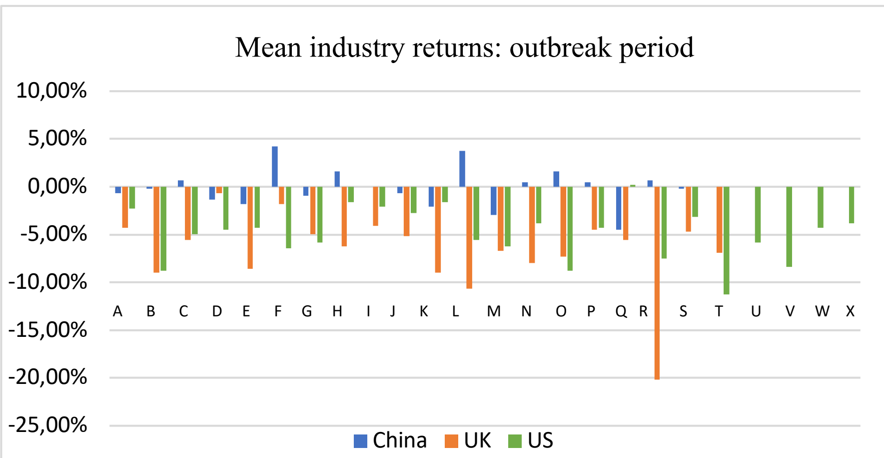
*Robust standard errors are reported in the parentheses. *, **, *** denote 10%, 5% and 1% significance levels, respectively*

Columns 4 through 6 of table 12 contain the interaction terms. The interaction between COVID19xSIZE enters positively and significantly for UK and the US. The interactions (COVID19xLEV) and COVID19xCASH are only (negatively) positively significant for the US. Finally, COVID19xROE is significant for all three countries. However, column 4 shows that companies in China that were more profitable pre-pandemic, had worse stock returns that US and UK firms, which show a positive stock reaction. This suggests that firms in China who were more profitable pre-pandemic, were more susceptible to the pandemic-driven market downturns during the outbreak period. This intriguing finding for China (although only significant at the 10% level), namely that lower profitability pre-2020 leads to higher stock returns, was also found by Song et al. (2021) for the US restaurant industry. The authors explain this finding by the gap between pre-pandemic and post-pandemic profitability. They argue that, from the perspective of shareholders and investors, the impact of the COVID-19 shock on a company's future financial performance may be greater for a company that was more profitable than its competitors prior to COVID-19.

4.2.2.2 Industry differences

Graph 1 shows the average returns by industry per country during the outbreak period. The letters, defined in Appendix 7, represent industry codes whose classification is based on a four-digit numeric code obtained from Worldscope -Thomson Reuters. It should be noted that the industries U, V, W, and X (tobacco, transportation, utilities, and miscellaneous, respectively) are only represented in the US sample. The graph shows that the worst performing industries, on average, are printing and publishing (Q) in China (-4.5%); recreation (R) in the UK (-20.2%), and textiles (T) in the US (-11.3%). The best performing industry, on average, during the outbreak period is construction (F) in China (+4.23%); the beverage market (D) in the UK (-0.69%), and printing and publishing (Q) in the US (+0.23%). While there are various industries in China who show positive returns during the outbreak period, nearly all sectors in the UK and US show negative returns.

Graph 1. *Industry returns: Outbreak period*



4.2.3 Regression analysis: Recovery period

This section presents the regression results by examining the recovery period that ranges from November 1, 2020 to January 31, 2021. Table 13 reports the regression results, that is, the relationship between the moderating role of firm characteristics, the development of COVID-19, and imposed government restrictions on weekly stock returns, while controlling for country and industry fixed effects.

Table 13. *Regression results: Recovery period*

Variables	(1) RETURN	(2) RETURN
COVID19_Cases	1.027***	1.764***
	(.043)	(.387)
STRINGENCY	-.004***	-.004***
	(0)	(0)
SIZE	-.001	.002
	(.001)	(.002)
LEV	.003***	.004**
	(.001)	(.002)
CASH	.028***	.001
	(.006)	(.012)
ROE	.016***	.048***
	(.004)	(.01)
COVID19xSIZE		-.038
		(.023)
COVID19xLEV		-.009
		(.02)
COVID19xCASH		.4***
		(.15)
COVID19xROE		.807***
		(.121)
_cons	.355***	.306***
	(.018)	(.034)
Observations	7956	7956
R-squared	.159	.165
country FE	Yes	Yes
industry FE	Yes	Yes

*Robust standard errors are reported in the parentheses. *, **, *** denote 10%, 5% and 1% significance, respectively*

First, the results of column 1 without interactions terms will be discussed, of which nearly all variables are statistically significant at the 1% level, apart from SIZE which is insignificant. The development of weekly COVID19_Cases shows a positive impact on weekly stock returns. In economic terms, the data shows that a one percent increase in COVID19_Cases, on average, results in 1.027% increase in RETURN, ceteris paribus. This result is attributed to the fact that during the recovery period the weekly growth rate of COVID-19 cases is on a downward trend as shown in Appendix 5. In addition, unlike the outbreak period, STRINGENCY has a negative relationship on weekly stock returns. Economically, the research model shows that a one percent increase in STRINGENCY is, on average, associated with approximately -0.4% decrease in RETURN, ceteris paribus. As previously suggested in section 4.2.1, this can possibly be attributed to the fact that the market views the imposed government policies as 'too restrictive' for business operations, which in turn leads to a negative market reaction to stock returns.

Furthermore, as shown in Appendix 8, STRINGENCY during the recovery period is much higher than during the outbreak period (Appendix 6), especially true for the UK and US. The following economic relationships, on average, are found between a one percent increase in the statistically significant pre-pandemic firm characteristic of interest and RETURN, holding all else fixed: LEV leads to a 0.3% increase; CASH leads to a 2.8% increase; and ROE leads to a 1.6% increase in RETURN. Overall, this implies that firms who were more leveraged, held more cash, and were more profitable pre-pandemic, experienced better stock price reactions compared to otherwise similar firms during the recovery period.

Noteworthy is the change in the sign for LEV, which is positive and significant during the recovery period, compared to the negative and significant sign during the outbreak period. The following explanation is suggested: highly leveraged firms are expected to face difficulties when the cash flow stop during the outbreak period, since it lowers their interest coverage ratio. As a result of halted business operations during the outbreak period, the interest coverage ratio worsens, and highly levered firms are more likely to become financially distressed. This increased risk of financial distress is perceived by investors as unfavorable, which in turn leads to a negative sign in the outbreak period. However, during the recovery period, positive developments related to the pandemic allow companies to resume regular business operations, improving the sales and therefore their interest coverage ratio. Altogether, investors consider leveraged firms to be risky during the outbreak period, but this leverage is seen as a benefit (additional value) in the recovery period, because of the tax shield (tax deductibility of interest expense) it provides.

Column 2 of table 13 includes the interaction terms to show which corporate characteristics mitigate or aggravate the positive effect of COVID19_Cases on RETURN during the recovery period. As illustrated in table 13, the interaction term COVID19xCASH shows a positive impact on weekly stock returns. The coefficient suggests that the positive impact of weekly confirmed cases on stock market returns strengthens when companies had more cash reserves pre-2020, i.e., CASH has a positive moderating effect on the relationship between COVID19_Cases and RETURN. In addition, firms who had higher profitability (COVID19xROE) pre-2020, were more likely to experience positive stock returns in response to COVID-19.

Specifically, consider two similar firms: one with CASH at the 25th percentile (0.055) and another at the 75th percentile (0.22). Holding all other factors fixed, the estimations in column 2 show that a firm with more cash reserves (75th percentile) would experience 3.7%[8] higher stock returns than a firm with less cash reserves (25th percentile) in response to COVID19_Cases. In a similar vein, firms at the 75th

[8] Computed as follows: (1.764+0.4*0.22) / (1.764+0.4*0.055) - 1)

percentile (0.259) that had higher profitability pre-2020, would experience 8.5% higher stock returns in response to COVID19_Cases during the recovery period, compared to those in the 25th percentile (0.067).

4.2.3.1 Geographical differences

Table 14 presents the same regression analysis as was done in the previous section, but now specified per country. Striking is the difference in the sign of COVID19_Cases on RETURN among the countries. In economic terms, the first three columns of table 14 show that a one percent increase in COVID19_Cases leads, on average, to a (-9.484%), 1.184% and 1.232% (decrease) increase in RETURN, for China, UK, and the US, respectively. This difference in sign is due to an increasing mean of weekly growth in COVID19 cases in China, while this weekly growth rate is on a downward trend in the UK and the US, as shown in Appendix 9. Furthermore, STRINGENCY, shows an inverse relationship among the countries compared to the outbreak period. STRINGENCY has a positive effect on RETURN in China (0.1%), while it has a negative effect on RETURN in the UK (-0.3%) and the US (-1%). Regarding the other corporate characteristics, the signs and values are somewhat similar across the countries, except for some significance levels for LEV, CASH and ROE. SIZE is found to be insignificant for all countries, which is consistent with the full sample as discussed in the previous section.

Table 14. *Regression results: Recovery period by country*

Variables	**(1) China**	**(2) UK**	**(3) US**	**(4) China**	**(5) UK**	**(6) US**
COVID19_Cases	-9.484***	1.184***	1.232***	-6.288***	.342***	2.871***
	(.738)	(.058)	(.051)	(13.071)	(.861)	(.807)
STRINGENCY	.001***	-.003***	-.01***	.001***	-.003***	-.01***
	(0)	(0)	(0)	(0)	(0)	(0)
SIZE	.003	-.002	-.001	.006	-.007	.007*
	(.003)	(.002)	(.001)	(.006)	(.005)	(.004)
LEV	.003	.003	.002***	.022***	-.004	.006*
	(.002)	(.002)	(.001)	(.005)	(.005)	(.003)
CASH	.019	.002	.032***	.017	-.066	-.094***
	(.015)	(.018)	(.006)	(.034)	(.047)	(.025)
ROE	.041***	.021**	.025***	-.15***	.171***	.018
	(.014)	(.009)	(.004)	(.033)	(.031)	(.019)
COVID19xSIZE				-.355	.058	-.098**
				(.778)	(.051)	(.047)
COVID19xLEV				-2.864***	.066	-.041
				(.696)	(.042)	(.04)
COVID19xCASH				.324	.671	1.546***
				(4.555)	(.429)	(.29)
COVID19xROE				28.003***	1.784***	.533**
				(4.422)	(.282)	(.231)
_cons	-.074	.139***	.597***	-.095	.214**	.461***
	(.049)	(.036)	(.02)	(.101)	(.088)	(.069)
Obs.,	1898	1001	5057	1898	1001	5057
R-squared	.113	.356	.282	.147	.383	.288
industry FE	Yes	Yes	Yes	Yes	Yes	Yes

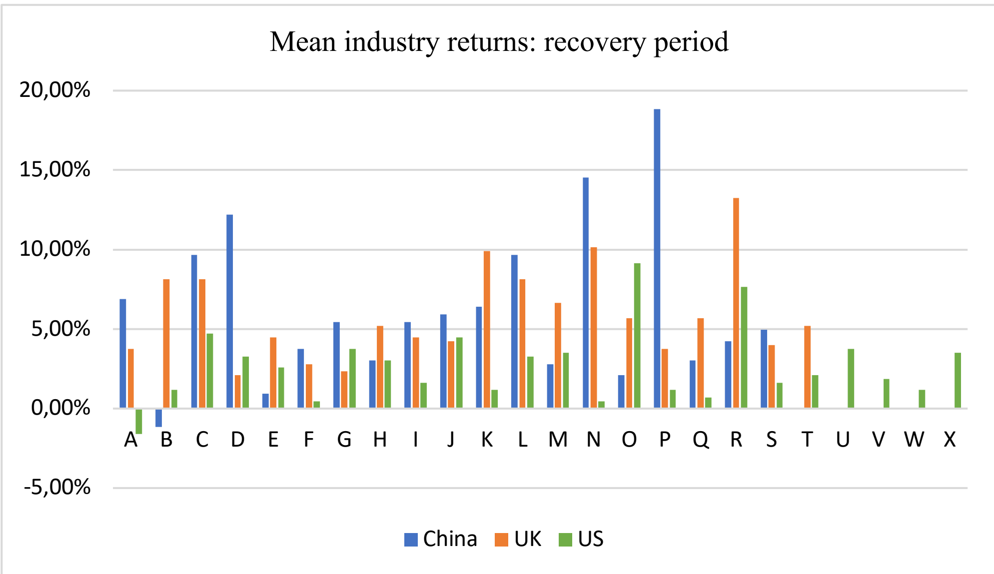
*Robust standard errors are reported in the parentheses. *, **, *** denote 10%, 5% and 1% significance, respectively*

Columns 4 through 6 of table 14 contain the interaction terms. The interaction terms COVID19xSIZE and COVID19xLEV are only negative and significant for the US and China, respectively. The interaction COVID19xCASH is only significant (and positive) for the US, although the samples representing China and the UK show similar signs. Lastly, COVID19xROE is significant and positive for all three countries. Overall, it can be concluded that all markets were positively affected by higher cash reserves and profitability (pre-2020) in response to COVID-19 during the recovery period.

4.2.3.2 Industry differences

Graph 2 shows the average industry returns per country during the recovery period. Note that, similar to the outbreak period, the industries U, V, W and X (tobacco, transportation, utilities, and miscellaneous, respectively) are only represented in the US sample. The graph shows that nearly all industries, on average, show positive returns during the recovery period, apart from the sector aerospace (A) in the US, and apparel (B) in China. The best performing industry, on average, is the paper industry (P) in China (+18.85%); recreation (R) in the UK (+13.24%), and the oil, gas, coal & related services sector (O) in the US (+9.14%). The graph suggests that nearly all industries partially, and in some cases fully, recovered relative to the impact of the pandemic during the outbreak period.

Graph 2. *Industry returns: Recovery period*



5. Conclusion

The magnitude of the impact following the COVID-19 crisis has been unprecedentedly overwhelming, not only can the pandemic be characterized as a worldwide health crisis in terms of confirmed cases and deaths, but it also completely disrupted the global economy and triggered financial challenges for companies operating in various industries. In particular, the financial impact on companies is centered in this research, and is examined by structurally answering the following research question:

What is the impact of COVID-19 on companies' market valuations since the onset of the crisis, both geographically and at the industry-level, and does this effect differ between companies with different characteristics?

To shed empirical light on this research question, the relationship between stock prices and corporate characteristics, variables indicating the severity of COVID-19, and policy measures introduced by a government in response to the crisis, have been investigated using a dataset consisting of nearly 600 publicly listed firms across 3 countries, namely the US, UK, and China. The existing literature regarding the impact of COVID-19 on equity markets and individual companies has grown vastly, with the main period of interest being the outbreak of the virus, i.e., late 2019 - early 2020, during which major regional stock markets plunged after the first wave of the outbreak. However, this research contributed by dividing the impact of COVID-19 in various waves more concretely. This was done by utilizing the event study methodology and a panel regression analysis. The remainder of this chapter outlines the results of both methodologies in order to conclude the hypotheses as formulated in section 2.6, and to structurally answer the main research question posed above.

The event study methodology was applied to assess the impact on companies' market valuations during the outbreak and recovery period based on three key developments concerning COVID-19, namely: (1) WHO's PHEIC declaration on January 30, 2020; (2) WHO's declaration of a pandemic on March 11, 2020; and (3) Pfizer-BioNTech's announcement of vaccine efficacy on November 9, 2020. The change (impact) on market valuations was measured by the cumulative average abnormal return (CAAR), which served as a proxy for the overall share price reaction around the key development (event) in question. Firstly, regarding the PHEIC announcement it can be concluded that despite the WHO's alarming message to countries, equity markets do not seem to incorporate the news, as the results are not consistent and significant. Explanation for the mixed results regarding the CAARs is that the PHEIC declaration was made early into the COVID-19 crisis, and the development of the number of confirmed COVID-19 cases, global spread, and potential imposed business restrictions, were still very unclear. Consequently, market participants were unsure how to respond to the development of the crisis. Hence, no supportive evidence for the hypothesis ***[H1]*** was found.

In contrast, strong evidence of negative abnormal returns is found during the pandemic announcement, supporting hypothesis ***[H2]***. The entire sample shows a negative CAAR of -1.019% in event window [-1,0] and -4.917% and -7.104% in the event windows [-5,5] and [-5,30], respectively, indicating that the abnormal returns were not only concentrated on the event day itself. More specifically, the negative CAAR becomes more pronounced once the event window is extended. Ultimately, China proved to be more resilient to negative abnormal returns than companies representing the US and UK. This may be due to the fact that the Chinese government immediately adopted an aggressive strategy to quarantine the outbreak of the virus, as evidenced by the stringency index in Appendix 6. This in turn may explain the minimal increase in the number of confirmed COVID-19 cases compared to the US and UK. In addition, the cross-sectional regression analysis indicates that firms with more cash reserves, higher profitability and with a larger market capitalization pre-2020 experienced higher abnormal returns around the pandemic announcement, that is, they mitigate the negative impact. Finally, by examining the Pfizer-BioNTech's vaccine effectiveness announcement, this study finds a positive CAAR of 0.868% in event window [-1,0], supporting hypothesis ***[H3]***. With that, following the cross-sectional regression, less leveraged and smaller companies pre-2020 experienced higher abnormal returns around the vaccine announcement.

A panel regression analysis was performed as the second method of analysis in order to study the time-varying relationship between stock returns and a proxy for the development of the COVID-19 crisis; imposed government restrictions (stringency); and pre-pandemic (fiscal year 2019) corporate characteristics (i.e., firm size, leverage, cash, and profitability). First, an increasing number of confirmed COVID-19 cases were expected to have a negative impact on companies' market valuations during both sample periods. Indeed, the results of the outbreak and recovery period find evidence for hypothesis ***[H4]*** and indicate that an increase in the number of confirmed COVID-19 cases leads, on average, to a decline in stock returns. The results make sense, as an increasing presence of the virus worsens the overall environment to conduct regular business operations. Secondly, evidence for hypothesis ***[H5]*** is mixed, as the stringency index shows a positive coefficient during the outbreak period and a negative coefficient during the recovery period. Note, that the mean of the index is 43.59 during the outbreak period, while the mean is 72.65 during the recovery period. Thus, there may be a pinpoint in the degree of stringency at which the market assesses the introduced policies by a government as "too restrictive" for business operations, which in turn leads to negatively affected stock returns. Finally, by examining pre-pandemic firm characteristics, this research found that companies who had a larger market capitalization, were less leveraged, had more cash reserves, and were more profitable pre-2020, experienced better stock price reactions during the outbreak period. The recovery period shows similar results, apart from firm size being insignificant and the coefficient for leverage being significant and positive. Thus, apart from hypothesis ***[H6]***, the results provide strong evidence for hypotheses ***[H7 - H9]***.

In terms of geographical differences, the variables representing COVID-19 cases development and stringency are particularly notable between China, the US and the UK. This is due to the difference in growth of the number of COVID-19 cases, which shows a more stable trend for China. In addition, the containment and closure measures immediately surged in China from January 2020, while the restrictions in the US and UK only sharply increased from March 2020, following the pandemic announcement. As for the corporate characteristics, the signs and values are somewhat similar across countries, apart from firm size that has a negative effect on returns in China, while it has a positive effect in the UK (though insignificant) and the US during the outbreak period. Finally, in terms of industry returns, the worst performing industries, on average, are printing and publishing in China; recreation in the UK; and textiles in the US. While several industries in China show positive returns during the outbreak period, nearly all sectors in the UK and US show negative returns. The recovery period shows that nearly all industries partially, and in some cases fully, recovered from the impact of the pandemic during the outbreak period. However, the results do support the hypothesis ***[H10]***, that is, there are no industries that appear to consistently perform better or worse than other industries during the investigated sample periods.

In conclusion, the results of this research contribute to the existing literature by providing a better understanding of the impact of COVID-19 during its various waves. Furthermore, the empirical results may be used as supportive evidence concerning the decision-making process of shareholders and potential investors in case of the ongoing COVID-19 pandemic or other unexpected crises to come. However, there are some limitations to this research that may be interesting to explore in further research. First, this study investigated the effect of the COVID-19 shock using a universe consisting of publicly traded companies from the S&P 500 (US); FTSE 100 (UK); and FTSE China A 200 (China). Therefore, the results of this study cannot be freely generalized to the context of other countries. Research on the impact of the crisis on other countries could provide more insight into the differences in changes in market valuations worldwide, for example between developed and emerging countries. Second, this research primarily focused on the changes in market valuations' to COVID-19 of listed companies. For further research, it may be interesting to consider the impact of the COVID-19 shock on private companies. Third, although this study attempted to use sample periods as long as possible to illustrate the average impact during several stages, that being the outbreak and recovery period, it may be interesting to investigate the impact of COVID-19 for other periods as well. A suggestion is to extend the sample further into 2021, as the number of approved vaccines has increased and vaccination programs have been initiated worldwide during this year, strengthening the overall environment for conducting regular business activities. Fourth, monetary measures taken by central banks (stimulus packages) and fiscal interventions by governments such as tax deferrals, wage subsidies and debt moratoria were beyond the scope of this study, but existing research shows that countries with larger, more targeted rescue packages and interventions seem to have experienced a stronger recovery than otherwise similar countries (OECD, 2020; Seven and Yilmaz, 2021). Hence, it might be interesting to investigate the impact of these monetary and governmental interventions on companies' market valuations during the crisis. Lastly, this research measured the impact of COVID-19 using a growth-based measure of confirmed cases. It would be worthwhile to utilize other measures of the development of the virus, i.e., number of deaths, number of recovered cases and the number of vaccinations, to comprehensively assess the overall impact and which may help to prevent the negative impact of a global pandemic from being unnecessarily inflated.

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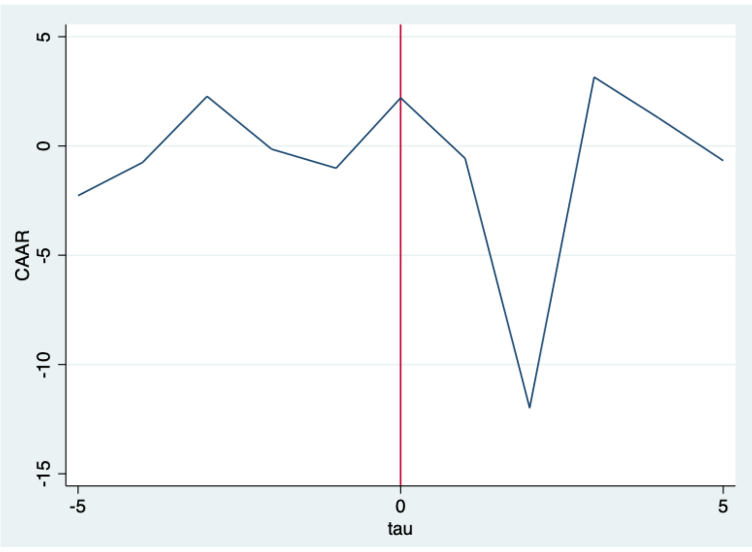
Appendix 1. PHEIC (30 January, 2020)

Table 15. *Abnormal returns individual trading days - PHEIC*

Individual trading days	(1) All	(2) China	(3) UK	(4) US
AR [-5]	-.004*** (.001)	-.035*** (.002)	-.01*** (.002)	.007*** (.001)
AR [-4]	-.001** (.001)	-.0004 (.0003)	.013*** (.001)	-.004*** (.001)
AR [-3]	.004*** (.001)	.003*** (.001)	-0.0004 (.001)	.005*** (.001)
AR [-2]	-.0002 (.0005)	-.003*** (.0002)	-.007*** (.002)	.002*** (.001)
AR [-1]	-.002*** (.001)	-.001*** (.0002)	.004** (.002)	-.003*** (.001)
AR [0]	.004*** (.001)	-.001** (.0003)	-.001 (.003)	.006*** (.001)
AR [1]	-.001 (.001)	.002*** (.001)	.011*** (.002)	-.004*** (.001)
AR [2]	-.02*** (.002)	-.103*** (.003)	-.009*** (.001)	.004*** (.001)
AR [3]	.005*** (.001)	.037*** (.004)	-.006*** (.002)	-.002*** (.001)
AR [4]	.002** (.001)	.011*** (.003)	-.007*** (.002)	.001 (.001)
AR [5]	-.001 (.001)	.024*** (.003)	-.01*** (.002)	-.007*** (.001)
Obs.,	598	123	76	399

*Robust standard error are reported in the parentheses. *, **, *** denote 10%, 5% and 1% significance, respectively*

Graph 3. *CAAR development during PHEIC announcement*



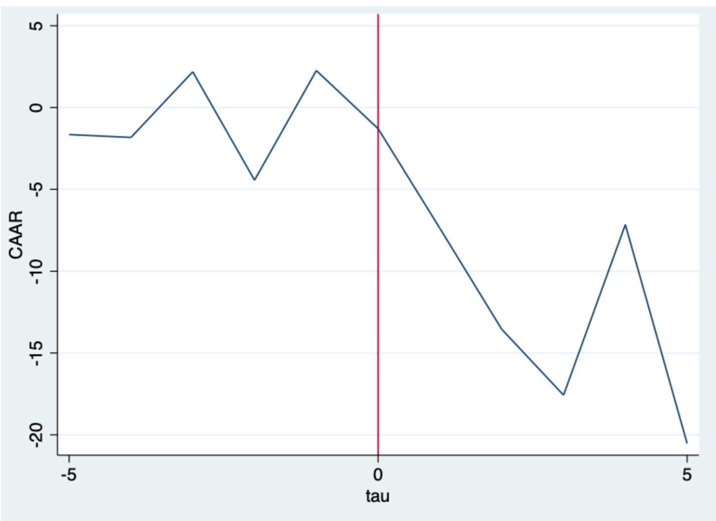
Appendix 2. Pandemic (11 March, 2020)

Table 16. *Abnormal returns individual trading days - Pandemic*

Individual trading days	(1) All	(2) China	(3) UK	(4) US
AR [-5]	-.003***	-.009***	-.004*	-.001
	(.001)	(.002)	(.002)	(.001)
AR [-4]	-.003***	-.002	-.007***	-.002***
	(.001)	(.002)	(.001)	(.001)
AR [-3]	.004***	.027***	-.003**	-.002***
	(.001)	(.002)	(.001)	(.0002)
AR [-2]	-.007***	.001	-.014***	-.009***
	(.001)	(.002)	(.002)	(.001)
AR [-1]	.004***	-.006**	.002	.007***
	(.001)	(.002)	(.001)	(.001)
AR [0]	-.002*	.015***	-.013***	-.005***
	(.001)	(.002)	(.002)	(.001)
AR [1]	-.012***	.005**	-.017***	-.017***
	(.001)	(.002)	(.002)	(.002)
AR [2]	-.023***	.003	-.037***	-.028***
	(.001)	(.003)	(.002)	(.002)
AR [3]	-.029***	.008***	-.02***	-.043***
	(.002)	(.003)	(.002)	(.002)
AR [4]	-.012***	-.028***	-.007***	-.008***
	(.001)	(.004)	(.002)	(.001)
AR [5]	-.034***	.003	-.048***	-.043***
	(.001)	(.003)	(.003)	(.001)
Obs.,	598	123	76	399

*Robust standard error are reported in the parentheses. *, **, *** denote 10%, 5% and 1% significance, respectively*

Graph 4. *CAAR development during pandemic announcement*



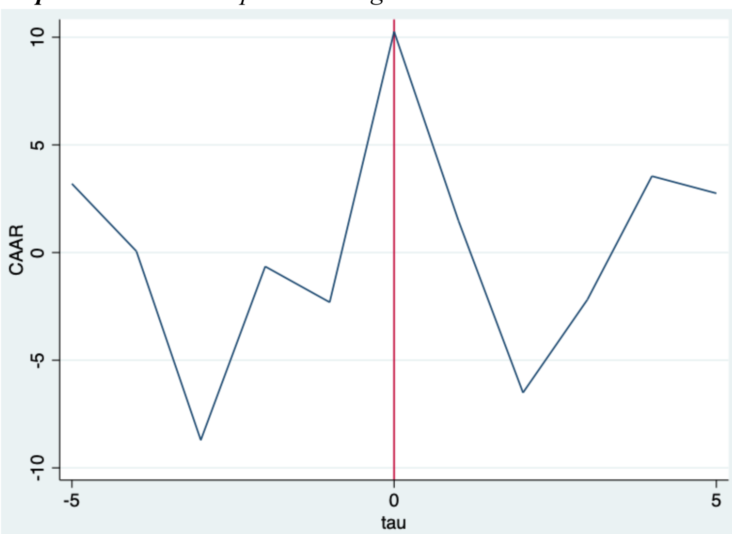
Appendix 3. Pfizer-BioNTech (9 November, 2020)

Table 17. *Abnormal returns individual trading days - Pfizer-BioNTech*

Individual trading days	(1) All	(2) China	(3) UK	(4) US
AR [-5]	.005*** (.001)	.009** (.003)	-.005* (.003)	.006*** (.001)
AR [-4]	.0001 (.001)	.003 (.002)	.014*** (.002)	-.003*** (.001)
AR [-3]	-.014*** (.001)	-.004* (.002)	-.009*** (.003)	-.019*** (.002)
AR [-2]	-.001 (.001)	.02*** (.002)	-.008*** (.003)	-.006*** (.001)
AR [-1]	-.004*** (.001)	-.006** (.002)	-.0004 (.002)	-.004*** (.001)
AR [0]	.017*** (.003)	.024*** (.003)	.029*** (.009)	.013*** (.004)
AR [1]	.002* (.001)	.016*** (.003)	.021*** (.004)	.005*** (.001)
AR [2]	-.011*** (.001)	-.028*** (.003)	-.0001 (.003)	-.007*** (.001)
AR [3]	-.004*** (.001)	.006*** (.002)	-.002 (.002)	-.007*** (.001)
AR [4]	.006*** (.001)	-.007*** (.002)	-.007*** (.002)	.012*** (.001)
AR [5]	.005*** (.001)	.009*** (.002)	.003 (.003)	.004*** (.001)
Obs.,	598	123	76	399

*Robust standard error are reported in the parentheses. *, **, *** denote 10%, 5% and 1% significance, respectively*

Graph 5. *CAAR development during vaccine announcement*



Appendix 4. CAAR per industry

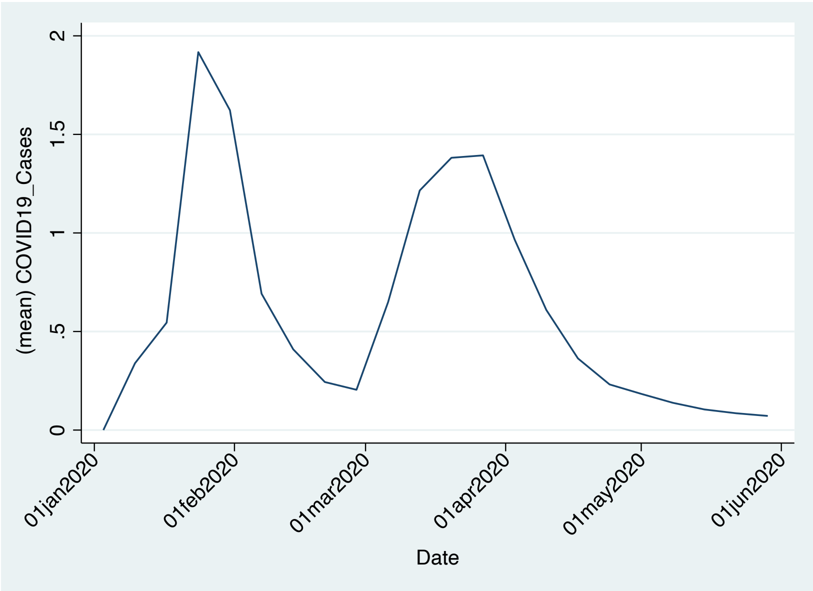
Table 18. *CAAR per industry*

Industries	CAAR [-5,5] PHEIC	CAAR [-5,5] Pandemic	CAAR [-5,5] Vaccine
Aerospace (base)			
Apparel	-7.996**	-8.26***	-10.646*
	(3.608)	(2.97)	(5.901)
Automotive	-6.438	-4.522	-3.066
	(4.01)	(2.945)	(5.883)
Beverages	-2.183	1.251	-3.168
	(2.784)	(1.922)	(5.194)
Chemicals	-.865	-2.337	-5.947
	(2.834)	(2.197)	(5.14)
Construction	-3.229	.144	-6.476
	(2.712)	(2.173)	(5.202)
Diversified	.966	-4.399**	-2.382
	(2.591)	(1.902)	(5.343)
Healthcare	1.178	.499	-6.166
	(2.507)	(1.946)	(5.054)
Electrical	-5.468**	.203	-2.819
	(2.485)	(2.712)	(5.218)
Electronics	.15	-.817	-5.301
	(2.459)	(1.9)	(5.047)
Food	-1.306	2.066	-6.737
	(2.49)	(2.247)	(5.041)
Machinery & equipment	-2.16	-.316	-3.955
	(2.906)	(1.987)	(5.09)
Metal Producers	-3.64	-2.876	-3.507
	(3.289)	(2.5)	(5.228)
Metal product manufactures	5.693	5.608	-4.202
	(5.025)	(4.386)	(6.311)
Oil, gas, coal & related	-6.272**	-10.116***	1.385
	(2.691)	(2.344)	(5.089)
Paper	-3.887	-4.846**	-4.392
	(2.7)	(2.327)	(5.097)
Printing & publishing	1.21	.189	-2.585
	(2.712)	(3.806)	(6.77)
Recreation	-2.57	-4.322*	-5.452
	(2.72)	(2.418)	(5.126)
Retailers	-3.233	-.379	-7.779
	(2.711)	(2.065)	(5.104)
Textiles	-3.088	-4.698	-1.052
	(2.516)	(5.11)	(6.12)
Tobacco	-1.78	-7.182***	-5.546
	(2.98)	(2.504)	(5.021)
Transportation	-2.866	-4.139*	-6.206
	(2.628)	(2.476)	(5.222)
Utilities	1.502	3.444	-2.161
	(2.714)	(2.176)	(5.046)
Miscellaneous	-.414	-.678	-4.816
	(2.458)	(1.758)	(5.032)
_cons	.992	-3.841**	5.461
	(2.367)	(1.605)	(5.005)
Observations	598	598	604
R-squared	.107	.119	.114

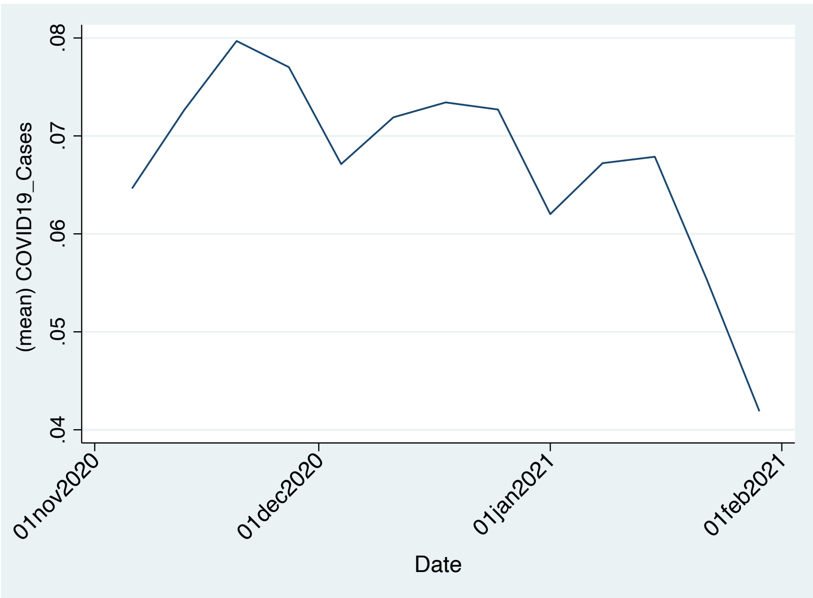
*Robust standard errors are in parentheses *, **, *** denote 10%, 5% and 1% significance, respectively*

Appendix 5. COVID-19 development

Graph 6. *Development COVID-19 cases during the outbreak period*

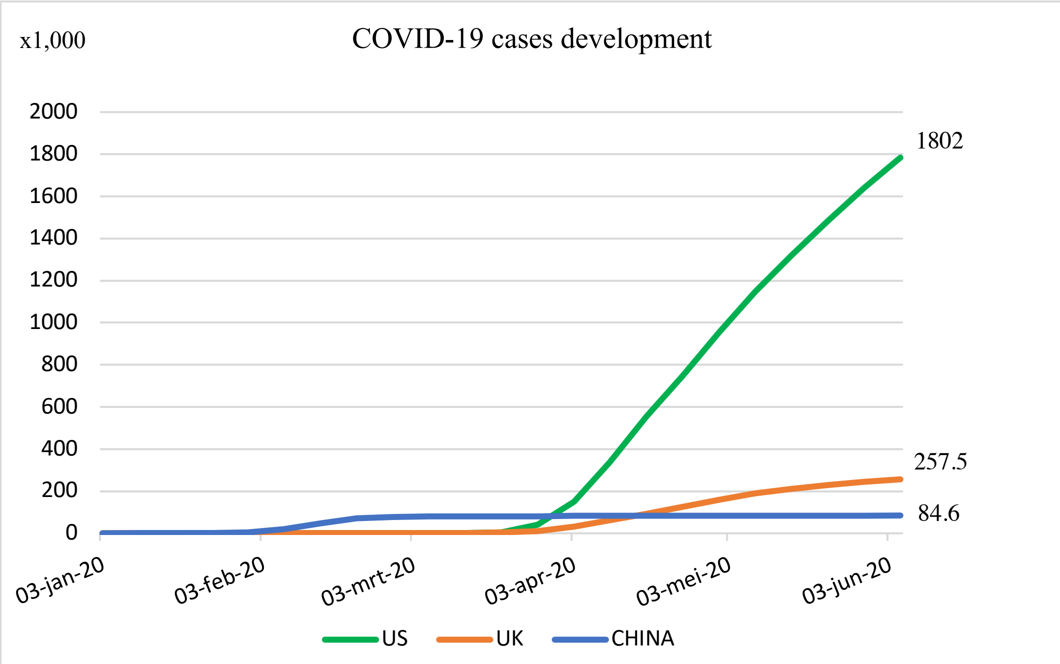


Graph 7. *Development COVID-19 cases during the recovery period*

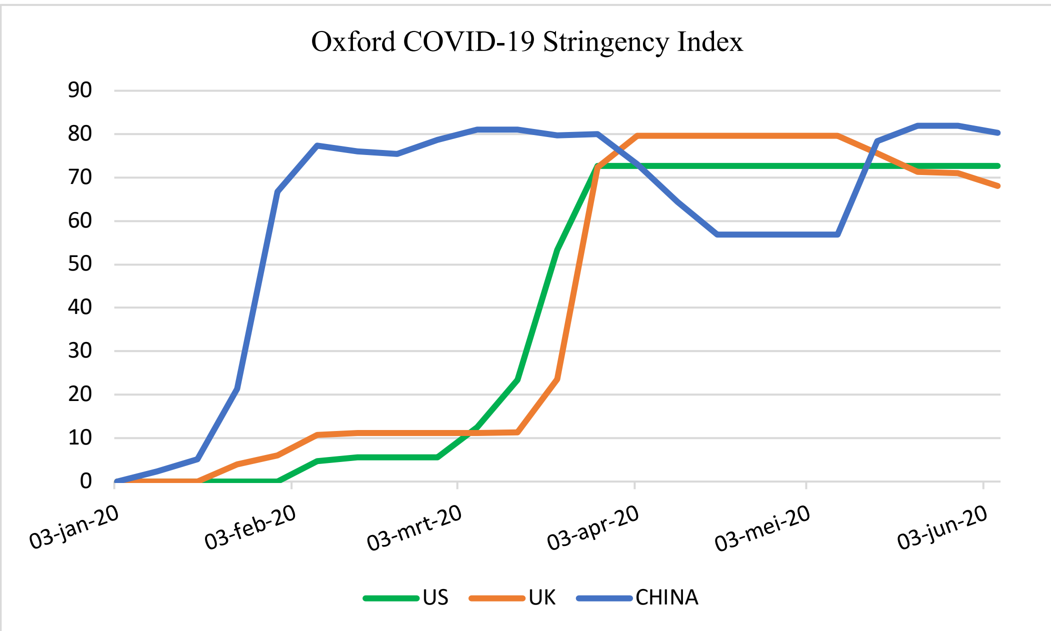


Appendix 6. Outbreak period

Graph 8. *Development COVID-19 cases per country - outbreak period*



Graph 9. *Stringency index per country - outbreak period*



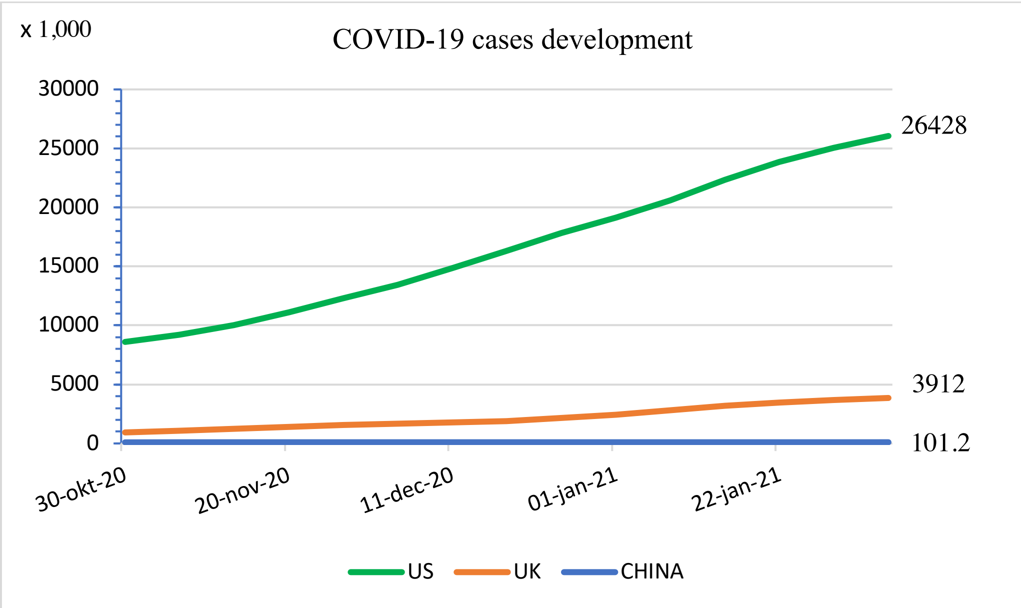
Appendix 7. Industry classification

Table 19. *Industry classification Worldscope - Thomson Reuters*

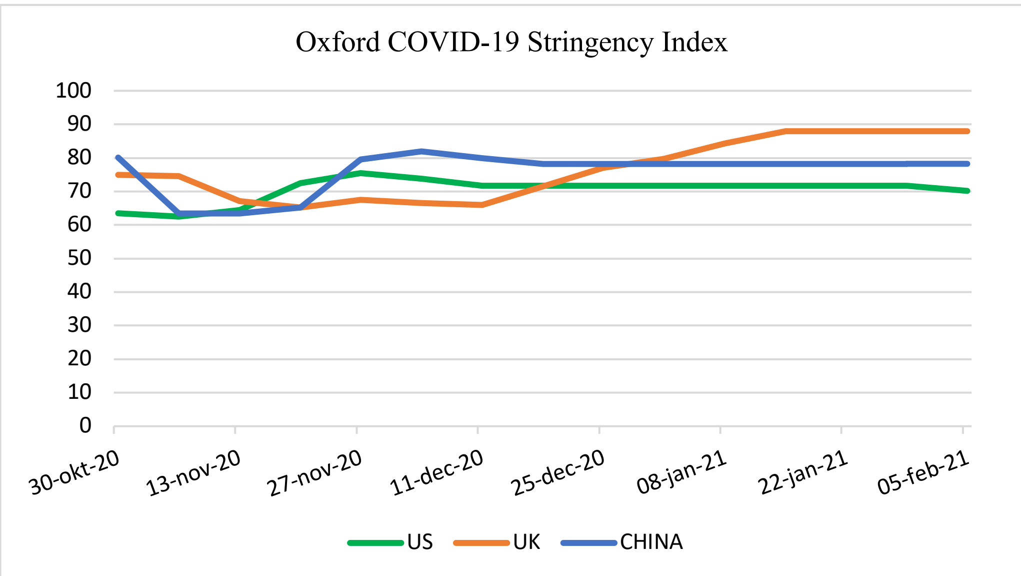
Letter	**Industry code**	**Major industry group**
A	1300	Aerospace
B	1600	Apparel
C	1900	Automotive
D	2200	Beverages
E	2500	Chemicals
F	2800	Construction
G	3100	Diversified
H	3400	Drugs, cosmetics & Healthcare
I	3700	Electrical
J	4000	Electronics
K	4600	Food
L	4900	Machinery & Equipment
M	5200	Metal producers
N	5500	Metal product manufacturers
O	5800	Oil, Gas, Coal & Related services
P	6100	Paper
Q	6400	Printing & Publishing
R	6700	Recreation
S	7000	Retailers
T	7300	Textiles
U	7600	Tobacco
V	7900	Transportation
W	8200	Utilities
X	8500	Miscellaneous

Appendix 8. Recovery period

Graph 10. *Development COVID-19 cases per country - recovery period*

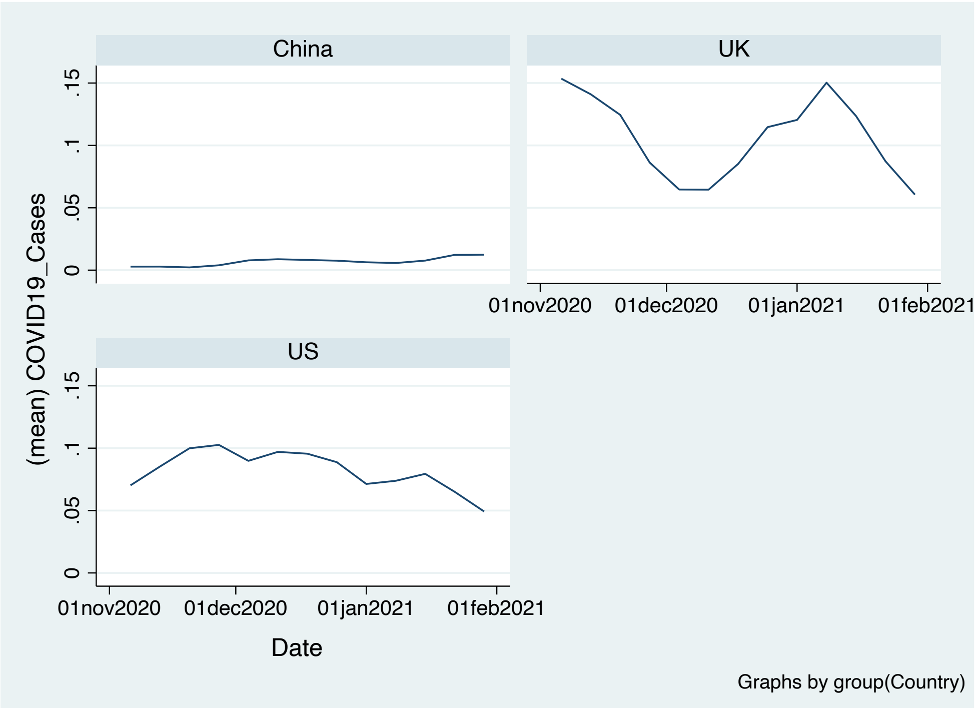


Graph 11. *Stringency index per country - recovery period*



Appendix 9. Development of (mean) COVID-19 cases

Graph 12. *Mean development COVID-19 cases per country - recovery period*



Graph 13. *Mean development COVID-19 cases China*