The stock market response to COVID-19 – Evidence from five developed markets

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Abstract

This study evaluates the connection between stock returns and the COVID-19 pandemic in five developed markets, including Canada, France, Germany, the United Kingdom, and the United States. The analysis is based on observations ranging from December 2019, when the first official cases of the new virus were discovered, to April 2022 and uses data from 3,120 firms. Stock returns reacted negatively to the growth of cumulative cases and deaths in the overall sample as well as across four of the five countries, except for the United Kingdom. While the relation between lockdowns and stock performance is also negative, fiscal stimuli seem to have a positive impact. Furthermore, I find that higher perceived risk and rising uncertainty, measured by Google search volume and a policy uncertainty index based on news, are also related to lower performance in most regression specifications. It can be observed that smaller companies in my sample suffer more from a higher growth rate of cumulative cases than medium-sized ones and the largest firms even experience a positive effect. Finally, I show that industry affiliation matters. The pandemic-related change in stock returns across industries varies in statistical and economic significance, with some coefficients being positive and others negative.

Key Words: COVID-19; Economic Crisis; Stock Prices; Cross-Country Analysis; Government Policies; Public Sentiment

A resposta da bolsa à COVID-19 - Evidência de cinco mercados desenvolvidos

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Sumário

Este estudo avalia a relação entre o retorno das acções e a pandemia da COVID-19 em cinco mercados desenvolvidos, incluindo Canadá, França, Alemanha, o Reino Unido e os Estados Unidos. A análise baseia-se em observações que vão desde Dezembro de 2019, quando foram descobertos os primeiros casos oficiais do novo vírus, até Abril de 2022, e utiliza dados de 3.120 empresas. Os retornos das acções reagiram negativamente ao crescimento de casos e mortes acumulados na amostra global, bem como em quatro dos cinco países, com excepção do Reino Unido. Embora a relação entre lockdowns e o retorno de acções seja também negativa, os estímulos fiscais parecem ter um impacto positivo. Além disso, considero que o maior risco percebido e a crescente incerteza, medida pelo volume de pesquisa do Google e um índice de incerteza política baseado em notícias, estão também relacionados com um desempenho inferior na maioria das especificações de regressão. Pode-se observar que as Menores empresas de minha amostra sofrem mais com uma taxa de crescimento mais elevada de casos cumulativos do que as de média dimensão e as maiores empresas experimentam mesmo um efeito positivo. Finalmente, mostro que a filiação na indústria é importante. A alteração relacionada com a pandemia nos retornos de stocks entre indústrias varia em termos de significância estatística e económica, com alguns coeficientes a serem positivos e outros negativos.

Palavras-chave: COVID-19; Crise Económica; Retorno das Acções; Análise Entre Países; Políticas Governamentais; Sentimento Público

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List of Abbreviations

CSR	Corporate Social Responsibility
EPU	Economic Policy Uncertainty
ESG	Environmental, Social, and Governance
ICU	Intensive Care Unit
SARS	Severe Acute Respiratory Syndrome
SIC	Standard Industrial Classification
WHO	World Health Organization

1 Introduction

Since early 2020, the COVID-19 pandemic has been exerting great influence over people and companies on a global scale and changing the way we live, work together, and conduct business. The first cases of the novel coronavirus were identified in late 2019 in the Chinese province of Hubei but at the time the economic risk stemming from this outbreak was perceived as low by the international community (Ramelli & Wagner, 2020). When the disease quickly spread all over the world shortly after and the threat of a looming global pandemic became apparent, the financial economy reacted heavily and in an unprecedented manner. In lots of countries, the stock markets crashed and major indexes lost over a third of their value, only to regain a large part of it within a short period (Demers, Hendrikse, Joos, & Lev, 2021; O'Donnell, Shannon, & Sheehan, 2021; Zhang, Hu, & Ji, 2020).

This initial shock was followed by multiple waves of infections and lengthy periods of government-imposed restrictions on individual freedoms and economic activity in the form of lockdowns (Scherf, Matschke, & Rieger, 2022; Zhang et al., 2020). Consequently, the pandemic can be described as a catastrophe, both in humanitarian and economic terms. Due to its nature, however, this crisis (meaning the financial aspect) is different from previous ones as it was not caused by underlying circumstances and systemic inadequacies but by an exogenous shock (Sharif, Aloui, & Yarovaya, 2020), making it similar to a natural disaster. This fact is particularly interesting for researchers since an exogenous shock on consumers and firms can be used to identify drivers of profitability, sustainable business practices, and corporate resilience. Since the onset of the pandemic, there has been a growing body of academic literature on the topic, and I want to contribute to this knowledge with my dissertation.

The purpose of this paper is to examine empirically how the pandemic, specifically the growth rate of cumulative cases and deaths, impacts stock returns across five major economies and to understand some of the drivers behind the developments. Existing studies mostly focus on the United States or China (Albulescu, 2021; Corbet, Larkin, & Lucey, 2020; Pham, Adrian, Garg, Phang, & Truong, 2021), with only a very limited number of articles following a more international approach (Bannigidadmath, Narayan, Phan, & Gong, 2022; Scherf et al., 2022). Furthermore, studying recent events and publishing the results takes time, leading to little available information about the impact of the pandemic after 2020. These issues should be addressed with the comparably long sample period until April 2022 and the cross-country approach adopted in this thesis.

Data: The analysis is based on daily log returns of stocks from five countries that are among the most severely impacted by the coronavirus: Canada, France, Germany, the United Kingdom, and the United States. I want to utilize a diverse selection of stocks for my investigation and therefore the sample consists of constituents of indexes covering large parts of the national markets instead of major indexes only including the biggest or most traded stocks. To develop a better understanding of the impact on stock returns throughout the pandemic until recently, the collected data ranges from December 2019 to April 2022. Applying these criteria leads to a panel dataset consisting of 3,120 firms across all countries and 2,006,224 related observations. Stock prices are retrieved from Refinitiv Datastream and used to calculate returns. Data on daily new coronavirus cases, deaths, and occupancy of the intensive care unit (ICU) are collected from Our World in Data (2022) for each country. Furthermore, individual corporate characteristics (e.g. cash, total assets, total debt, …) are also downloaded from Refinitiv Datastream and used to compute commonly applied control variables. The five factors by Fama and French (2015) constitute another set of controls.

Methodology: To identify the impact of several COVID-19 metrics on stock returns I am employing an ordinary least squares (OLS) regression model with various specifications. First, the effect of the growth rate of new coronavirus cases, deaths, or ICU occupancy is estimated on a standalone basis, followed by an analysis including government measures such as lockdowns and fiscal stimuli or measures of public sentiment. Second, I try to pinpoint some of the drivers of the observed relationships by using the fact that the crisis is like a natural disaster in that it is an exogenous shock to consumers and markets. Specifically, the role of company size and industry affiliation is examined using interaction terms with my COVID-19 variables. Controls for corporate characteristics and the five factors defined by Fama and French (2015) are added. Furthermore, I use combined fixed effects (country-time and industry-time) whenever applicable, thereby filtering out time-varying differences by industry and country.

Main findings: My first (baseline) hypothesis suggests that stock returns are negatively related to the metrics quantifying the severity of the pandemic. While the hypothesis can be confirmed for the growth rate of cumulative cases and deaths, the same cannot be concluded for ICU occupancy, which lacks statistical significance. Additionally, I compute the baseline regression using the growth rate of cumulative covid cases as the main explanatory variable for each country in the sample individually. Results support the hypothesis for all countries but the United Kingdom, where the coefficient is not statistically significant. The degree of economic significance varies across countries.

The second hypothesis refers to the impact of government responses, consisting of lockdown policies and fiscal stimuli, and proposes that stock returns are negatively related to the introduction of these measures. While other researchers concluded that lockdowns were in fact what hurt the markets and not the pandemic itself (Scherf et al., 2022), my findings do not support this statement. Generally, my results suggest a mixed impact of the government responses on country-level stock returns. Lockdowns were found to harm stock returns, no matter the model specification (i.e. tested along the growth rate of cumulative covid cases or deaths as well as combined with the stimulus variable). The coefficients for stimuli were mostly positive, suggesting investors believe that stimulus spending by the government has a positive impact on expected future cash flows.

The third hypothesis states that measures of public sentiment, here Google Trends and the Economic Policy Uncertainty (EPU) Index (Baker, Bloom, & Davis, 2016), are negatively related to stock returns. With higher perceived risk or uncertainty, stock returns would decrease. Looking at the results, the hypothesis can be confirmed without restriction for Google Trends and, except for the model combining both measures of public sentiment, also for the EPU index. It can be concluded that with rising uncertainty stock returns are affected negatively.

The fourth hypothesis proposes that stock returns of companies with distinct corporate characteristics are affected differently. I decided to explore the role of company size and industry affiliation in two separate regression models (therefore actually testing two hypotheses that are very similar and hence summarized under this point). For size, I allocated each company to one of three groups based on its relative market value in December 2019 (resulting in the groups small, medium, and large). Looking at the coefficients for the interaction term between a dummy indicating the size and the measure for growth of COVID-19 cases or deaths reveals that small companies are most negatively impacted by the pandemic, followed by medium-sized firms. Interestingly, large corporations in my sample are beneficiaries and have a positive and significant coefficient. For industry affiliation, I used two-digit Standard Industrial Classification (SIC) codes to allocate each stock to one of ten industries and conducted the same analysis as for company size. I expected results to be mixed with some industries suffering, others benefitting, and the rest showing insignificant coefficients, which is exactly what the computations have revealed. Higher COVID-19 numbers significantly influence stock returns in six industries, where Mining, Construction, Retail Trade and Finance, Insurance & Real Estate exhibit negative coefficients and Manufacturing along with Transportation & Public Utilities positive ones.

2 Literature Review

Stock markets continuously incorporate newly available information into security prices. Consequently, returns are influenced by all kinds of major events (Al-Awadhi, Alsaifi, Al-Awadhi, & Alhammadi, 2020). Previous research found effects that are, inter alia, attributable to natural disasters (Shelor, Anderson, & Cross, 1992), environmental accidents (Carpentier & Suret, 2015), terrorism (Arin, Ciferri, & Spagnolo, 2008), news (Birz & Lott, 2011), and politics (Wisniewski, 2016). Similarly, there are studies on the impact of public health crises, such as the circulation of Ebola in West Africa from 2014 to 2016 or the severe acute respiratory syndrome (SARS) outbreak in Taiwan in 2003. For example, M.-H. Chen, Jang, and Kim (2007) found a significant connection between negative stock returns and the spread of SARS. This paper relates to this research by analyzing how firms and investors are responding to the ongoing pandemic caused by the novel coronavirus SARS-CoV-2 (hereafter simply referred to as coronavirus or COVID-19). Several aspects potentially influence the reaction of the stock markets, i.e., the investors' expectations about future cash flows, profits, and dividends, to the new disease, a selection of which are the speed and severity at which the pandemic is spreading, the responses of local governments and the international community as well as public interest in the developments. Hence, I will start with a review of general findings on the effect of COVID-19 on the stock markets. Afterwards, I will summarize research on lockdowns and policy stimuli as well as the role of public sentiment with regard to stock returns.

The outbreak of COVID-19 reportedly started in December 2019, when several cases of pneumonia, some of which required treatment in a hospital, were identified in the Chinese city of Wuhan in the Hubei province (Sohrabi et al., 2020). At first, attention to these developments outside of China was quite limited and the *Global Risk Report* of the World Economic Forum, which was published in January 2020, identified environmental issues as the top risks for the global economy. Infectious diseases were recognized in the report but are still characterized as unlikely events (Ramelli & Wagner, 2020). Soon after, repercussions materialized on a global scale and disrupted people's lives and financial systems. In the first quarter of 2020, the rapid spread of COVID-19 led to steep stock market declines in a lot of major economies. According to data collected by Johns Hopkins University, some of the most affected countries early in the pandemic with regards to health (but also economically) were the United States, Germany, Italy, Spain, the United Kingdom, Canada, South Korea, and France (Dong, Du, & Gardner, 2020). After peaking only in February, the S&P 500 lost over a third of its value compared to that high by March 23, 2020 (Demers et al., 2021). Furthermore, March also saw "the US stock market hit the circuit breaker mechanism four times in ten days" (Zhang et al., 2020). The mechanism, which was designed for preventing panic sales by temporarily halting trading, was only triggered once before since the corresponding law was passed in 1987. Similar developments could be observed internationally (Zhang et al., 2020). However, these losses were followed by large gains within a short time, causing volatility to soar (O'Donnell et al., 2021). Sharif et al. (2020) compare the volatility during this time to levels previously observed in other big crises, such as the stock market crash in 1929, Black Monday in October 1987,andr the global financial crisis in December 2008.

While there are similarities in the consequences of the various shocks, the COVID-19 pandemic is described as truly different from these past events by various scholars. According to Sharif et al. (2020), the global financial crisis resulted from underlying issues in the economic structure, whereas the pandemic constitutes a severe shock caused by an exogenous factor, a virus. Consequently, the current situation is more comparable to natural disasters than previous economic events. Due to these circumstances, there is a particular interest for scholars and policymakers to understand how the coronavirus affects markets and investments and to use the shock to identify drivers of profitability, sustainable business practices, and resilience, resulting in a rapidly growing body of research since the onset of the pandemic.

First, it is interesting to examine the relationship between the number of covid cases or the resulting deaths and the returns on financial instruments. As one would expect, most studies find a negative correlation between confirmed cases/confirmed deaths and stock returns (e.g. (Al-Awadhi et al., 2020; Pham et al., 2021). This effect is also observable for other asset classes such as cryptocurrencies or commodities (Corbet et al., 2020). When looking at volatility instead of returns as a dependent variable, the literature suggests similarly obvious results, i.e. a positive relationship between infections and volatility (Albulescu, 2021). Advances in the clinical trials (Chan, Chen, Wen, & Xu, 2022), as well as vaccination numbers after the approval (Rouatbi, Demir, Kizys, & Zaremba, 2021), mitigate the negative effects of the pandemic on returns and volatility to a certain extent.

Previous crises have shown that certain firm characteristics, such as location, financial standing, and a focus on environmental, social, and governance (ESG) factors as well as corporate social responsibility (CSR) may lead to more stable prices and better returns. Ding, Levine, Lin, and Xie (2021) find that stocks of firms with favorable financial conditions, such as access to cash, less indebtedness, and higher profitability perform better in response to COVID-19 than their counterparts. Similar conclusions concerning debt and cash are drawn by Ramelli and Wagner (2020). While CSR activities have a positive impact on returns during the pandemic (Ding et al., 2021; Pham et al., 2021), the issue is not as clear when it comes to ESG. On the one hand, Albuquerque, Koskinen, Yang, and Zhang (2020) show that stocks with a better ESG rating demonstrate higher returns, lower volatility, and a higher profit margin during the first wave of the pandemic. On the other hand, Demers et al. (2021) find that ESG ratings do not have significant explanatory power for more robust returns. The location of the firm's headquarters and its operations as well as local resources play an important role since increases in infections or deaths in one location are followed by negative returns in the same. However, the effect is less pronounced in regions with better health care services (such as a greater number of hospital beds per capita) and a higher likelihood of receiving help from the government (Pham et al., 2021).

Secondly, the literature also studies the effects of government reactions to the spread of the coronavirus, namely lockdowns, fiscal stimuli, and other restrictions such as travel bans. After China seemed to succeed in slowing down the growth rate of the disease by shutting down entire parts of the country, other nations followed suit and implemented similar measures (Fernandes, 2020). Having said that, the introduced quarantine policies (meaning for people that tested positive but as well for the general population in the form of lockdowns) halted business operations and hurt the economy (Zhang et al., 2020). According to Scherf et al. (2022), the lockdowns, and not the disease itself, were the primary cause for these negative implications and show that the stock markets tend to underreact to the announcement and overreact to the actual implementation of the measure. The effect is afterwards corrected. When analyzing their sample of global stock indices, they find no significant effect of new coronavirus cases on yields, but a positive correlation between lockdown measures and returns. Bannigidadmath et al. (2022) looked into government policies in 25 countries and their impact on the benchmark index of the respective country. Their results suggest similar consequences for the stock market, indicating that both lockdown and stimulus package announcements hurt the returns in around half of the countries they examined. Yet, in other countries, they found either no significant correlation at all or, in rare cases, a positive effect of the measures on the stock markets. It was also concluded that travel bans affected returns the least. A third study presents conflicting results compared to the other ones, as it suggests a positive reaction of the markets (i.e. less negative returns) to the introduction of lockdowns and stimuli in the G7 countries, with lockdowns being presented as the most effective measure. The authors suggest that these policies work since they have a calming effect on investors and because market movements are driven by investor sentiment (Narayan, Phan, & Liu, 2021). Especially during the first part of the pandemic, investor reactions seem to be largely caused by sentiment rather than facts (Cox, Greenwald, & Ludvigson, 2020).

Thirdly, the previously described notion warrants a further look into public sentiment and its effect on returns. In the past, scholars identified several ways to measure public sentiment with popular ones being news articles (H. Chen, De, Hu, & Hwang, 2014; Li et al., 2014), Twitter (Sul, Dennis, & Yuan, 2017) and Google Trends (Bijl, Kringhaug, Molnár, & Sandvik, 2016; Da, Engelberg, & Gao, 2011). With regard to the stock market during the COVID-19 pandemic, there has been some research on this topic. Salisu and Vo (2020) investigate the role of health news as a predictor of stock performance, showing that they are a significant source of variation in stock prices. Moreover, Twitter sentiment also proves to be important, with positive (negative) sentiment leading to a short-term (long-term) increase (decrease) in stock prices (Katsafados, Nikoloutsopoulos, & Leledakis, 2021). Finally, Google Trends are proven to be an adequate predictor of market movements, especially during adverse situations. This seems to hold also during the current crisis, with Google Trends playing a significant role in explaining stock returns (Costola, Iacopini, & Santagiustina, 2021).

3 Research Hypotheses

Based on the reviewed literature several issues warrant further investigation. This is mainly because the published research at the time of writing this dissertation focuses almost exclusively on the beginning of the global pandemic in the first half of 2020. Exceptions exist when it comes to studies on the implications of the global vaccine rollout (Chan et al., 2022; Rouatbi et al., 2021), however, the number of papers is very limited. Additionally, most academic articles focus on the US- and Chinese markets, although there are some international studies as well. This makes sense considering the size and affectedness of these countries by the virus. Nevertheless, it may well be interesting to shed light on the situation in other countries, which is why I focus on Canada, France, Germany, and the United Kingdom in addition to the United States. The selection of countries is based on a sample of the most affected countries identified in the literature (Dong et al., 2020). Likewise, the question arises if new cases equally affect the stock markets after the initial period of the pandemic, since we are still dealing with high numbers of infections two and a half years after the discovery of the novel coronavirus.

0. Stock returns are negatively related to the growth rate of covid cases or deaths.

Based on the existing literature, there is evidence of a negative relationship between stock returns and the number or growth rate of new covid cases and deaths attributed to the disease. However, it should be determined whether this relationship still holds after living with the virus for an extended period and if and how it changes when looking at different countries.

After the severity of the crisis for people's health became apparent, governments swiftly introduced countermeasures to combat the spread of the virus, such as lockdowns and international travel bans. However, these policies were not without effect on the real economy, e.g. businesses temporarily closing and people losing jobs, and the stock markets (Narayan et al., 2021). Empirical results concerning the impact of the governments' reactions are mixed, but several studies suggest a negative reaction of stock returns to lockdowns and fiscal stimuli (Bannigidadmath et al., 2022; Scherf et al., 2022).

1. Stock returns are negatively related to the introduction of government policies, such as lockdowns and fiscal stimuli.

As mentioned above, a third important factor that influences markets is public sentiment. There are several ways to measure this and limited research on the topic with regard to the pandemic. However, current findings suggest that price movements are related to investor sentiment, meaning that negative sentiment measured through natural language processing and higher search volumes for COVID-19-related topics on Google lead to lower returns (Costola et al., 2021; Katsafados et al., 2021). The analysis in this dissertation will focus on the widely used Google Trends indicator as well as a second, less frequently used indicator, which is the Economic Policy Uncertainty (EPU) index as introduced by Baker et al. (2016).

2. Stock returns are positively related to public sentiment.

While these hypotheses investigate the effect of the measures on stock returns in general, it is safe to assume that not all stocks reacted the same way and that there are different effects depending on firm-individual characteristics and circumstances. For instance, Ding et al. (2021) look at how pre-pandemic financials influenced returns during the first COVID-19 wave in 2020. Another study elaborates on the lack of a significantly positive effect of a good ESG rating for performance in the recent crisis (Demers et al., 2021). I want to focus on two other characteristics that might play an important role, especially during the pandemic, namely firm size and industry affiliation. The impact of the pandemic on larger firms' stock returns might be less negative due to more diversified revenue sources concerning geography as well as business lines. Furthermore, the operations of small firms that happen to be in a region with more severe outbreaks might be more disrupted due to policy measures such as lockdowns, leading to negative investor expectations and therefore lower returns. Since the pandemic was compared to a natural disaster, literature on this topic might also provide information on what to expect. Lanfear, Lioui, and Siebert (2017) confirm small firms exhibit larger negative returns in the aftermath of a natural disaster such as a hurricane.

3a. Stock returns of small, medium, and large firms are affected differently.

Similarly, some industries might suffer more under the pandemic than others. For example, Cho and Saki (2022) show that the apparel industry was more heavily impacted by the spread of the coronavirus than other industries such as entertainment and transportation. Furthermore, considering the consequences of lockdowns and work-from-home policies, it is also conceivable that some companies benefit from the crisis (e.g. companies offering digital communication services).

3b. The effect on stock returns varies across industries.

In addition, I conduct various robustness checks to verify the validity of my results and especially of the first hypothesis. Therefore, I employ alternative samples and add further controls. First, I divide my sample into two subsamples, corresponding to the first and second year of the pandemic. The first year starts in March 2020, since this is the month when all countries in my sample, except for France[1], identified the 100^{th} case. The second year, therefore, commences in March 2021 and ends in February 2022. Secondly, I identify winner and loser stocks in my sample (on a per-country basis) and run the regression with these panels. Thirdly, another subsample consisting only of stocks that are part of large benchmark indexes is applied. Lastly, I test the robustness when controlling for population age and the effects of the Brexit negotiations between the United Kingdom and the European Union.

[1] In France, the mark of 100 positive cases was hit on February 29, 2020.

4 Data and Methodology

4.1 Data

The following section describes the data used for the analysis of the effects of COVID-19 on stock returns. Table 1 contains a description of the variables used in the empirical model.

Table 1 – Variable Description

The table provides the name, description, and source for all the variables used within my research.

Variable Name	Description	Source
Return	Daily stock returns, calculated as the natural logarithm of returns based on daily closing prices.	Refinitiv Datastream, Own Calculations
Covid19	Growth rate of reported COVID-19 cases in a country. For country c on day t, Covid19 = LN(1 + Cumulative cases on day t) – LN(1 + Cumulative cases on day t-1). Cumulative cases consist of the cumulative positive infections in a given country.	Our World in Data
Covid_Deaths	Growth rate of reported deaths connected to COVID infections. For country c on day t, Covid_Deaths = LN(1 + Cumulative deaths on day t) – LN(1 + Cumulative deaths on day t-1). Cumulative deaths mean the cumulative number of deaths in a given country.	Our World in Data
Covid_ICU	Growth rate of COVID-19 cases treated in an intensive care unit. For country c on day t, Covid_ICU = LN(1 + ICU occupancy on day t) – LN(1 + ICU occupancy on day t-1). ICU occupancy describes the number of people admitted to the ICU in a given country on a given day.	Our World in Data
Lockdown	Dummy variable indicating whether a lockdown policy is in place.	Oxford COVID-19 Government Response Tracker
Stimulus	Dummy variable indicating whether a fiscal stimulus is provided by the government.	Oxford COVID-19 Government Response Tracker
Covid_Sentiment	A measure of search volume in COVID-19-related terms in a country.	trends.google.com
EPU	Economic Policy Uncertainty as defined by (Baker et al., 2016) and normalized to values between 0 and 1.	policyuncertainty.com
Cash	The amount of cash divided by total assets.	Refinitiv Datastream, Own Calculations
Leverage	Total debt divided by total assets.	Refinitiv Datastream, Own Calculations
MTB	The ratio of market value of equity to book value of equity.	Refinitiv Datastream, Own Calculations

ROA	Earnings before interest and taxes (EBIT) divided by total assets.	Refinitiv Datastream, Own Calculations
Size	The natural logarithm of market capitalization.	Refinitiv Datastream, Own Calculations
MKT	Daily Fama and French (2015) market risk premium[2].	Kenneth French Data Library
SMB	Daily Fama and French (2015) size factor.	Kenneth French Data Library
HML	Daily Fama and French (2015) value factor.	Kenneth French Data Library
RMW	Daily Fama and French (2015) profitability factor.	Kenneth French Data Library
CMA	Daily Fama and French (2015) investment style factor.	Kenneth French Data Library
Age_65	Percentage of the population of a country that is 65 or above at the beginning of 2020.	World Development Indicators
Brexit	Dummy variable indicating whether official Brexit negotiations rounds or meetings take place. On these dates, the dummy takes the value of 1 in the UK, France, and Germany.	Council of the European Union

4.1.1 Stock Returns

For the construction of the stock returns, daily closing prices for the period of December 2019 to April 2022 were obtained from Refinitiv Datastream. Often, studies focus on major indexes such as the S&P 500 or FTSE 100 and therefore on the companies with the highest market capitalization or turnover. However, I want to research the effect of COVID-19 on stock returns based on a bigger sample that includes a more diverse selection of securities. Therefore, I am using the constituents of the S&P/TSX Composite Index, CAC All-Share, Composite DAX, FTSE All-Share, and NYSE Composite (that are incorporated in the United States), to reflect the stock markets in Canada, France, Germany, the United Kingdom, and the United States, respectively. The study includes all firms that were part of one of these indexes as of December 1, 2019, and stayed in the index for at least 100 days. This precaution is taken to rule out distortion of the results based on firms that were delisted before the pandemic started. Stocks that joined the index after the cutoff date, were not included for a similar reason. Results may have been influenced by companies that performed particularly well during the crisis and hence

[2] Country-specific data on the Fama and French factors is only available for the United States. For France, Germany and the United Kingdom, the Europe dataset was used as a proxy. For Canada I used the data for North America. Detailed descriptions of these datasets can be found on the Kenneth French Data Library website.

were able to execute an initial public offering or be otherwise included in the index. Furthermore, the initial sample included several so-called penny stocks. These stocks, trading for less than one unit of the local currency, were also excluded from the analysis. Finally, various stocks were taken out of the sample due to a particularly low trading volume. Looking at price variation and trading volumes, it was deemed reasonable to exclude shares with less than one thousand trades per day on average. This data cleaning process resulted in a total sample size of 3120 stocks across all countries. *Return* was calculated as

$$Return_{i,t} = ln\left(\frac{Closing\ Price_{i,t}}{Closing\ Price_{i,t-1}}\right)$$

where *i* and *t* denote the company and day, respectively.

4.1.2 COVID-19 Measures

As described before, COVID-19 is caused by a newly discovered coronavirus and constitutes a disease mainly affecting the respiratory system. After initially being recorded in China, the virus rapidly spread across the globe. The World Health Organization (WHO) declared a pandemic on March 11, 2020 (Ding et al., 2021). As of April 30, 2022, more than 513.8 million positive cases and 6.46 million deaths were recorded globally (Dong et al., 2020; Our World in Data, 2022). I retrieved information on COVID-19 cases, deaths, and ICU occupancy from *Our World in Data*, a project by the Oxford Martin School at the University of Oxford. They collect and aggregate data from various national and international sources. The main database used for COVID-19 cases and deaths is the *Center for Systems Science and Engineering* at Johns Hopkins University, which is maintained by Dong et al. (2020).

I constructed the three COVID-19 variables following the definition in Ding et al. (2021) but used daily data instead of weekly data. *Covid19* is the main explanatory variable and describes the growth rate of total reported COVID-19 cases in a country from one given day to the next. Since there are no stock returns on weekends and other non-trading days, *Covid19* is also not computed for these periods. However, the growth rate on Mondays is still based on the difference between cumulative cases on Sundays and Mondays. For each country and day, I calculate *Covid19* as

$$Covid19_{c,t} = ln\left(1 + Cumulative\ Cases_{c,t}\right) - ln\left(1 + Cumulative\ Cases_{c,t-1}\right)$$

where *c* and *t* denote the country and day and $Cumulative\ Cases_{c,t}$ consists of the cumulative positive infections in country *c* as of day *t*. *Covid_Deaths* and *Covid_ICU* are computed using the same formula (the exact definition can be found in Table 1). Consequently, the three variables denote the daily growth of confirmed cases (deaths, ICU occupancy) over a given day *t* in country *c*. Since the vaccine was proven to reduce the number of deaths caused by COVID-19 (Watson et al., 2022), there is no need to include vaccination statistics in the analysis as the effects should be sufficiently captured by the variable *Covid_Deaths*. Other research (Pham et al., 2021) includes not only a figure for ICU occupation but hospitalizations in general. However, this could not be realized in this work due to the incomparability of data published by the countries in my sample.

4.1.3 Government Responses

The government policies analyzed in this dissertation are lockdowns and fiscal stimuli introduced by the national governments. As described before, I use a dummy variable for both types of measures. The corresponding data is obtained from the Oxford COVID-19 Government Response Tracker (Hale et al., 2021). The dummy *Lockdown* is based on eight indicators of containment and closure policies: Closing of schools and universities, closing of workplaces, canceling public events, limits on gatherings, closing of public transportation, stay-at-home orders, restrictions on internal movement between cities/regions, and restrictions on international travel (Hale et al., 2021). If any of these policies are implemented the dummy will take the value 1 for the given day and country. The dummy *Stimulus* is based on four indicators of economic policies: Direct cash payments to unemployed people or people that cannot work, freezing of financial obligations for households, announced economic stimulus spending, and announced offers of aid spending to other countries (Hale et al., 2021). Similarly, if any of these indicators are positive, the dummy will take the value 1 for the day and country in question.

4.1.4 Public Sentiment

To determine the impact of public sentiment on stock returns during the pandemic I employ two variables: *Covid_Sentiment*, which is based on Google search volumes, and the *EPU* index as defined by Baker et al. (2016). In the case of a pandemic, Google Trends can be seen as a reflection of uncertainty in the population and a measure of perceived risk (Costola et al., 2021). Therefore, *Covid_Sentiment* is a proxy for public concern about the coronavirus. Following the methodology of Costola et al. (2021), I am looking at terms related to COVID-19. Google Trends gives the user several options to inspect search volumes, either by looking at a specific word, such as “pandemic” or a whole group of search terms related to a specific topic and summarized by Google under an umbrella term. To gauge sentiment correctly and cover as many of the relevant Google searches as possible, the second option seems more suitable for this study. To find the umbrella term that was most frequently used in each country, I compared search volumes for multiple variations of umbrella terms. This led to the final selection of "Coronavirus Disease 2019" for all countries but Germany, where the relevant group was simply called "Coronavirus". Since Google Trends does not provide absolute search volumes but rather relative volumes per country and sample period the retrieved values need to be standardized to be able to compare them with each other. This can be achieved by using the same method as Bijl et al. (2016). *Covid_Sentiment* was computed as

$$Covid\_Sentiment_{c,t} = \frac{GSV_t - \frac{1}{n}\sum_{c=1}^{n} GSV_c}{\sigma_{GSV}}$$

where GSV stands for Google Search Volume and c and t denote the country and day, respectively.

Another means to quantify public sentiment or perceived risk is the EPU index, which is based on an analysis of large newspapers and their coverage of relevant policy-related issues. Additionally, and for the US only, the index also takes changes in tax provisions and contrary opinions of economic prognoses into consideration (Baker et al., 2016). The EPU data was downloaded from the official website of Baker et al. (2016). Since the index is constructed in slightly different ways for the countries in the sample resulting in different scales, the data is normalized to range between 0 and 1.

Table 2 gives an overview of the summary statistics of the variables used in my dissertation.

Table 2 – Summary Statistics

The table provides the descriptive statistics for the main dependent and independent variables used within this research.

Variable	N	Mean	SD	P10	P25	P50	P75	P90
Return (%)	2,006,224	-0.002	3.766	-3.067	-1.270	0.000	1.266	3.045
Covid19 (%)	2,006,224	0.020	0.066	0.031	0.125	0.420	1.144	2.265
Covid_Deaths (%)	2,006,224	0.015	0.65	0.000	0.001	0.002	0.005	0.012
Covid_ICU (%)	869,993	0.001	0.048	-0.041	0.000	0.000	0.000	0.042
Lockdown	869,993	0.801	0.298	0.000	1.000	1.000	1.000	1.000
Stimulus	869,993	0.666	0.341	0.000	0.000	1.000	1.000	1.000
Covid_Sentiment	2,006,224	-0.022	0.991	-0.800	-0.600	-0.170	0.210	0.730
EPU	2,006,224	0.248	0.195	0.070	0.110	0.190	0.330	0.530
Cash	1,868,977	0.114	0.129	0.009	0.030	0.070	0.155	0.270
Leverage	1,868,977	0.308	0.234	0.032	0.140	0.292	0.441	0.581
MTB	1,868,977	2.439	4.245	0.479	0.922	1.653	3.297	7.004
ROA	1,868,977	0.043	0.221	-0.071	0.011	0.050	0.104	0.162
Size	2,006,224	21.437	2.047	18.787	20.055	21.481	11.840	24.088
MKT (%)	2,006,224	0.035	1.530	-1.56	-0.560	0.110	0.790	1.450
SMB (%)	2,006,224	0.000	0.760	-0.840	-0.410	0.100	0.400	0.860
HML (%)	2,006,224	0.022	1.202	-0.137	-0.640	-0.035	0.790	1.430
RMW (%)	2,006,224	0.023	0.581	-0.690	-0.319	0.000	0.340	0.740
CMA (%)	2,006,224	0.027	0.550	-0.570	-0.280	0.000	0.330	0.690
Age_65	2,006,224	0.180	0.017	0.166	0.166	0.166	0.186	0.208
Brexit	2,006,224	0.128	0.167	0.000	0.000	0.000	0.000	1.000

4.2 Methodology

This section describes the development of the empirical model used to test the aforementioned hypotheses about the effect of COVID-19 metrics on returns. To start, the impact of the growth of cumulative cases, cumulative deaths, and ICU occupancy will be examined on a standalone basis for the entire sample as well as for each of the countries independently. In a second step, I am adding variables capturing government policy responses to the model, which is followed by an analysis of the influence of factors of public- and investor sentiment. Lastly, I am investigating the role of industry affiliation and company size by introducing an interaction term of these metrics with my variable *Covid19*. I am using an OLS regression to estimate the relationship between stock returns and the explanatory variables. Moreover, I am adding common control variables related to firm characteristics as applied by Pham et al. (2021) as well as "combined" fixed effects as seen in the analysis by Ding et al. (2021). This approach seems adequate considering the heterogenous structure of my dataset. Due to the nature of the pandemic, it is safe to assume that there are numerous unobservable differences in my panel, for example between countries and industries. The fixed effects built as a combination of time (month) and a second variable compensate (partly) for this heterogeneity, by reducing the "sources of bias to time-varying variables that correlate with […] the outcome over time" (Collischon & Eberl, 2020). I employ country-time and industry-time fixed effects. To estimate the relationship between stock returns and COVID-19 metrics, I employ the following OLS regression models:

Model 0 – Baseline

$$Return_{i,t} = \alpha_i + \beta \cdot Covid19_{c,t} + \gamma \cdot Controls_{i,t} + \delta_{j,m} + \delta_{c,m} + \varepsilon_{i,t}$$

where i, t, c, j, and m index company, day, country, industry, and month, respectively. The dependent variable is the daily return of the stock of company i on day t. The daily growth rate of cumulative cases in country c on day t is denoted by $Covid19_{c,t}$. $Controls_{i,t}$ is a vector of control variables, consisting of firm characteristics such as *Cash*, *Leverage*, *MTB*, *ROA,* and *Size*, as well as the factors from the five-factor model (*MKT*, *SMB*, *HML*, *RMW*, *CMA*) by Fama and French (2015). The industry-time $\delta_{j,m}$ (based on the first two characters of the Standard Industrial Classification (SIC) by month) and country-time $\delta_{c,m}$ fixed effects, filter out time-varying differences by industry and country, such as "reactions to the crisis and differences in legal, cultural, institutional, and political systems" (Ding et al., 2021). The same regression is run with the variables $Covid\_Deaths_{c,t}$, and $Covid\_ICU_{c,t}$ instead of $Covid19_{c,t}$, and for each country in the sample individually (excluding the country-time fixed effects $\delta_{c,m}$). The baseline model allows me to estimate the relative effect of a covid outbreak on the stock returns in a country.

Model 1 – Government Responses

$$Return_{i,t} = \alpha_i + \beta_1 \cdot Covid19_{c,t} + \beta_2 \cdot Government\ Response_{c,t} + \gamma \cdot Controls_{i,t} + \delta_{j,m} + \delta_{c,m} + \varepsilon_{i,t}$$

where i, t, c, j, and m index company, day, country, industry, and month, respectively. Variable definitions are the same as previously described for the baseline model. $Government\ Response_{c,t}$ is a vector for the two dummy variables $Lockdown_{c,t}$ and $Stimulus_{c,t}$, which take the value of one whenever a specific policy belonging to the respective category is in place during the sample period. The effect of both policy measures is tested independently from each other as well as together and for both explanatory variables $Covid19_{c,t}$ and $Covid\_Deaths_{c,t}$. Estimating the second regression may provide information as to whether the number of sick people, government policies, or both had an impact on the economy and the stock markets specifically.

Model 2 – Public Sentiment

To measure how public- or investor sentiment affects returns along the growth of COVID-19-related cases or deaths, the following regression is considered:

$$Return_{i,t} = \alpha_i + \beta_1 \cdot Covid19_{c,t} + \beta_3 \cdot Public\ Sentiment_{c,t} + \gamma \cdot Controls_{i,t} + \delta_{j,m} + \delta_{c,m} + \varepsilon_{i,t}$$

where i, t, c, j, and m index company, day, country, industry, and month, respectively, with the remaining variables being defined in the baseline model. The vector Public $Sentiment_{c,t}$ again includes two variables. $Covid\_Sentiment_{c,t}$ is based on the standardized Google Trends Index for COVID-19-related searches in each country, which acts as a proxy for uncertainty and perceived risk. $EPU_{c,t}$ is the normalized EPU index as defined by Baker et al. (2016) and constitutes the second measure of uncertainty based on newspaper articles. Model 2 allows suggestions about the role of public sentiment with regard to stock returns during the pandemic.

Model 3 – Company Size and Industry Affiliation

To determine how firm size and industry affiliation shape stock price reactions to the pandemic, I introduce an interaction term to the baseline regression. The model investigating the role of company size is

$$Return_{i,t} = \alpha_i + \beta \cdot (Covid19_{c,t} \cdot Size\_D_{i,pre2020}) + \gamma \cdot Controls_{i,t} + \delta_{j,m} + \delta_{c,m} + \varepsilon_{i,t}$$

and the model specification testing the interaction with industry affiliation is

$$Return_{i,t} = \alpha_i + \beta \cdot (Covid19_{c,t} \cdot Industry\_D_{i,pre2020}) + \gamma \cdot Controls_{i,t} + \delta_{c,m} + \varepsilon_{i,t}$$

where i, t, c, j, and m index company, day, country, industry, and month, respectively. $Size\_D_{i,pre2020}$ is a proxy for the relative size of the company and consists of dummy variables identifying each company as small, medium, or large based on the variable *Size* before the start of the pandemic in December 2019. Similarly, *Industry_*$D_{i,pre2020}$ consists of dummy variables denoting the primary industry of each company in December 2019 based on the two-digit SIC code (resulting in ten major industries). The interaction terms follow the logic of Ding et al. (2021) and identify whether relative exposure to COVID-19 affects stock returns differently based on the size of the company or its industry affiliation, i.e. the coefficients measure the differences between these groups (Angrist & Pischke, 2009). The computations are repeated using the variable *Covid_Deaths*$_{c,t}$ instead of *Covid19*$_{c,t}$.

Afterwards, I will check the robustness of my results by running calculations with different subsamples and further controls for the share of the population over 65 years, which is at the most risk from a coronavirus infection, and Brexit negotiations which happened in 2020 and 2021 and might have affected stock returns in Europe as well.

All of the regression models include heteroskedasticity-robust standard errors (Petersen, 2009), clustered at the firm level, which "accounts for the possible correlation between observations of the same firm over time" (Petersen, 2009).

5 Results

The following section covers the results of my analyses and is divided into five parts. I will start by describing the baseline results, reflecting the estimation of Model 0, which is followed by the investigation of government measures (Model 1), public sentiment (Model 2), and the models including an interaction term (Model 3). Afterwards, I will describe the results of the robustness checks such as applying the regression to alternative samples and adding additional controls for population age and Brexit negotiations.

5.1 Baseline results (COVID-19 metrics only)

First, it is essential to check the basic effect of measures of the spread and severity of COVID-19 on stock returns. Three measures were used to quantify the evolution of the pandemic, namely the growth rate of cumulative confirmed cases, the growth rate of cumulative confirmed deaths, and the growth rate of ICU occupancy, which are expressed by the variables *Covid19*$_{c,t}$, *Covid_Deaths*$_{c,t}$, and *Covid_ICU*$_{c,t}$, respectively. The goal is to show that the pandemic is related to negative effects on the stock markets. Moreover, the hypothesis should be tested in each country that is part of the sample individually.

Table 3 reports the results from the baseline model. In columns (1) to (3), I investigated the effect of different measures of COVID-19 on the stock returns across all countries. Column (1) shows the relation between the growth of country-level cumulative coronavirus cases (*Covid19*) and stock returns, column (2) considers the growth of cumulative death cases *(Covid_Deaths),* and column (3) utilizes the growth rate of hospital occupancy (*Covid_ICU*). The results are largely consistent with the existing literature on the topic (e.g. (Al-Awadhi et al., 2020; Pham et al., 2021). For both *Covid19* and *Covid_Deaths,* I find a significant negative relationship between the measures of severity of the pandemic and stock returns on the 1% level. For instance, the coefficient for *Covid19* in column (1) suggests that a 1% increase in the growth rate of cumulative positive cases leads to an average decrease in daily returns of 0.937 percentage points and therefore also an economically significant effect. However, the same connection cannot be observed for *Covid_ICU* since the corresponding coefficient does not have statistical significance. Still, summarizing the outcome of columns (1) and (2), it becomes apparent that countries with a faster-growing outbreak of COIVD-19 experience lower returns on the stock market.

In columns (4) to (8), I repeat the regression of daily log returns on *Covid19* for each of the countries independently to confirm the findings of the entire sample at the country level. Again, all but one of the coefficients are statistically significant at the 1% level and confirm the expected negative relationship. The only country where Covid19 does not significantly relate to stock returns is the United Kingdom. The observed effect is most pronounced in Canada, where an increase of 1% in the growth of cumulative cases leads to the biggest decline in stock returns of -1.825 percentage points. France exhibits the least negative coefficient out of the four countries with significant results, although a COVID-19 outbreak influences stock returns in an economically meaningful way in all of them. Furthermore, it becomes apparent that my model explains the variation of stock returns due to my explanatory variables in the sample countries to a different degree, with the US having the highest R-Squared value. There, the independent variables explain 26.20% of the variation in stock returns.

Table 3 – Baseline Results

This table reports the regression estimates from the baseline model and shows how stock returns respond to changes in the growth of confirmed cases, deaths, and ICU occupancy for the entire sample (1-3) and confirmed cases for each country individually. The dependent variable is daily log returns (*Return*). The main independent variable used in columns 1 and 4-8 is *Covid19*, while columns 2 and 3 explore the effects of *Covid_Deaths* and *ICU_Occupancy*. Industry-time fixed effects are included for each case and columns 1-3 also include country-time fixed effects. Heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%.

	Daily Stock Return							
				Canada	France	Germany	UK	USA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Covid19	-0.937***			-1.825***	-0.825***	-1.016***	0.006	-1.422***
	(0.042)			(0.106)	(0.106)	(0.119)	(0.056)	(0.072)
Covid_Deaths		-0.857***						
		(0.054)						
Covid_ICU			-0.114					
			(0.109)					
Cash	-0.003	-0.005	0.033	0.036	0.075	0.046	-0.019	-0.013
	(0.028)	(0.029)	(0.031)	(0.067)	(0.052)	(0.093)	(0.057)	(0.040)
Leverage	-0.065***	-0.065***	-0.077***	0.086*	-0.130***	-0.034	-0.128***	-0.053***
	(0.014)	(0.014)	(0.023)	(0.047)	(0.049)	(0.045)	(0.030)	(0.018)
MTB	-0.000	-0.000	0.0001***	0.000	0.0001***	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA	0.131***	0.134***	0.165***	0.383***	0.058	0.119**	0.199***	0.118***
	(0.034)	(0.035)	(0.035)	(0.059)	(0.051)	(0.056)	(0.066)	(0.037)
Size	0.020***	0.020***	0.010***	0.051***	0.007***	0.002	0.025***	0.030***
	(0.002)	(0.002)	(0.003)	(0.007)	(0.002)	(0.007)	(0.003)	(0.002)
MKT	0.942***	0.946***	0.853***	0.793***	0.844***	0.832***	0.930***	1.000***
	(0.006)	(0.006)	(0.009)	(0.020)	(0.019)	(0.022)	(0.015)	(0.007)
SMB	0.599***	0.599***	0.437***	0.288***	0.428***	0.328***	0.687***	0.565***
	(0.014)	(0.014)	(0.022)	(0.028)	(0.036)	(0.032)	(0.033)	(0.015)
HML	0.335***	0.334***	0.209***	0.283***	0.196***	-0.026	0.356***	0.388***
	(0.011)	(0.011)	(0.021)	(0.047)	(0.045)	(0.045)	(0.034)	(0.014)
RMW	0.266	0.003	0.010	-0.225***	-0.082*	-0.137***	0.459***	-0.928***
	(0.014)	(0.014)	(0.026)	(0.050)	(0.046)	(0.046)	(0.034)	(0.017)
CMA	-0.124***	-0.118***	-0.014	-0.119*	0.068	-0.118**	0.216***	-0.887***
	(0.016)	(0.016)	(0.024)	(0.061)	(0.045)	(0.046)	(0.035)	(0.020)
Fixed Effects								
Industry-time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-time	Yes	Yes	Yes	No	No	No	No	No
Observations	1,868,977	1,868,977	869,993	124,565	185,935	185,261	307,439	1,060,913
Adjusted R^2	0.2239	0.2239	0.1560	0.2242	0.1380	0.1053	0.1883	0.2620

5.2 Government Responses

This section elaborates on the effect of government responses to the pandemic on stock returns by extending the baseline model by two variables, *Lockdown* and *Stimulus*, which are dummy variables indicating the presence of policy measures in each country. The findings in the existing literature were somewhat contradictory. Scherf et al. (2022) present a negative impact of lockdowns on the economy, while Narayan et al. (2021) conclude that the opposite is true and lockdowns as well as fiscal stimuli have a positive impact on stock returns. Therefore, it is of interest to investigate the measures on a standalone basis as well as their combination.

Table 4 outlines the regression estimates for Model 1. Columns (1) to (3) study the impact of the policy instruments separately and together along the growth rate of cumulative cases *Covid19*. Columns (4) to (6) repeat the analysis with a different measure of pandemic exposure, *Covid_Deaths*. Analyzing not only the infection numbers but also the deaths related to the coronavirus has the advantage that possible effects of the vaccination are also captured since the vaccines were proven to prevent severe courses of the disease and death quite successfully, but mere infection to a lesser degree (Watson et al., 2022).

My regression results are somewhat similar to the findings of Bannigidadmath et al. (2022) and suggest a mixed impact of the government responses on country-level stock returns. First of all, it should be noted that my findings do not confirm the conclusion of Scherf et al. (2022) that the policy measures and not the number of infections itself were responsible for the negative impact on the markets. No matter which policy (or their combination) was added to my model, the coefficients for *Covid19* and *Covid_Deaths* kept their negative sign and statistical significance at a 1% level. Likewise, the magnitude of the coefficients signals persisting economic significance. In all instances, lockdowns were found to be negatively related to stock returns, confirming the research by Scherf et al. (2022) and large parts of the study by Bannigidadmath et al. (2022). Looking at fiscal stimuli, the picture becomes a bit more diverse. Column (2) provides a negative relation between *Stimulus* and *Return*; however, in all other regressions that contain the variable (and therefore all models where the main independent variable is *Covid_Deaths*), its sign flips and positive coefficients can be reported.

Table 4 – Government Responses

This table shows the OLS results from Model 1, which investigates the impact of *Lockdown* and fiscal *Stimulus* (for variable definitions see Table 1) introduced by the national governments. The dependent variable is daily log returns (*Return*). The main independent variable is *Covid19* in columns 1-3 and *Covid_Deaths* in columns 4-6. Industry-time and country-time fixed effects are included. Heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%.

	Daily Stock Return					
	(1)	(2)	(3)	(4)	(5)	(6)
Covid19	-0.732***	-0.675***	-0.598***			
	(0.049)	(0.051)	(0.052)			
Covid_Deaths				-0.993***	-0.980***	-0.934***
				(0.098)	(0.099)	(0.099)
Lockdown	-0.067***		-0.245***	-0.046***		-0.260***
	(0.013)		(0.024)	(0.013)		(0.024)
Stimulus		-0.029***	0.201***		0.059***	0.237***
		(0.011)	(0.021)		(0.010)	(0.020)
Cash	0.037	0.034	0.037	0.035	0.032	0.036
	(0.031)	(0.031)	(0.032)	(0.031)	(0.031)	(0.032)
Leverage	-0.075***	-0.074***	-0.074***	-0.075***	-0.073***	-0.073***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
MTB	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA	0.159***	0.151***	0.154***	0.158***	0.148***	0.151***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.033)	(0.033)
Size	0.010***	0.010***	0.010***	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
MKT	0.849***	0.848***	0.846***	0.848***	0.845***	0.844***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
SMB	0.431***	0.430***	0.430***	0.433***	0.430***	0.426***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
HML	0.210***	0.210***	0.212***	0.206***	0.207***	0.209***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
RMW	0.009	0.009	0.009	0.008	0.008	0.008
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
CMA	-0.022	-0.026	-0.030	-0.017	-0.023	-0.029
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Fixed Effects						
Industry-time	Yes	Yes	Yes	Yes	Yes	Yes
Country-time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	869,993	869,993	869,993	869,993	869,993	869,993
Adjusted R^2	0.1563	0.1562	0.1564	0.1563	0.1563	0.1565

In terms of explaining these results, I would follow the reasoning that market movements are driven by investor sentiment (Narayan et al., 2021), however with a slightly different argumentation. Investors might have different opinions about the effect of the two measures on the markets: While lockdowns are generally seen as detrimental to the performance of companies, stimuli, and in particular economic stimulus spending as one of the four components making up the variable, might be viewed as generally favorable and calm investors. What is also interesting is the interaction between the two sets of measures. When adding only one of them to my model, coefficients are low, suggesting only a minor (economic) impact on stock returns. On the contrary, adding both variables to the model yields coefficients that are several times higher. For example, when looking at column (6), the results suggest a change in stock returns by -260 (+237) basis points upon introduction of a lockdown (stimulus) policy, all else equal. All coefficients for *Lockdown* and *Stimulus* are statistically significant at the 1% level.

5.3 Public Sentiment

I continue with an exploration of the role of public sentiment as measured by Google Trends (*Covid_Sentiment*) and the economic policy uncertainty (*EPU*) in a country. Therefore, I add the two variables to the baseline model. Based on the existing literature (Costola et al., 2021) and logical reasoning I expect to find a negative relation between both measures of public sentiment and stock returns, meaning that when perceived risk concerning COVID-19 (measured by Google Trends) and uncertainty (measured by the EPU index) increase, stock returns should decrease.

Table 5 – Public Sentiment

This table outlines the results from regression Model 2, which analyses the relation between stock returns and *Covid_Sentiment* and the *EPU*. The dependent variable is daily log returns (*Return*). The main independent variable is *Covid19* in columns 1-3 and *Covid_Deaths* in columns 4-6. Industry-time and country-time fixed effects are included. Heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%.

	Daily Stock Return					
	(1)	(2)	(3)	(4)	(5)	(6)
Covid19	-0.510***	-0.921***	-0.498***			
	(0.043)	(0.043)	(0.043)			
Covid_Deaths				-0.310***	-0.840***	-0.304***
				(0.070)	(0.055)	(0.070)
Covid_Sentiment	-0.056***		-0.062***	-0.062***		-0.068***
	(0.003)		(0.004)	(0.004)		(0.005)
EPU		-0.038***	0.089***		-0.030**	0.087***
		(0.013)	(0.015)		(0.013)	(0.015)
Cash	0.001	-0.002	0.000	0.001	0.000	-0.000
	(0.029)	(0.029)	(0,029)	(0,029)	(0,029)	(0,029)
Leverage	-0.064***	-0.065***	-0.064***	-0.064***	-0.065***	-0.064***
	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
MTB	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA	0.128***	0.130***	0.130***	0.130***	0.133***	0.132***
	(0.033)	(0.034)	(0.034)	(0.033)	(0.035)	(0.034)
Size	0.020***	0.020***	0.020***	0.020***	0.020***	0.020***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MKT	0.942***	0.943***	0.941***	0.943***	0.946***	0.942***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
SMB	0.599***	0.600***	0.598***	0.599***	0.599***	0.598***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
HML	0.335***	0.335***	0.336***	0.335***	0.334***	0.335***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
RMW	0.002	0.003	0.002	0.002	0.003	0.002
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
CMA	-0.125***	-0.124***	-0.126***	-0.122***	-0.118***	-0.122***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Fixed Effects						
Industry-time	Yes	Yes	Yes	Yes	Yes	Yes
Country-time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977
Adjusted R^2	0.2241	0.2239	0.2241	0.2240	0.2239	0.2241

Similar to the preceding model, adding measures of public sentiment does not reduce the statistical significance of the COVID-19 measures (which are still statistically significant at the 1% level). Table 5, columns (1) to (3) utilize *Covid19* as the main explanatory variable and test the sentiment proxies separately as well as together. Columns (4) to (6) follow the same logic, with the difference being the main explanatory variable *Covid_Deaths*. As expected, the variable based on Google Trends has a negative coefficient in each case and is statistically significant at the 1% level. For *EPU* I get the same result if the variable is added to the model independently, but not if included along *Covid_Sentiment*. EPU shows statistical significance at the 1% level in all columns but column (5), where significance is measured at the 5% level. In columns (3) and (6) the sign for the coefficient for *EPU* becomes positive, which is somewhat puzzling and cannot be explained by any of the findings by other researchers or logical inference. Nevertheless, these observations allow the conclusion that with rising uncertainty, be it measured by search queries for COVID-19-related topics or the sentiment of newspaper coverage regarding economic policy, stock returns are affected negatively.

5.4 Company Size and Industry Affiliation

5.4.1 Company Size

To investigate the vulnerability of stock returns to COVID-19 metrics conditional on firm size, I introduced an interaction term of the variables *Covid19/Covid_Deaths* and *Size_D* to the baseline regression. Based on the reasoning given in section three, I expect to find a more severe impact among smaller firms. A confirmation of this assumption would be given by a negative and significant coefficient of the interaction between the growth rate of cases or deaths and the dummy for small companies, while the coefficients for the interaction term including the dummies for medium or large companies should be greater. All the following models control for the same variables that were used throughout the dissertation, but coefficients are not shown anymore.

Table 6 shows that the results are largely as expected. Irrespective of the measurement used as a proxy for the severity of the pandemic, the coefficients for the interaction terms are always statistically significant at the 1% level for small and large firms and the 5% level for medium ones.

Table 6 – Interaction COVID-19 and Company Size

This table gives an overview of the results when including an interaction term consisting of a measurement of the pandemic severity and a dummy for company size. The dependent variable is daily log returns (*Return*). The main independent variable used in columns 1-3 is *Covid19*, while columns 4-6 explore the effects of *Covid_Deaths*. Industry-time and country-time fixed effects are included. Heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%.

	Daily Stock Return					
	Small	Medium	Large	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)
Covid19 Size_D*	-1.065***	-0.274**	1.470***			
	(0.122)	(0.109)	(0.096)			
Covid_Deaths Size_D*				-2.048***	-0.273**	1.887***
				(0.135)	(0.123)	(0.103)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Industry-time	Yes	Yes	Yes	Yes	Yes	Yes
Country-time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977
Adjusted R^2	0.224	0.224	0.224	0.224	0.224	0.224

Small companies suffer the most, with columns (1) and (4) suggesting that stock returns of firms with the lowest market value (*Size* is based on market value) decrease with firm-level exposure to *Covid19* and *Covid_Deaths*. An increase of 1% in the growth of cumulative cases (deaths) leads on average to a decline in stock returns of small companies of 1.065 (2.048) percentage points. For medium-sized corporations, the effect is still negative, although to a lesser extent. In addition to the aforementioned arguments, research suggests that smaller companies were more fragile at the beginning of the pandemic and found it harder to access financial resources (Bartik et al., 2020). Interestingly, when looking at the biggest companies in the sample, the sign of the coefficient turns positive, meaning that stock returns in this group increased with exposure to the pandemic. Although I assumed the coefficients for large companies to be less negative than for small and medium ones, the positive sign and magnitude are surprising. I suspect the superior access to liquidity and better geographical diversification to be the main drivers of this result; however, the existing literature does not provide adequate reasoning for this observation.

5.4.2 Industry Affiliation

Besides company size, the industry might also play an important role for performance during the crisis. Using the same approach as in the previous section, I worked with an interaction term combining the two COVID-19 metrics and a dummy for industry affiliation. Based on anecdotal evidence from the news and other non-academic sources, it would be reasonable to expect differing results across industries, with some of them suffering from the pandemic and others emerging as beneficiaries. To put this notion to an empirical test, I estimated regressions with an interaction term including industry dummies. An overview of the number of companies in every industry can be found in the Appendix.

Table 7 confirms the previous statement as the coefficients show varying significance and signs. In both Panel A and B, results for firms in Construction (column (3)), Manufacturing (4), Transportation & Public Utilities (5), and Retail Trade (7) are statistically significant. Furthermore, a significant coefficient can also be observed for Mining (2) in Panel A and Finance, Insurance & Real Estate (8) in Panel B. The remaining industries do not show any meaningful results for the interaction term. In Construction as well as Retail Trade, the estimated coefficients are negative and significant at the 1% level, apart from Retail Trade in Panel B, where it is 5%. The negative effect on the Construction industry can be explained by the initial, indefinite postponement of most developments and projects due to economic uncertainty (Gamil & Alhagar, 2020). The impact on Retail Trade might be largely driven by lockdown policies as well as economic uncertainty, although it is likely that a more granular look at the industry would reveal a more differentiated picture (Retail Trade includes various subcategories, such as food stores, apparel, and home improvement stores for which investors might have opposite expectations). The coefficients for Manufacturing (significant at 1%) and Transportation & Public Utilities (significant at 5%/10% in Panel A/B, respectively) are positive, meaning stock returns in these industries reacted positively to exposure to COVID-19. The positive effect on Manufacturing is somewhat puzzling since I expected the pandemic (lockdowns and employees on sick leave in particular) to influence investor expectations negatively. I suspect the effect in column (5) to be largely driven by communications stocks, which form a subcategory in this industry since public transportation should have suffered under stay-at-home orders. The negative and significant (1%) coefficients in columns (2) and (8) are hard to explain, especially since they are only significant in Panel A or B, but not in both. One factor resulting in the negative effect observable in column (8) might be credit defaults and insurance claims resulting from the pandemic and its effects on the real economy.

Table 7 – Interaction COVID-19 and Industry

This table reports the results when including an interaction term consisting of a measurement of the pandemic severity and a dummy for industry. The dependent variable is daily log returns (*Return*). The main independent variable used in Panel A is *Covid19*, while Panel B uses *Covid_Deaths*. Country-time fixed effects are included. Heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%.

Panel A

	Daily Stock Return									
	Agriculture, Forestry, Fishing	Mining	Construction	Manu-facturing	Transpor-tation, Public Utilities	Wholesale Trade	Retail Trade	Finance, Insurance, Real Estate	Services	Public Administration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Covid19	0.437	-2.128***	-0.953***	0.574***	0.388**	-0.074	-0.780***	0.013	0.210	-1.150
	(0.604)	(0.338)	(0.370)	(0.119)	(0.180)	(0.286)	(0.302)	(0.127)	(0.141)	(1.199)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977
Adjusted R^2	0.223	0.223	0.223	0.223	0.223	0.223	0.223	0.223	0.223	0.223

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Covid_Deaths	0.600	-0.329	-1.014***	0.605***	0.247*	-0.084	-0.694**	-0.472***	0.040	-1.341
	(0.677)	(0.451)	(0.302)	(0.120)	(0.170)	(0.283)	(0.307)	(0.138)	(0.156)	(1.125)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977	1,868,977
Adjusted R^2	0.223	0.223	0.223	0.223	0.223	0.223	0.223	0.223	0.223	0.223

5.5 Robustness Checks

5.5.1 Alternative Samples Based on Time

To test the robustness of the results the sample was divided into different subgroups according to time. I decided to create two subsamples corresponding to Year 1 and Year 2 of the pandemic, where Year 1 commences in March 2020 because this is the month when 4 out of the 5 countries in the sample reported the 100th positive case (France communicated the same on February 29, 2020). Accordingly, Year 2 starts in March 2021. By rerunning the baseline regression and the regression including both measures of public sentiment, I hope to show how the influence of the pandemic on stock returns changes over time. The government responses are not tested because they were drastically reduced in Year 2.

Table 8 – Alternative Samples Based on Time

This table reports the regression estimates from the baseline model and model 2 considering alternative samples based on time. I divided the sample into two periods lasting one year each, with the first period starting in March 2020 and the second in March 2021. The dependent variable is daily log returns (*Return*). The main independent variable used in columns 1-4 is *Covid19*, while columns 5-8 explore the effects of *Covid_Deaths*. Furthermore, the difference between Year 1 and Year 2 with regard to public sentiment is computed. Industry-time and country-time fixed effects are included. Heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%.

	Daily Stock Return							
	Year 1 (1)	Year 2 (2)	Year 1 (3)	Year 2 (4)	Year 1 (5)	Year 2 (6)	Year 1 (7)	Year 2 (8)
Covid19	-0.882*** (0.210)	-0.863 (1.217)	-0.509** (0.223)	-3.135** (1.319)				
Covid_Deaths					-0.120*** (0.092)	-10.153* (5.630)	-0.031 (0.093)	7.083 (4.921)
Covid_Sentiment			-0.145*** (0.013)	0.056*** (0.015)			-0.149*** (0.013)	0.041*** (0.014)
EPU			0.464*** (0.070)	-0.066 (0.057)			0.507*** (0.065)	-0.050 (0.059)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects								
Industry-time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	764,720	744,788	764,720	744,788	764,720	744,788	764,720	744,788
Adjusted R^2	0.2750	0.1372	0.2752	0.1372	0.2749	0.1372	0.2752	0.1372

Table 8 reports the results of the alternative samples by time. Columns (1) to (4) are again based on *Covid19*, while the remaining columns are based on *Covid_Deaths*. Columns (1) and (2) as well as (5) and (6) show estimations using the baseline model but yield different results. While *Covid19* does have significant explanatory power of stock returns in Year 1, the same does not apply to the second year. This could be related to a familiarization effect and people's attention shifting away from COVID-19 (which can for example be seen when looking at the Google search volumes in 2022 relative to 2021). In contrast, *Covid_Deaths* is still significant in Year 2, albeit only at a 10% level, which suggests that investors still care about deaths, though no longer about infections. Moreover, the coefficient for *Covid_Deaths* in Year 2 is comparably high, but this does not necessarily mean that the absolute effect is greater. The high coefficient largely stems from the way the variable is defined. As the number of cumulative death cases grows, growth rates become smaller and smaller. When a daily growth rate of 1% was still realistic in 2020, the same growth rate is unthinkable in 2022, when the cumulative number of deaths in the United States alone surpassed 1,000,000. Columns (3) to (4) and (7) to (8) explore the subsamples based on model two. Interestingly, *Covid19* exhibits statistical significance at the 5% level in both years, while *Covid_Deaths* is not significant in either of the years in this model. *Covid_Sentiment* is statistically significant at the 1% level in both years, but in Year 2 gets a positive sign. This could be a hint that the variable loses its usefulness as a proxy for uncertainty or perceived risk in Year 2 and the search volume generated has another root, for example, a general interest in the development of the pandemic for informative purposes but not out of uncertainty. *EPU* is statistically significant at the 1% level only in Year 1 and relates positively to daily stock returns. Again, this result is somewhat puzzling, and no plausible explanation has been identified in the literature yet. The variable becomes insignificant in Year 2. Lastly, one can observe that there is a substantial difference in the adjusted R^2 values among the years, which is true for all columns. My models explain the variation in the daily stock returns to a higher degree in Year 1.

5.5.2 Alternative Samples Based on Stock Characteristics

In a second step, I created further subsamples based on factors that characterize the shares of a company. I divided the companies into groups, based on if they belong to the group of winner or loser stocks per country and if they are part of a leading index in their country. Table 9 gives an overview of the analyses. Winners (Losers) are defined according to the methodology of Richards (1997) and consist of the 25% of best (worst) performing stocks for each country over the entire sample period. Leading indexes were chosen for each country and consist of the S&P/TXS60, CAC40, DAX, FTSE100, and NASDAQ100 for Canada, France, Germany, the United Kingdom, and the United States, respectively. As previously described, columns (1) to

(3) run the baseline regression with *Covid19* as the main explanatory variable and the remaining columns utilize *Covid_Deaths*. The results show that my previous findings largely hold when employing the alternative samples. The coefficients for *Covid19* suggest a negative relation with stock returns and are significant at the 1% level for all three columns. Furthermore, it can be observed that the effect is slightly more pronounced for Loser stocks than for the Winners. When comparing the coefficient in column (3) with the result from the baseline regression in Table 3, it can be derived that for stocks that are part of a leading index in their country, returns are less related to *Covid19* than for the ones that are not part of such an index, since the coefficient for the entire sample was smaller by a factor of almost three. The same applies to the Winner and Loser stocks when running the regression with *Covid_Deaths* as the main independent variable. In the sample Leading Index, *Covid_Deaths* loses statistical significance.

Table 9 – Alternative Samples Based on Stock Characteristics

This table gives an overview of the results from the baseline model considering alternative samples based on stock characteristics. On the one hand, I created subsamples based on winner and loser stocks over the entire sample period. On the other hand, I am investigating if the previous findings hold for stocks that are part of leading indexes. The dependent variable is daily log returns (*Return*). The main independent variable used in columns 1-3 is *Covid19*, while columns 4-6 explore the effects of *Covid_Deaths*. Industry-time and country-time fixed effects are included. Heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%.

	Daily Stock Return					
	Winners (1)	Losers (2)	Leading Index (3)	Winners (4)	Losers (5)	Leading Index (6)
Covid19	-1.018***	-1.306***	-0.347***			
	(0.086)	(0.106)	(0.075)			
Covid_Deaths				-1.046***	-1.269***	-0.270
				(0.120)	(0.131)	(0.270)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
Industry-time	Yes	Yes	Yes	Yes	Yes	Yes
Country-time	Yes	Yes	Yes	Yes	Yes	Yes
Observations	442,062	436,864	124,063	442,062	436,864	124,063
Adjusted R^2	0.2185	0.1990	0.2997	0.2185	0.1990	0.2997

5.5.3 Additional Controls

I conduct two additional tests to verify the robustness of my results. Since a large proportion of deaths occurs within the older population[3] it makes sense to control for the share of people in a country that is 65 or older (*Age_65*). Table 10, columns (1) and (3) show that the findings from the baseline regression do not change when including the share of the population in each country that is most vulnerable to the coronavirus due to its age as a control variable. Finally, another economically important event, the Brexit negotiations, could have influenced stock returns at the same time as the pandemic (both because of investors' expectations towards the future after Brexit and because of measures by individual countries used as negotiation tactics).

Table 10 – Additional Controls

This table reports regression estimates from the baseline model considering two additional control variables, the first one being the share of the population that is over 65 (*Age_65*) and therefore especially vulnerable in the case of an infection with COVID-19. The second control is *Brexit*, which is a dummy variable that takes the value 1 for France, Germany, and the United Kingdom when official negotiations rounds take place. The dependent variable is daily log returns (*Return*). The independent variable in columns 1-2 is *Covid19*, whereas it is *Covid_Deaths* in columns 3-4. Industry-time and country-time fixed effects are included. Heteroskedasticity-robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%.

	Daily Stock Return			
	(1)	(2)	(3)	(4)
Covid19	-0.927***	-0.930***		
	(0.064)	(0.043)		
Covid_Deaths			-0.852***	-0.856***
			(0.169)	(0.154)
Age_65	0.013		0.013	
	(0.211)		(0.209)	
Brexit		-0.029**		-0.064***
		(0.012)		(0.012)
Controls	Yes	Yes	Yes	Yes
Fixed Effects				
Industry-time	Yes	Yes	Yes	Yes
Country-time	Yes	Yes	Yes	Yes
Observations	1,868,977	1,868,977	1,868,977	1,868,977
Adjusted R^2	0.2228	0.2228	0.2228	0.2239

[3] As of April 2022, 74.7% of deaths related to COVID-19 in the United States occurred in the population older than 65 years (CDC, 2022).

Therefore, I controlled for this issue by introducing a dummy variable that takes the value one whenever official Brexit negotiations or important meetings took place (according to data from the Council of the European Union (2021)). Columns (2) and (4) show that Brexit has a statistically significant effect at the 5% (1%) level for *Covid19* (*Covid_Deaths*) on stock returns but does not change the results from the baseline regression qualitatively.

6 Conclusion

This study is a cross-country analysis of the impact of the coronavirus pandemic on stock returns and tries to pinpoint some of the driving factors of the identified relationships. OLS regressions including common control variables and fixed effects were applied to gather insights on the relationship between stock returns and measures of the pandemic as well as government responses and public sentiment. Furthermore, I constructed interaction terms between the COVID-19 metrics and company size as well as industry affiliation, using the exogenous nature of the shock to determine the role of the underlying firm characteristics (size and industry).

Looking at the results of my empirical models shows that the pandemic has an overall negative impact on stock returns, which is in line with expectations and the existing literature. The same applies to lockdowns, while the coefficients for fiscal stimuli are mostly positive, meaning that investors see these measures as having a positive impact on future cash flows and dividends. Increases in perceived risk or economic uncertainty, both measures of public sentiment, generally negatively relate to stock returns, confirming findings by other scholars. These results are robust when using alternative samples based on timing (first/second year of the pandemic), stock characteristics (winner/loser stocks and stocks that are part of leading indexes), or adding further controls like the share of the population that is 65 years or older and the dates of official Brexit negotiations. I also find an importance of company size and industry affiliation. Negative effects are more pronounced for smaller firms than for medium-sized ones and large companies even seem to benefit during the pandemic. Lastly, I discover that industry affiliation matters with varying signs, magnitudes, and levels of statistical significance across industries.

To conclude, I want to point out some limitations of my work that warrant critical reflection and further investigation. First, sample selection introduces bias in various ways. Although I included multiple countries in my analysis, the results are driven by US stocks which account for around half of the firms. In addition, a generalization of results on an international level is hardly possible because of the small number of countries (5) which are very similar in terms of structure and their status as developed markets. An analysis with more countries, also including emerging markets could be interesting. Second, while there is a vast amount of data surrounding COVID-19, data quality is varying among countries, and it is conceivable that many cases are not even discovered but might still have an impact on the economy. However, including deaths related to COVID-19 in the models should decrease the severity of this issue. Moreover, the explanatory variable *Covid19* correlates much more with stock returns at the beginning of the pandemic than after the introduction of the vaccine. This problem is partly addressed by looking at the growth rate (instead of absolute numbers) but utilizing another measure, such as excess deaths might be more appropriate. Due to data availability and comparability constraints of excess deaths, my analysis focuses on new cases and deaths. Third, it can be questioned if a linear model is the best option in the case of a pandemic, whose effects are potentially non-linear and therefore might lead to inaccurate regression results. Lastly, in future research, the exogenous nature of the shock should be exploited to generate more information on causal relationships and identify factors making firms more resilient in turbulent times like this.

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Appendix

Appendix 1 – Industry Overview

The table provides the number of companies allocated to a specific industry.

Industry	# Firms (1)
Agriculture, Forestry, And Fishing	10
Mining	217
Construction	67
Manufacturing	970
Transportation and Public Utilities	346
Wholesale Trade	84
Retail Trade	177
Finance, Insurance, and Real Estate	716
Services	528
Public Administration	5
Total	3,120