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The Impact of COVID-19 Policy Measures on European Companies – Empirical Evidence from Belgium, The Netherlands, Denmark and Norway

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Abstract

This study investigates the economic consequences of COVID-19 policy measures in Belgium, The Netherlands, Denmark and Norway. Using panel data analysis, I examine the effects of various government interventions such as lockdowns or economic support measures on risk-adjusted stock returns of companies in these countries. The findings show that both lockdown-related measures and economic support measures have a positive influence on stock returns. This positive influence is robust against competing effects such as the financial situation of companies and the pandemic itself. This study further finds that the positive influence of policy measures is consistent for companies belonging to sectors that are severely or positively affected by the pandemic. Thereby, this study contributes to the understanding of how COVID-19 policy measures affect companies and closes a research gap by considering these effects in northern European countries. It shows that lockdown-related restrictions have a positive economic impact by hindering the spread of the disease and that economic support measures ease the burden of the pandemic and are thus beneficial.

Keywords: COVID-19; government interventions; financial markets; stock returns; Northern Europe.

1. Introduction

COVID-19 came as a surprise to the public, emerging in China in December 2019 and rapidly spreading to the world in early 2020.[1] The disease was declared a Public Health Emergency of International Concern by the WHO on the 30th of January, received the name COVID-19 on the 11th of February and was declared to be a pandemic on the 11th of March.[2] The virus spread to the globe swiftly, hitting South Korea and Iran with major outbreaks.[3] The wave of infections reached Europe in March 2020, causing high fatality rates in Italy.[4] The virus has continued to spread to this day, with the number of infections rising and falling in waves but staying on a high level.[5]

To slow the spread of COVID-19 and protect their citizens, many countries adopted stringency measures such as travel restrictions, workspace closings or stay-at-home-requirements. In Europe, the first stringency measures were taken in January 2020 and sharply tightened in March 2020, reacting to the dramatic rise in the number of infections.[6] Many restrictions have remained in place until this day.[7] These measures, together with the pandemic itself, lead to dramatic economic consequences.[8] To counter these, many governments have adopted measures supporting households and companies economically. This includes measures such as income support to households, debt and contract relief or corporate debt purchase.[9] Both the stringency and the economic support measures have a multitude of influences on companies not fully understood yet.

These economic consequences of policy measures can be observed particularly well on stock markets, as they quantify expectations regarding the future economic impact of

[1] See Ding, Levine, Lin, and Xie (2021), p. 4.
[2] See Ding et al. (2021), p. 4.
[3] See Zhang, Hu, and Ji (2020), p. 2.
[4] See Zhang et al. (2020), p. 2.
[5] See Johns Hopkins University and Medicine (2021).
[6] See Blavatnik School of Government, University of Oxford (2021).
[7] See Blavatnik School of Government, University of Oxford (2021).
[8] See Sheridan, Andersen, Hansen, and Johannesen (2020), p. 20468; Zaremba, Kizys, Aharon, and Demir (2020), p. 2.
[9] See Ding et al. (2021), p. 11.

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policy measures on a daily basis.[10] Stock returns thus offer insights into economic implications of the crisis that could hardly be quantified otherwise.[11] The pandemic and the policy measures have led to unprecedented stock market reactions, showing very high market volatilities especially at the beginning of the crisis.[12] After the initial shock in March 2020, the stock markets began to recover globally from April 2020 onwards.[13]

This thesis aims at understanding the economic consequences of COVID-19 policy measures in Belgium, The Netherlands, Denmark and Norway. It contributes to the ongoing discussion about how policy interventions affect companies, an important question not fully answered yet. The thesis especially fills gaps in the literature concerning the pandemic consequences in the countries of the sample. Utilizing the government response indices developed by Hale et al. (2021) at the University of Oxford,[14] I investigate the influence of stringency and economic support measures on stock returns while controlling for the pandemic itself, company financial performance indicators, attention to the pandemic and whether a company is classified as being an essential business or not. I investigate a timeframe of over a year, from January 2020 to February 2021 using a panel data structure. To focus on pandemic-related effects, I adjust stock returns using the Fama-French three factor model and look at the excess returns over returns predicted by that model.[15] In the beginning, I investigate how stringency measures affect stock returns in general. After that, I specifically consider different economic support measures, providing an understanding of the various effects these policy interventions have on companies. In the end, I look at sectors that are severely or positively affected by the pandemic and how their stock returns are influenced by the stringency and economic support measures. I also critically discuss my methodology and results and draw conclusions from the effect of policy measures on stock returns to their effect on companies in general.

2. Literature

In this section, I present the literature on the topic of economic consequences of COVID-19 policy measures and develop my hypotheses.

2.1. Literature overview

Research into the economic consequences of COVID-19 and various policy measures began very early after the outbreak of the pandemic and has produced a growing body of literature since. An important field of research in this aspect is the impact of the pandemic itself on stock returns. It appears to be clear that COVID-19 negatively influences stock returns,[16] but the nature of that influence is not obvious. One of the topics discussed in the literature in that regard is whether the stock markets react stronger to cases or to deaths related to the virus. In their study, Al-Awadhi et al. (2020) conclude that both daily growth in confirmed cases and in confirmed deaths negatively influences stock returns.[17] Heyden and Heyden (2021) find a stronger negative market reaction to the first death in a country than to the first case of COVID-19,[18] whereas Ashraf (2020c) discovers stock markets to react strongly to cases but not to deaths.[19]

As found by Alfaro, Chari, Greenland, and Schott (2020), not only actual cases negatively influence stock returns, but also cases predicted by pandemic models, with a decrease in predicted infections having a positive impact on stock returns and vice versa.[20]

Apart from the pandemic itself, the literature suggests that attention to COVID-19-related news negatively influences stock returns.[21] Cepoi (2020) finds media coverage of the pandemic negatively influencing stock returns in the US and European countries[22] while Engelhardt et al. (2020) conclude that news attention to the topic has an even larger negative effect on stock returns than rational investor's expectation.[23]

A different factor is investigated by Ashraf (2020a), finding that national cultures influence stock returns, especially a high uncertainty avoidance negatively affecting returns when COVID-19 cases increase.[24]

Apart from these factors, a major focus of interest for many scientists is investigating the effects COVID-19 policy measures have on stock markets. Comparing COVID-19 to previous pandemics, Baker et al. (2020) find government restrictions and voluntary social distancing to be the major causes of the unprecedentedly volatile stock market reaction to COVID-19 in the US, hitting a service-oriented economy especially hard.[25] Confirming these results in a study covering more countries, Zaremba et al. (2020) discover government interventions to increase stock market volatility even when controlling for the pandemic itself.[26]

Apart from market volatility, stock returns are also affected by the policy measures, found for example by Yang and Deng (2021), who investigate a time period of over half

[10] See Ramelli and Wagner (2020), p. 623.
[11] See Ramelli and Wagner (2020), p. 623.
[12] See Baker, Davis, Kost, Sammon, and Viratyosin (2020), p. 755; Baker et al. (2020), p. 743.
[13] See Ding et al. (2021), p. 7.
[14] See Hale et al. (2021), pp. 20-27.
[15] See Fama and French (1993), p. 5.
[16] See Al-Awadhi, Alsaifi, Al-Awadhi, and Alhammadi (2020), pp. 3f; Heyden and Heyden (2021), pp. 3f; Ashraf (2020c), pp. 4-6; See Ding et al. (2021), pp. 13f.
[17] See Al-Awadhi et al. (2020), pp. 3f.
[18] See Heyden and Heyden (2021), pp. 3f.
[19] See Ashraf (2020c), pp. 4-6.
[20] See Alfaro et al. (2020), p. 1.
[21] See Cepoi (2020), pp. 3f; Engelhardt, Krause, Neukirchen, and Posch (2020), p. 10.
[22] See Cepoi (2020), pp. 3f.
[23] See Engelhardt et al. (2020), p. 10.
[24] See Ashraf (2020a), p. 5.
[25] See Baker et al. (2020), pp. 755f.
[26] See Zaremba et al. (2020), p. 6.

a year and conclude that stringency measures increase the negative effects of the pandemic on stock returns.[27] Looking specifically at the travel and leisure sector in the US, Chen, Demir, García-Gómez, and Zaremba (2020) similarly find stringency measures negatively affecting Fama-French-adjusted stock returns when accounting for the influence of COVID-19.[28] But even economic support measures, aimed at cushioning the negative influences of the pandemic and the stringency measures, might not only have positive effects, as Zhang et al. (2020) find the pandemic leading to unprecedented stock market movements and unconventional policy interventions like unlimited quantitative easing creating more uncertainty, especially in the long run.[29] Shanaev, Shuraeva, and Ghimire (2020) go even further with arguing that the negative effect of COVID-19 itself is very small, but that an irrational panic surrounding the pandemic and especially national lockdowns and economic stimulus measures have severe negative consequences on stock markets.[30] The policy measure they recommend are regional lockdowns, as these do not lead to large market effects at all.[31]

However, not all papers conclude that policy measures have adverse effects on the stock markets. Investigating dividend futures, Gormsen and Koijen (2020) find that growth expectations are heavily influenced by the crisis and that, after strongly decreasing, long-term growth expectations were stabilized by the announcement of fiscal policies at the beginning of the crisis.[32] Even stringency or lockdown measures are found to have a positive influence on stock markets by mitigating the effect of the pandemic, as argued by Narayan, Phan, and Liu (2021) in their study of G7 stock market returns.[33] Similarly, Ding et al. (2021) discover a negative effect of COVID-19 cases and a positive effect of lockdown and stimulus measures on market returns when investigating the effects of country characteristics and policy measures.[34] When examining aggregate spending in Denmark and Sweden, Sheridan et al. (2020) also find COVID-19 itself to be responsible for more economic harm than the policy measures.[35] Heyden and Heyden (2021) come to a mixed conclusion by discovering that fiscal policy measures add uncertainty whereas monetary policy measures calm markets.[36]

This is a very interesting phenomenon, as the literature is clearly divided into some studies indicating negative and some studies indicating positive effects of policy interventions. Ashraf (2020b) addresses this phenomenon of policy measures having both positive and negative consequences, stating that stringency measures have both direct, negative effects on stock returns due to their adverse influence on economic activities and indirect, positive effects due to them reducing COVID-19 cases.[37] In his contribution, he largely finds economic support measures, testing and quarantining programs to exert a positive impact on stock returns.[38]

Similarly, economic support measures have a positive, intended effect on the economy by providing economic and financial support for companies. On the other hand, they may increase uncertainty about the crisis[39] and lead to negative consequences for the stock market.[40] Whether the positive or the negative effects are more important is not clear in the literature, both for stringency and economic support measures.

Another question addressed in the literature is which companies suffer most during the pandemic and which companies suffer less or are even positively affected. One of the factors in this regard is the industry in which the company operates. Considering the impact of COVID-19 on different sectors of the Chinese economy, He, Sun, Zhang, and Li (2020) find for example the transportation, mining and electric industries to be severely affected, whereas information technology, public management and entertainment are positively affected.[41] Apart from that, energy, apparel, real estate and the service industry are found to be severely affected and telecom, pharma/biotech and software are found to be positively affected by the crisis, amongst others.[42] Especially the travel and leisure industry is often investigated, as this sector is considered to be hit particularly hard by travel restrictions and social distancing measures.[43] Indeed, when looking specifically at the travel and leisure sector in the US, Chen et al. (2020) find the stringency measures negatively affecting Fama-French-adjusted stock returns, even when controlling for the pandemic itself.[44] Lin and Halk (2021) find similar results in their study of the Scandinavian (Denmark, Finland, Sweden) travel and leisure sector, concluding that this sector is affected by the pandemic, with especially international transport companies suffering while online casinos benefit from the crisis.[45]

Apart from the sector in which a company operates, different corporate characteristics can have an influence on how a company is affected by the pandemic. In their study, Ramelli and Wagner (2020) find the international orientation and financial position of companies influencing their stock returns during the early pandemic, expressing the positive impact of cash holdings and the negative impact of close relations with China in that period.[46] Ding et al. (2021) investigate the influence of corporate characteristics, including financial performance indicators, international orientation,

[27]See Yang and Deng (2021), p. 4.
[28]See Chen et al. (2020), p. 5.
[29]See Zhang et al. (2020), p. 5.
[30]See Shanaev et al. (2020), p. 42.
[31]See Shanaev et al. (2020), p. 42.
[32]See Gormsen and Koijen (2020), p. 574.
[33]See Narayan et al. (2021), p. 5.
[34]See Ding et al. (2021), p. 13.
[35]See Sheridan et al. (2020), p. 20471.
[36]See Heyden and Heyden (2021), pp. 3f.
[37]See Ashraf (2020b), p. 7.
[38]See Ashraf (2020b), p. 7.
[39]See Zhang et al. (2020), p. 5.
[40]See Shanaev et al. (2020), p. 42f.
[41]See He et al. (2020), p. 2206.
[42]Ramelli and Wagner (2020), p. 633; Baker et al. (2020), p. 752; Xiong, Wu, Hou, and Zhang (2020), p. 2236.
[43]See Chen et al. (2020), p. 1.
[44]See Chen et al. (2020), pp. 4f.
[45]See Lin and Halk (2021), p. 15.
[46]See Ramelli and Wagner (2020), pp. 637-643.

corporate governance and ownership structure on stock returns during the early days of COVID-19, similarly finding that a strong pre-pandemic financial position and less international orientation, amongst other characteristics, lead to better stock returns during the crisis.[47] Looking at the stock market in China, Xiong et al. (2020) also find companies having larger profits, a greater size and less fixed assets to show higher stock returns during the pandemic.[48]

So far, not much research has been done considering the economic consequences of COVID-19 specifically in Belgium, The Netherlands, Denmark and Norway. Hoekman, Smits, and Koolman (2020) investigate regional differences in the Netherlands, finding that the economic shock in this country was relatively mild in the early phase of the pandemic.[49] Lin and Halk (2021) examine the situation of the travel and leisure sector in Scandinavia (Denmark, Finland, Sweden)[50] and Sheridan et al. (2020) study economic activities during the crisis in Denmark and Sweden.[51]

2.2. Hypothesis formulation

Looking at the literature, it is obvious that the economic consequences of COVID-19 policy measures are not fully understood yet. As mostly China[52], the US[53] or larger sets of countries[54] have been investigated so far, studying a set of smaller countries in northern Europe might result in interesting findings and fills a gap in the literature.

As stated above, a major issue in which the literature is unclear is whether policy interventions, both stringency measures and economic support measures, have positive or negative effects on stock returns. I address this research question in my thesis. Following the results of Ding et al. (2021) and Narayan et al. (2021), I assume a positive relationship between stringency measures and adjusted stock returns, as it appears reasonable that these measures mitigate the negative effects of COVID-19.[55] This leads to the first hypothesis:

> H1: Stringency measures are positively correlated with adjusted stock returns.

Similarly, it appears sensible to assume that economic stimulus measures have a positive relationship with adjusted stock returns as these measures support companies and potentially calm markets, following the results of Gormsen and Koijen (2020), Ashraf (2020b) and Ding et al. (2021).[56] This leads to the second hypothesis:

> H2: Economic support measures are positively corelated with adjusted stock returns.

A noteworthy phenomenon during the COVID-19 pandemic is that different sectors of the economy are affected differently by the crisis, with some industries struggling and others performing well, as visualized by Ramelli and Wagner (2020).[57] A broad range of researchers finds different sectors to be severely or positively affected by the pandemic.[58] Here, it is interesting how the effect of the stringency measures on companies belonging to sectors regarded as severely or positively affected by the pandemic looks like. For companies belonging to sectors regarded as being severely affected by the pandemic, it appears logical to assume that the stringency measures have a negative relationship with adjusted stock returns, partly explaining the severe affection by the crisis. For companies belonging to sectors regarded as being positively affected by the pandemic, however, the stringency measures should have a positive relationship with adjusted stock returns, partly explaining the positive affection by the crisis. This leads to hypothesis 3, divided into two sub-hypotheses:

> H3a: For companies belonging to a sector regarded as being severely affected by the pandemic, the stringency measures are negatively correlated with adjusted returns.

> H3b: For companies belonging to a sector regarded as being positively affected by the pandemic, the stringency measures are positively correlated with adjusted returns.

The rest of this thesis is organized as follows: Section 3 explains the methodology of testing the hypotheses, section 4 shows the data sources, data collection and data treatment. Section 5 presents the results of the analyses and their interpretation and section 6 discusses the methods and results with their limitations. Section 7 concludes the thesis.

3. Methodology

In this section, I describe the methods I use to test the hypotheses. I explain the used variables and the regression models.

3.1. Variables

To examine the impact of COVID-19 policy measures on stock returns, I use multiple linear ordinary least squares (OLS) regressions on a panel data structure. The dependent variable are always risk-adjusted stock returns, using the Fama-French three factor model to adjust the returns.[59] The three factors of this model explain a part of the variance of stock returns by considering the relative performance of a stock compared to the overall market, the return differences between small and big companies and the influence of the

[47] See Ding et al. (2021), p. 25.
[48] See Xiong et al. (2020), p. 2240.
[49] See Hoekman et al. (2020), p. 620.
[50] See Lin and Halk (2021), pp. 2f.
[51] See Sheridan et al. (2020), pp. 20468f.
[52] See Xiong et al. (2020), p. 2234; He et al. (2020), p. 2202.
[53] See Ramelli and Wagner (2020), p. 631; Chen et al. (2020), p. 3.
[54] See Ding et al. (2021), p. 6; See Ashraf (2020a), pp. 2f.
[55] See Ding et al. (2021), p. 13; Narayan et al. (2021), p. 5.
[56] See Gormsen and Koijen (2020), p. 574; Ashraf (2020b), p. 7; Ding et al. (2021), p. 13.
[57] See Ramelli and Wagner (2020), p. 633.
[58] See Ramelli and Wagner (2020), p. 633; Baker et al. (2020), p. 752; Xiong et al. (2020), p. 2236; He et al. (2020), p. 2206.
[59] See Fama and French (1993), p. 5.

market-to-book ratio on stock returns.[60] These risk factors therefore account for influences on stock returns not related to the pandemic. By utilizing excess returns over returns predicted by the model, I leave the part of return variance that cannot be explained by Fama-French risk factors for the analyses. A definition of all used variables can be found in Appendix 1.

My main explanatory variables are the Stringency Index and the Economic Support Index from the Oxford COVID-19 Government Response Tracker, developed by Hale et al. (2021) at the University of Oxford.[61] I regard these Oxford indices as a very good measurement of policy responses, as they account for most, especially the most important, policy measures, use unified scales, cover the entire time period of the pandemic and are commonly used in research, for example by Alfaro et al. (2020), Ding et al. (2021), Ashraf (2020b) and Chen et al. (2020).[62] The Stringency Index measures policy interventions aimed at preventing the spread of the pandemic like workspace closing or travel restrictions and the Economic Support Index measures policy interventions aimed at financially supporting households.[63] I use the Stringency Index as the main explanatory variable in hypotheses 1, 3a and 3b and the Economic Support Index as the main explanatory variable in hypothesis 2. When an index is not the main explanatory variable, I use it as a control variable to account for its effect on adjusted stock returns. For some of the models testing hypothesis 2, I also use the individual economic support measures E1 income support, E2 debt and contract relief and E3 other fiscal measures to gain a more detailed insight into the effects of certain policy measures. That way, I can estimate the economic impact of individual policy measures and assess whether some measures have different effects than others.

In addition to these variables, I use control variables to account for effects on stock returns not explained by the Oxford indices. To control for the influence of a company's financial structure on its stock returns, I use several financial performance indicators that are employed by Ding et al. (2021) or Ramelli and Wagner (2020) or both:[64] Firm size as the logarithm of total assets, leverage, cash by assets, ROA and book-to-market equity. I include firm size and book-to-market equity although they are already considered by the Fama-French three factor model because the influence of these parameters on stock returns might have changed during the crisis.

During a global pandemic severely affecting multinational supply chains, the international orientation of a company is an important factor to consider.[65] To assess the international orientation of a company, I use the foreign sales ratio, defined as the percentage of total revenues that is generated in foreign countries by the company as a variable, as done by Ramelli and Wagner (2020).[66] As the data for this variable is very incomplete, with 160 companies lacking data on foreign sales completely, I use this variable as a robustness check rather than a major control variable to maintain a larger sample in the main analyses.

An important influence on stock returns is the pandemic itself, as shown by Ding et al. (2021), Ashraf (2020c) and Al-Awadhi et al. (2020).[67] To measure this influence, I utilize COVID-19 cases as a control variable in the analyses. Using deaths from COVID-19 would also be possible, as it measures the severe consequences of the pandemic, but Ashraf (2020c) finds that stock markets react stronger to cases than they do to deaths[68] and Al-Awadhi et al. (2020) find that both indicators are correlated.[69] I use two variables to estimate COVID-19 cases, both based on formulas used by Ding et al. (2021):[70] AdjustedCases is the main variable and measures the change in the ratio of positive test results and UnadjustedCases is a variable I use for robustness checks and measures the growth of confirmed cases. For both formulas, I use cases of the previous day and the day before, similarly to Ashraf (2020c),[71] because new cases of a day are unlikely to affect the stock markets on the same day.

Especially at the beginning of the crisis, when actual cases were low and few policy measures were in place, attention to COVID-19 had an influence on the stock markets, as Engelhardt et al. (2020), Baker et al. (2020) and Cepoi (2020) find.[72] To measure this attention, I use the Google Search Volume Index for the term "corona" at the beginning of the pandemic as a control variable, that measure being similarly used by Ramelli and Wagner (2020) and Engelhardt et al. (2020).[73]

An important difference between companies during the pandemic is whether they belong to essential industries or not. As essential industries are considered to provide services necessary for society, they are often excluded from lockdown measures or receive special support.[74] I therefore use a dummy variable as a control variable which is one if a company belongs to an essential industry.

In addition to these variables, I use fixed effects (FE) to account for influences not captured by the variables but of importance for the results. I use Industry FE to account for effects varying across industries but constant over time, like Heyden and Heyden (2021) and Ramelli and Wagner (2020).[75] Similar to the GICS industry groups used by

[60] See Fama and French (1993), p. 5.
[61] See Hale et al. (2021), p. 27.
[62] See Alfaro et al. (2020), p. 12; Ding et al. (2021), p. 11; Ashraf (2020b), p. 2; Chen et al. (2020), p. 3.
[63] See Hale et al. (2021), pp. 20-27.
[64] See Ding et al. (2021), p. 7; Ramelli and Wagner (2020), p. 635.
[65] See Ramelli and Wagner (2020), pp. 634f; Ding et al. (2021), pp. 7f.
[66] See Ramelli and Wagner (2020), pp. 634f.
[67] See Ding et al. (2021), pp. 14f; Ashraf (2020c), pp. 5f; Al-Awadhi et al. (2020), p. 3.
[68] See Ashraf (2020c), pp. 5f.
[69] See Al-Awadhi et al. (2020), p. 3.
[70] See Ding et al. (2021), pp. 4-6.
[71] See Ashraf (2020c), p. 2.
[72] See Engelhardt et al. (2020), p. 10; Baker et al. (2020), p. 749; Cepoi (2020), pp. 3f.
[73] See Ramelli and Wagner (2020), p. 630; Engelhardt et al. (2020), p. 3.
[74] See Wales (2020), pp. 3f; Heyden and Heyden (2021), p. 3.
[75] See Ramelli and Wagner (2020), p. 638; Heyden and Heyden (2021),

Ramelli and Wagner (2020), I use the first two numbers of the ICB code to classify the industries.[76] I use Country FE to account for effects varying across countries but constant over time, like Ashraf (2020b), Heyden and Heyden (2021) and Ding et al. (2021).[77] As done by Narayan et al. (2021) and Zaremba et al. (2020), I use Weekday FE to account for effects varying across days of the week but constant over companies and weeks.[78] Finally, I use Company FE in some models to account for effects varying across companies but constant over time. Upon adding Company FE, all other variables constant for a company drop out of the model. Industry and Country FE are automatically included in Company FE. As financial performance indicators are constant for some companies but have two values for others, the model would not completely drop them automatically, resulting in multicollinearity. When using Company FE, I therefore manually drop financial performance indicators.

3.2. Regression models

For each hypothesis, I run multiple regressions using different variables. I generally start with only the main explanatory variable or variables, then add COVID-19-related variables (Attention, AdjustedCases and essential) and then add company-related variables (financial performance indicators), before finally adding company fixed effects. This enables me to assess the effects various variables have on the regression results and how the effects of the main explanatory variables are changed by adding other variables.

To counter issues of heteroscedasticity, I use robust standard errors clustered by company in all regressions.

The formula for model 3 of hypothesis 1 looks as follows:

$$\begin{aligned}\alpha_{i,t} = {} & b_0 + b_1 SI_{c,t} + b_2 ESI_{c,t} + b_3 Size_{i,t} + b_4 Leverage_{i,t} \\ & + b_5 CashByAssets_{i,t} + b_6 ROA_{i,t} + b_7 BookToMarket_{i,t} \\ & + b_8 Attention_{c,t} + b_9 AdjustedCases_{c,t} + b_{10} essential_i \\ & + \mu_{ind} + \mu_c + \mu_w + u_i + \varepsilon\end{aligned} \tag{1}$$

where $\alpha_{i,t}$ is the adjusted return of company i on day t, $SI_{c,t}$ is the value of the Stringency Index for country c on day t, $ESI_{c,t}$ is the value of the Economic Support Index for country c on day t, $Size_{i,t}$ is the value of the variable Size for company i and day t, $Leverage_{i,t}$ is the value of the variable Leverage for company i and day t, $CashByAssets_{i,t}$ is the value of the variable CashByAssets for company i and day t, $ROA_{i,t}$ is the value of the variable ROA for company i and day t, $BookToMarket_{i,t}$ is the value of the variable BookToMarket for company i and day t, $Attention_{c,t}$ is the value of the variable Attention measuring attention to COVID-19 for country c and day t, $AdjustedCases_{c,t}$ is the value of the variable AdjustedCases measuring COVID-19 cases for country c and day t, $essential_i$ is the value of the binary variable indicating whether company i belongs to a sector classified as essential or not, μ_{ind}, μ_c, μ_w are Industry, Country and Weekday fixed effects, $u_i + \varepsilon$ is the error term for robust standard errors clustered by company, b_0 is the intercept and b_1 to b_{10} are the coefficients. A definition of the variables used can be found in Appendix 1. This is the model for hypothesis 1 containing most variables. All other models, for this and the other hypotheses, are just variations of this model, with some variables being added, removed, or replaced according to the regression tables. Therefore, this is the main model of the thesis.

For hypotheses 3a and 3b, I run the regressions on subsamples of companies, using companies belonging to industries regarded as being severely affected by the pandemic for hypothesis 3a and companies belonging to industries regarded as being positively affected by the pandemic for hypothesis 3b.

4. Data

In this section, I describe the data sources, data collection and data treatment for the data used in the analyses. I furthermore present descriptive statistics for the used variables. In the end, I briefly consider regression diagnostics for the main model.

4.1. Adjusted stock returns

The adjusted stock returns are excess returns, calculated as the difference between the actual, raw returns and the returns predicted by the Fama-French three factor model. To obtain raw returns, I download daily data for the return index (RI) from Refinitiv Datastream (2021) for all companies in the full sample beginning on the 26th of January 2018 and ending on the 26th of February 2021. I choose these timepoints for the following reasons: The 26th of February 2021 is the last day for which data necessary for calculating adjusted returns was provided on Kenneth French's website for the Fama-French three factor model at the time of the download.[79] As the 27th of January 2020 is the date on which one of the countries in the sample had a Government Response Index, the most comprehensive Oxford index,[80] larger than zero for the first time, I choose this date as the beginning of the observation period. To receive good estimates for the betas of the Fama-French three factor model, I use the two years before the observation period as the beta-calculating period, beginning on the 27th of January 2018. To calculate a meaningful value for the first raw return, I also include the 26th of January 2018 in the download of the return index.

To clean the data, I apply several screens based on the screens conducted by Hanauer and Windmüller (2020) and

p. 5.

[76]See Ramelli and Wagner (2020), p. 638.

[77]See Ashraf (2020b), p. 6; Heyden and Heyden (2021), p. 5; Ding et al. (2021), p. 13.

[78]See Narayan et al. (2021), pp. 3-5; Zaremba et al. (2020), pp. 4f.

[79]See French (2021).

[80]See Hale et al. (2021), p. 27.

Schmidt, von Arx, Schrimpf, Wagner, and Ziegler (2019).[81] The screens aim at deleting dead companies, abnormal returns, returns on holydays and other data potentially disturbing the results. To conduct some of the screens, I download the unadjusted prices (UP) for the entire time period for all companies in the sample after some of the screens. A detailed description of these screens is given in Table A.2. Static screens are mostly unnecessary, as I use the company list of Hanauer and Windmüller (2020) on which static screens had already been applied by these researchers.[82] I take care not to delete any company delisted during the observation period to exclude the possibility of survivorship bias.

I conduct the data preparation in Excel and R, using R version 4.0.4 for most of the preparation steps for all variables. The R file containing the data preparation code is provided in Attachment 14. However, it does not use the raw data files also attached, as I prepare some datasets in Excel before loading them into R.

I calculate the raw returns as the daily change of the return index relative to the return on the previous day. I run a regression over the beta-calculating period for each company to estimate the coefficients of the Fama-French three factor model using the regression equation of that model:

$$r_{i,t}-r_{f,t} = \alpha_i+\beta_{i,1}\left(r_{m,t}-r_{f,t}\right)+\beta_{i,2}\times SMB_t+\beta_{i,3}\times HML_t+\varepsilon \tag{2}$$[83]

where $r_{i,t}$ is the (raw) return of company i on day t, $r_{f,t}$ is the risk-free return on day t, $r_{m,t}$ is the market return on day t, SMB_t is the Small Minus Big factor and HML_t is the High Minus Low factor of the Fama-French three factor model on day t, ε is the error term (equals zero on average), α_i is the intercept and the three betas are the regression coefficients. The market return and the factors of the Fama-French three factor model are downloaded from Kenneth French's website as daily data for the European market for the entire time period.[84] Using the estimated betas, I calculate the adjusted returns by subtracting the returns predicted by the Fama-French three factor model from the raw returns for each company and each day of the observation period using the formula described above. A detailed description of the calculation of the adjusted returns is given in Appendix 2.

4.2. COVID-19 policy measures

I download the Oxford dataset, only keeping data for indicators, countries and time points I use in my analyses from the website of the Blavatnik School of Government of the University of Oxford.[85] The indicator M1, a wild card for policy measures not fitting into any other category, does not contain any information, so I do not regard this indicator. To adjust the values of E3, which are given in absolute US Dollar amounts, to the financial strength of a country, I divide the E3-value by the country's GDP of 2019. I download data on the GDP values, which are \$ 533,097,455,830 for Belgium, \$ 907,050,863,150 for The Netherlands, \$ 350,104,327,660 for Denmark and \$ 403,336,363,640 for Norway from the website of the World Bank.[86] I delete data from weekends for all indices, as they are also not included in the return data, adding E3-values of weekends to the next Monday. Further data manipulation is not necessary.

4.3. Control variables

The financial performance indicators are calculated as follows, following the approaches of Ding et al. (2021) or Ramelli and Wagner (2020) or both:[87] Size is the natural logarithm of total assets;[88] Leverage is the total debt divided by total assets;[89] CashByAssets is cash and short-term investments divided by total assets;[90] ROA is the net income before extraordinary items divided by total assets[91] and BookToMarket is the book value of equity divided by the market value of equity.[92] To do these calculations, I download the required data from Refinitiv Worldscope (2021), Refinitiv Datastream (2021) and Orbis (2021), using mainly Refinitiv Worldscope (2021) data and filling data gaps with Orbis (2021) data. To avoid extreme values from influencing the results, I winsorize all financial performance indicators at 1% and 99%. For all financial performance indicators, I use values calculated utilizing accounting data from the fiscal year 2019 until the end of the company's fiscal year 2020 and from the fiscal year 2020 thereafter if that data was already available at the time of the download, resorting to 2019 data if not. Similar to the data truncation done by Ramelli and Wagner (2020),[93] I set all Leverage values larger than 1 to 1 prior to winsorizing the data, as larger values are hardly possible and could potentially change the results of my analyses. The values of 7 companies are thus changed. I multiply all Leverage, CashByAssets and ROA values by 100 to obtain percentage values. Details on the data preparation steps for the company financial performance indicators can be found in Appendix 2.

I download the foreign sales in percent of total sales (WC07101) from Refinitiv Worldscope (2021) along with the company financial data for 2019 and 2020, this item being very similar to the foreign sales ratio used by Ramelli and Wagner (2020).[94] I apply the same data preparation steps as I do to the company financial performance indicators, winsorizing the data at 1% and 99% and using 2019 foreign sales data until the end of a company's fiscal year 2020 and

[81] See Hanauer and Windmüller (2020), p. 64; Schmidt et al. (2019), Online Appendix p. 19.
[82] See Hanauer and Windmüller (2020), pp. 61-63.
[83] See Fama and French (1993), p. 9f.
[84] See French (2021).
[85] See Blavatnik School of Government, University of Oxford (2021).
[86] See World Bank (2021).
[87] See Ding et al. (2021), p. 7; Ramelli and Wagner (2020), p. 635.
[88] See Ding et al. (2021), p. 7.
[89] See Ding et al. (2021), p. 7; Ramelli and Wagner (2020), p. 635.
[90] See Ding et al. (2021), p. 7; Ramelli and Wagner (2020), p. 635.
[91] See Ding et al. (2021), p. 7; Ramelli and Wagner (2020), p. 635.
[92] See Ramelli and Wagner (2020), p. 635.
[93] See Ramelli and Wagner (2020), p. 636.
[94] See Ramelli and Wagner (2020), pp. 634f.

2020 foreign sales data thereafter, if available. Similar to Leverage, I set all foreign sales values larger than 100 to 100 prior to winsorizing the data, changing the values of 8 companies.[95]

The formulas used to calculate the two variables measuring COVID-19 cases are the following, based on formulas used by Ding et al. (2021):[96]

AdjustedCases:

$$ac_{c,t} = \ln\left(1 + \frac{culcases_{c,t-1}}{tottest_{c,t-1}}\right) - \ln\left(1 + \frac{culcases_{c,t-2}}{tottests_{c,t-2}}\right)^{97} \quad (3)$$

UnadjustedCases:

$$uc_{c,t} = \ln\left(1 + culcases_{c,t-1}\right) - \ln\left(1 + culcases_{c,t-2}\right)^{98} \quad (4)$$

Where $culcases_(c,t)$ are the cumulative COVID-19 cases of country c on day t and $tottests_(c,t)$ is the number of all tests conducted in country c before and on day t. For the reason given above, I use cases of the previous day and the day before in both formulas. I download the required data on COVID-19 cases and tests for the countries in the sample from the website of the Foundation for Innovative New Diagnostics,[99] an organization having a partnership with the World Health Organization and the Bill & Melinda Gates Foundation, a source also used by Ding et al. (2021).[100] I delete the data for timepoints outside of the observation period and calculate the variables, replacing the fractions in the formula for the AdjustedCases with zero if the total number of tests is zero on a day. I remove data for weekends, multiply both variables by 100 to match them with the rest of the data and winsorize them at 1% and 99%, as done with the financial performance indicators and foreign sales.

I download the Google Search Volume Index for the term "corona" for the countries in my sample from the 27th of January 2020 until the 11th of May 2020 from Google Trends.[101] I use this term, as other terms associated with the pandemic were only created later on, like the novel disease being given the name COVID-19 on the 11th of February 2020 by the WHO.[102] As the pandemic and policy measures responding to it have vast effects on the economy, I assume that attention to the pandemic remains high even after the Search Volume Indices have reached their peaks. I therefore only keep the original Search Volume Indices until an index reaches 100 and replace all later values with 100. As done with the other variables, I delete all data for weekends.

I use the essential workforce classification by Wales (2020), issued by the US Cybersecurity and Infrastructure Security Agency[103] as basis for my essential industry classification as recommended by Heyden and Heyden (2021), because although every country defines essential businesses slightly differently, the classification is mostly done in a very similar way.[104] I classify companies as essential if the industry they belong to is mentioned as being an essential business by Wales (2020) using the companies' SIC codes and a website explaining SIC code meanings.[105] This classification is of course not perfectly precise, but should be sufficient for this purpose. A list of all industries I classified as essential and their corresponding SIC codes can be found in Table A.4.

To identify companies belonging to severely or positively affected industries, I use the results of Ramelli and Wagner (2020), Baker et al. (2020), Xiong et al. (2020) and He et al. (2020).[106] I therefore classify companies as belonging to sectors regarded as being severely or positively affected if the industries they belong to are described as being such, using SIC codes as done for the essential classification. Industries regarded as being severely affected include consumer services, tourism and hospitality and transportation, amongst others. Industries regarded as being positively affected include telecom, pharma/biotech and software companies, amongst others. A list of all industries I classify as severely or positively affected and their corresponding SIC codes can be found in Appendix 2, including Table A.5 and Table A.6.

4.4. Descriptive Statistics

Table 1 presents descriptive statistics for the used variables. It can be seen that the adjusted returns are centered very much around zero, with about half of the values being less than one percentage point away from that number. However, the large SD implies that more extreme values exist. This indicates that the Fama-French three factor model is able to explain a large part of the return variance, but not all of it. The values of the mean, the median and the percentiles show that the distribution of the variable is not alarmingly skewed.

In contrast, SI and ESI show a lot of variance with standard deviations and interquartile ranges between 20 and 50. As these indices can take values between 0 and 100,[107] the distributions indicate multiple changes of policy measures. Figure 1 confirms this observation, the figure presenting the development of stringency measures in the countries of the sample over time. The figure shows that stringency measures were sharply increased around March 2020 and remained high until the end of the observation period, only temporarily being eased during summer and autumn 2020 in the four countries. Interestingly, the four countries have very similar lines in the figure, tightening and easing stringency measures almost at the same time. The figure and the distribution of

[95] See Ramelli and Wagner (2020), p. 636.
[96] See Ding et al. (2021), pp. 4-6.
[97] See Ding et al. (2021), p. 6.
[98] See Ding et al. (2021), p. 4.
[99] See Foundation for Innovative New Diagnostics (2021).
[100] See Ding et al. (2021), p. 6.
[101] See Google LLC (2021).
[102] See Ding et al. (2021), p. 4.
[103] See Wales (2020), pp. 7-23.
[104] See Heyden and Heyden (2021), p. 2.
[105] See SIC-NAICS LLC (2021).
[106] See Ramelli and Wagner (2020), p. 633; Baker et al. (2020), p. 752; Xiong et al. (2020), p. 2236; He et al. (2020), p. 2206.
[107] See Hale et al. (2021), p. 29.

Table 1: Descriptive statistics

This table shows the descriptive statistics of the variables used in my analyses. The definitions and data sources for all variables can be found in Appendix 1. Reported are the number of non-missing observations for each variable (N), the mean and standard deviation (SD) of the variable and the value of the variable at the 25th percentile, 50th percentile (Median) and 75th percentile of the distribution of the variable.

Variable	N	Mean	SD	p(25)	Median	p(75)
AdjustedReturn	117,936	0.062	3.221	-1.053	-0.047	0.949
SI	129,675	52.244	20.366	40.7	56.0	66.7
ESI	129,675	57.762	30.962	37.5	62.5	87.5
E1	129,675	1.749	0.652	2	2	2
E2	129,675	0.899	0.908	0	1	2
E3	129,675	0.0002	0.004	0	0	0
AdjustedCases	129,675	-0.014	0.148	-0.02	-0.002	0.005
UnadjustedCases	129,675	2.742	7.718	0.2	0.7	1.6
Attention	129,675	89.629	29.079	100	100	100
Size	129,390	20.129	2.432	18.584	20.248	21.736
Leverage	129,100	27.798	21.753	10.031	24.399	40.564
CashByAssets	125,970	13.869	20.280	2.138	6.182	15.505
ROA	129,390	-2.013	24.360	0.090	1.919	5.152
BookToMarket	129,390	0.946	3.548	0.285	0.643	1.152
ForeignSales	82,855	46.669	37.793	1.000	50.890	81.900
essential	129,675	0.574	0.495	0	1	1
severelyAffected	129,675	0.312	0.463	0	0	1
positivelyAffected	129,675	0.141	0.348	0	0	0

the variable suggest a skewness of SI, as it contains many rather high values and a few very low values from the beginning of the observation period. ESI and its components E1 and E2 do not have a large temporal variation, as these measures often remain active for a long time.[108] The individual economic support indicators E1 and E2 can only take values between 0 and 2[109] and E3 can only be positive and less than 1 and is generally very small due to its definition. The variance of E1 and E2 is of course similar to the one of ESI, with E2 showing more variation.

Considering the control variables, the measurements for COVID-19-cases are logarithmic, changing the distribution compared to non-logarithmic variables. Attention is obviously skewed, as is to be expected regarding the definition of that variable. The financial performance indicators do not offer unexpected findings, the huge differences between the means and medians of CashByAssets and ROA suggest that outliers influence the distributions of these variables. However, mean and median are within one standard deviation from each other in both cases. The dummy variables show that a slight majority of companies is classified as being essential, about a third belongs to severely affected sectors and only a few companies belong to positively affected sectors.

Generally, the distribution of all variables is similar to their distribution in the literature I base the variable on. The distribution of the adjusted returns is similar to the distribution of CAPM-adjusted returns used by Ramelli and Wagner (2020).[111]

4.5. Regression diagnostics

To ensure the assumptions underlying multiple linear regressions are fulfilled, I perform regression diagnostics for the main model, the formula of which is given in section 3.2.

I consider the following assumptions, as provided on the website of the University of California, Los Angeles: Linearity, normality of residuals, homoscedasticity, independence, model specification, influential values, collinearity.[112] I further look at the randomness of the sample and possible issues of endogeneity, these being the regression assumptions described by Roberts and Whited (2013) that are not automatically fulfilled or already covered by the assumptions above.[113]

I check for linearity using the Residuals vs Fitted plot, shown in Figure A.1. A straight red line indicates no issues with the linearity assumption, which is the case.

I check for normality of residuals using a normal Q-Q-plot of the residuals, shown in Figure A.2. The plot shows that the residuals are not distributed normally, but follow a broader distribution, having long tails. However, no signs of skewness can be seen in the plot. This is not a problem for the calculated coefficients, which just rely on the residuals being identically and independently distributed, which should be

[108] See Blavatnik School of Government, University of Oxford (2021).
[109] See Hale et al. (2021), p. 22.
[110] See Blavatnik School of Government, University of Oxford (2021).
[111] See Ramelli and Wagner (2020), p. 636.
[112] See University of California, Los Angeles (2021).
[113] See Roberts and Whited (2013), pp. 497f.

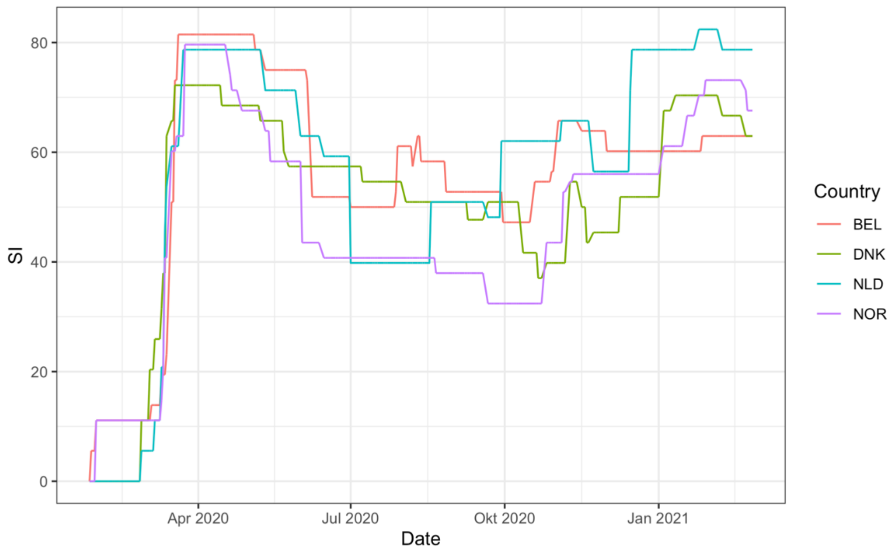

Figure 1: Stringency Index over time

This figure visualizes the values of the Stringency Index over time during the observation period for each country of the sample. Data source is the Oxford COVID-19 Government Response Tracker.[110] The time is displayed on the x-axis, the values of the Stringency Index (SI) are displayed on the y-axis. The colors represent the different countries. Variable definitions can be found in Appendix 1.

the case.[114] The t- and F-tests, however, are not fully valid.[115] I keep the data as it is, as changing the distribution would delete a large part of the data's variance, but p-values close to significance thresholds should be handled with care, which is a constraining factor.

I check for homoscedasticity using the Scale-Location plot, shown in Figure A.3. A straight red line indicates no issues with heteroscedasticity. In this case, the red line is slightly curved, but not alarmingly so. The error variance should therefore be relatively constant. All heteroscedasticity left is dealt with using robust standard errors.

Independence, meaning that the errors associated with one observation are not corelated with errors of any other observation, is addressed by clustering standard errors by company.[116]

Model specification refers to the model including all relevant and excluding all irrelevant variables.[117] A statistical test for the model specification is the Ramsey RESET test, which creates new predictor variables and checks whether any of them are significant.[118] I perform this test using both a power of 2 and 3 on the model without clustered robust standard errors (as using them gave an error) and both were significant, indicating that the model has a specification error. Further considerations of omitted variables will be given in the paragraph discussing endogeneity.

I check for influential values using the Residuals vs Leverage and the Cook's distance plot, Figures A.4 and A.5. Observations are considered influential if they have large residuals and deviate far from the mean, with the most common measurement for influential values being the Cook's distance.[119] A Cook's distance greater than 4/n with n being the number of observations is considered especially large, in this model the critical distance is $3.495*10^{-5}$.[120] Many observations exceed that value in the model. Considering the three observations having the highest Cook's distances, their values are not extremely different from the mean and I cannot find any reason for these observations to be abnormal. I therefore keep all observations in the sample, but the generally large Cook's distance is a minor constraining factor.

I check for collinearity by calculating the variance inflation factors (VIFs) for the model. Looking at the VIFs, no variable has a value larger than 10, indicating that collinearity is not an issue in this model.[121]

Concerning the randomness of the sample, it is sufficient to assume "that the error term is independent of the sample selection mechanism conditional on the covariates."[122] As the sample is given, that assumption is not to be tested.

No real check for endogeneity exists, but three main reasons for this phenomenon can be considered: Omitted variables, simultaneity and measurement errors.[123] The model specification test implies that some important variables might be omitted. However, when carefully checking the literature, I could not find important variables which I do not include in the model. Usage of fixed effects also takes care of some

[114]See University of California, Los Angeles (2021).
[115]See University of California, Los Angeles (2021).
[116]See University of California, Los Angeles (2021).
[117]See University of California, Los Angeles (2021).
[118]See University of California, Los Angeles (2021).
[119]See University of California, Los Angeles (2021).
[120]See University of California, Los Angeles (2021).
[121]See University of California, Los Angeles (2021).
[122]Roberts and Whited (2013), p. 497.
[123]See Roberts and Whited (2013), pp. 498-501.

factors otherwise omitted. Furthermore, when looking at the regression results (Table 2), the effect of SI remains significant when adding control variables and fixed effects, reducing concerns of omitted variable bias. Omitted variable bias therefore possibly exists, but I am probably not missing any important variables commonly used in this research area.

To estimate whether simultaneity is an issue in the model, I lag SI ten working days into the future and look at the regression results. Comparing the coefficients of SI, a change from 0.009 to -0.003 can be noted, that being a reduction in magnitude and a change in sign. Both coefficients are significant at 1% and the R^2 slightly decreases. These results show that simultaneity should not be a large issue, as the previously seen effect of SI on the adjusted returns vanishes.

To minimize the possibility of measurement errors occurring, I use variables carefully selected and successfully used in previous research. Only Attention is significantly altered in comparison to the literature, but not to a great extent and it is not a major variable. I can therefore say that all variables should be good at measuring what they are supposed to measure, but the possibility of measurement errors can never be fully ruled out.

5. Results

In this section, I present, discuss and interpret the results of the analyses. The R code used to generate these results is provided in Attachment 15, using the dataset in Attachment 13 as an input. This code can also generate the descriptive statistics and regression diagnostics tests.

5.1. Hypothesis 1

Hypothesis 1 concerns the relationship between stringency measures and adjusted stock returns, hypothesizing that a positive correlation exists. Table 2 reports the results of the analysis of this hypothesis. Model 1 is the baseline specification, only including SI as a predictor variable. In model 2, COVID-19 related control variables are added, as are industry, country and weekday fixed effects. Model 3 is the main model, including pandemic-related and company-related control variables and ESI as a control variable. Model 4 includes company fixed effects, therefore dropping the essential dummy and financial performance variables. Figure 2 illustrates the relationship between SI and the adjusted returns, it visualizes model 1.

The results report a significant, positive correlation between SI and the adjusted returns in all models, thereby providing support for hypothesis 1. This finding is in line with the results of Narayan et al. (2021) and Ding et al. (2021).[124] In the main model (model 3), for an increase of SI by one SD (20.366), the adjusted returns on average rise by 0.1833 percentage points (20.366*0.009), which is 0.0569 standard deviations (0.1833/3.221) of the adjusted returns. This shows that the correlation is positive and significant, but of small magnitude. This is also shown in Figure 2, where the adjusted returns are distributed around zero for all values of the Stringency Index. The generally positive slopes of SI can be explained by the reasoning Ashraf (2020b) provides, concluding that the positive effect of stringency measures on stock returns stems from stringency measures mitigating the negative effects of COVID-19 itself, while the direct effects of stringency measures on the economy are adverse.[125] The operations of companies might therefore be negatively affected by the stringency measures, but their stock returns can show a positive correlation for this reason, as the economic situation would be worse without these measures in the eyes of the market. For that reason, the stringency measures are potentially beneficial for companies.

Interestingly, the slope of SI is positive and significant even when not controlling for COVID-19 cases, that variable having a negative and significant slope in all models. However, the slope of SI is lower in the first model compared to the models where COVID-19 cases are included. This further supports the suggestion made by Ashraf (2020b) that stringency measures mitigate the negative effects of COVID-19.[126]

The slopes of ESI will be subject to investigation in the second hypothesis. Concerning the company financial performance variables, only Size and BookToMarket have significant coefficients at conventional significance levels, even after adjusting for the Fama-French three factor model. This implies that company financial performance, measured by Leverage, CashByAssets and ROA does not have a significant effect on adjusted stock returns in this sample, in contrast to the results of Ding et al. (2021).[127] Size has a negative coefficient and BookToMarket has a positive one, suggesting that the market prefers small companies and companies with a relatively higher book value of equity compared to their market value during the crisis. Attention has a small, but negative and significant correlation with adjusted stock returns where an increase of Attention by one SD (29.079) relates to a decrease of the adjusted returns of 0.1454 percentage points (-0.005*29.079) in the main model. Rising attention to the pandemic is thereby suggested to have a negative impact on stock returns, although not a strong one. Not being significant in any model and with a changing sign, the essential classification does not seem to exert important influence on adjusted stock returns. This is in line with the results of Heyden and Heyden (2021), who also find essential companies not to react differently to policy measures than companies on average.[128]

Special attention should be given to the adjusted cases of COVID-19, that variable being the primary measurement for the influence of the pandemic itself. As stated above, the coefficients for this variable are negative and significant in all models it is included in. For an increase of AdjustedCases by one SD (0.148), the adjusted returns decrease by 0.05831

[124] See Narayan et al. (2021), p. 5; Ding et al. (2021), p. 13.

[125] See Ashraf (2020b), p. 7.

[126] See Ashraf (2020b), p. 7.

[127] See Ding et al. (2021); pp. 14f.

[128] See Heyden and Heyden (2021), p. 3.

Table 2: Effect of stringency measures on adjusted stock returns

This table shows the regression results of how adjusted returns react to measures captured in the Oxford Stringency Index while controlling for economic support measures, company financial performance indicators, attention to COVID-19, COVID-19 cases and whether a company is classified as an essential business. Variable definitions and data sources can be found in Appendix 1. Fixed effects are included when stated as such. Robust standard errors clustered by company are denoted in parentheses. ***, ** and * report statistical significance levels at 1%, 5% and 10%, respectively, using clustered robust standard errors.

	Dependent variable: AdjustedReturn			
Variable	(1)	(2)	(3)	(4)
SI	0.006***	0.009***	0.009***	0.009***
	(0.0004)	(0.001)	(0.001)	(0.001)
ESI			0.004***	0.004***
			(0.001)	(0.001)
Size			-0.024***	
			(0.006)	
Leverage			-0.0001	
			(0.001)	
CashByAssets			0.001	
			(0.001)	
ROA			0.0004	
			(0.001)	
BookToMarket			0.011***	
			(0.001)	
Attention		-0.002***	-0.005***	-0.005***
		(0.0005)	(0.001)	(0.001)
AdjustedCases		-0.391***	-0.394***	-0.406***
		(0.081)	(0.083)	(0.078)
essential		-0.020	0.010	
		(0.024)	(0.026)	
Industry FE	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes
Weekday FE	No	Yes	Yes	Yes
Company FE	No	No	No	Yes
Observations	117,936	117,936	114,440	117,936
Adj. R squared	0.00153	0.00321	0.00386	-0.00044
F Statistic	215.91***	62.459***	57.485***	34.833***
	(df = 1)	(df = 30)	(df = 36)	(df = 8)

percentage points (-0.394*0.148) in the main model, on average. It has to be kept in mind that this variable is logarithmic, altering the slope of the coefficients in comparison to other variables and making the magnitude of its impact more difficult to assess. Such a negative correlation is in line with the results of Ding et al. (2021) and Ashraf (2020b).[129] This implies that the pandemic itself has a negative effect on companies and that the market takes this negative effect into consideration. A possible reasoning behind this is that the economic consequences of the pandemic become worse when more cases are reported, thus leading to decreased stock returns. This could also explain the negative effect of Attention, as attention to the pandemic and its adverse effects can have a negative influence on the stock market as well. The suggested negative impact of the pandemic itself on companies also supports the explanation of the positive slopes of SI, mitigating these negative influences.[130]

A factor that has to be addressed is the low adjusted R^2 of all models, which is at most 0.0386% (in the main model) and is even negative in model 4. This is to be expected, however, as I use risk-adjusted returns, leading to the adjusted R^2 only measuring what percentage of return variance, which was not explained by the Fama-French factors, the model additionally explains. As the Fama-French three factor model explains a large part of the return variance,[131] small adjusted R^2 are not an issue. The models are all valid in explaining a part of the return variance because the F-statistics measuring whether the models explain anything at all are all significant.

[129] See Ding et al. (2021), p. 14; Ashraf (2020b), pp. 6f.

[130] See Ashraf (2020b), p. 7.

[131] See Fama and French (1993), p. 5.

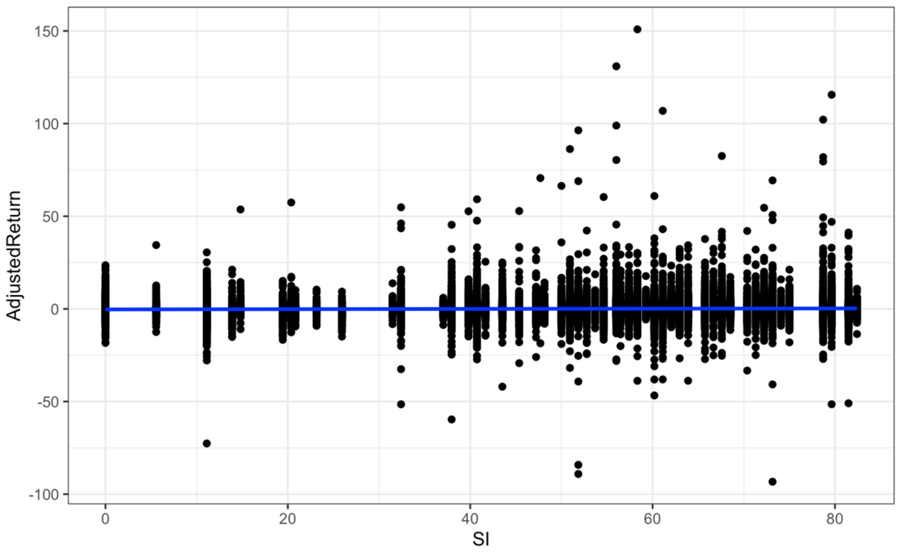

Figure 2: Relation of stringency measures and adjusted stock returns

This figure visualizes the relationship between stringency measures and adjusted stock returns without using any control variables, essentially column (1) of table 2. The blue line represents the regression line of the relationship. The values of the Stringency Index (SI) are displayed on the x-axis, the values of the adjusted returns (AdjustedReturn) are displayed on the y-axis. Variable definitions and data sources can be found in Appendix 1.

These results contradict the findings of various researchers, including Yang and Deng (2021), Chen et al. (2020) and Shanaev et al. (2020).[132] The different results might be due to a different empirical setting, considered timeframe or the sample consisting of different companies from different countries.

5.2. Hypothesis 2

Hypothesis 2 concerns the relationship between economic support measures and adjusted stock returns, hypothesizing that a positive correlation exists. To analyze this hypothesis, I consider the Economic Support Index and E3 in table 3 and the individual support measures E1, E2 and E3 in table 4 in order to gain specific insights into the effects of the individual policy measures. In both tables, control variables and fixed effects are added following the same sequence as in table 2, with the third model always containing most control variables. The only difference is the earlier addition of policy measure control variables, with the Stringency Index, the effect of which already having been investigated, being added in the second model already. As it is possible that ESI and E3 are collinear, I calculate the VIFs for model 3 of table 3 to exclude the possibility of multicollinearity falsifying the results. As all VIFs are below 10, multicollinearity is not an issue.

The results partly support hypothesis 2 by reporting a significant, positive correlation between ESI and the adjusted returns in all models. This is in line with a broad range of literature, including Narayan et al. (2021), Ding et al. (2021), Gormsen and Koijen (2020) and Ashraf (2020b).[133] For an increase of ESI by one SD (30.962), the adjusted returns increase by 0.09289 percentage points (30.962*0.003), on average in the third model. This is again much less than a standard deviation of the adjusted returns (3.221), showing that the effect, although significant, has a rather small magnitude. A possible explanation for this is presented by Ashraf (2020b), describing that the Economic Support Index measures support given to households and not to businesses, which results in stock market reactions to the measures not being very strong.[134] Still, a positive and significant correlation is observed, implying that economic support measures can indeed be beneficial for companies.

The situation looks differently for E3. The coefficient is negative and statistically significant in all models, with an increase of E3 by one SD (0.004) being related to a decrease of -0.03842 percentage points (-9.607*0.004) of the adjusted returns in the third model, on average. This finding contradicts the previous results showing a positive correlation between economic support measures and adjusted returns. However, these adverse effects of economic support measures on stock returns are also shown in the literature, where Zhang et al. (2020) and Shanaev et al. (2020) arrive at similar results.[135] Heyden and Heyden (2021) find a similar ambivalent relationship, reaching the conclusion that fiscal policies add uncertainty whereas monetary policies calm markets.[136] Another factor possibly explaining these results are the differ-

[132] See Yang and Deng (2021), p. 4; Chen et al. (2020), pp. 3f; Shanaev et al. (2020), p. 42.

[133] See Narayan et al. (2021), p. 5; Ding et al. (2021), p. 13; Gormsen and Koijen (2020), p. 574; Ashraf (2020b), p. 7.

[134] See Ashraf (2020b), p. 5.

[135] See Zhang et al. (2020), p. 5; Shanaev et al. (2020), pp. 42f.

[136] See Heyden and Heyden (2021), pp. 3f.

Table 3: Effect of economic support measures on adjusted stock returns

This table shows the regression results of how adjusted returns react to economic support measures captured in the Economic Support Index and E3 of the Oxford Indices while controlling for stringency measures, company financial performance indicators, attention to COVID-19, COVID-19 cases and whether the company is classified as an essential business. Variable definitions and data sources can be found in Appendix 1. Fixed effects are included when stated as such. Robust standard errors clustered by company are denoted in parentheses. ***, ** and * report statistical significance levels at 1%, 5% and 10%, respectively, using clustered robust standard errors.

	Dependent variable: AdjustedReturn			
Variable	(1)	(2)	(3)	(4)
ESI	0.002***	0.003***	0.003***	0.003***
	(0.0003)	(0.001)	(0.001)	(0.001)
E3	-9.644***	-9.826***	-9.607***	-9.594***
	(3.312)	(3.367)	(3.451)	(3.363)
SI		0.009***	0.009***	0.009***
		(0.001)	(0.001)	(0.001)
Size			-0.024***	
			(0.006)	
Leverage			-0.0001	
			(0.001)	
CashByAssets			0.001	
			(0.001)	
ROA			0.0004	
			(0.001)	
BookToMarket			0.011***	
			(0.001)	
Attention		-0.004***	-0.005***	-0.005***
		(0.001)	(0.001)	(0.001)
AdjustedCases		-0.383***	-0.392***	-0.404***
		(0.081)	(0.083)	(0.078)
essential		-0.020	0.010	
		(0.024)	(0.026)	
Industry FE	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes
Weekday FE	No	Yes	Yes	Yes
Company FE	No	No	No	Yes
Observations	117,936	117,936	114,440	117,936
Adj. R squared	0.0005	0.0036	0.00398	-0.00031
F Statistic	29.477***	59.374***	56.512***	31.42***
	(df = 2)	(df = 32)	(df = 37)	(df = 9)

ences between ESI and E3. Whereas ESI measures policies of income and debt relief active over a long period of time, E3 measures additional monetary support on individual days.[137] It is therefore possible that the stock market reaction to these interventions differs. Furthermore, the effect has very small magnitude, even smaller than SI or ESI. Still, the negative and significant correlation implies that not all economic support measures are favored by the market.

Even when stock market reactions to economic support measures are negative, this does not automatically mean that these measures are negative for companies. As Zhang et al. (2020) and Heyden and Heyden (2021) point out, the major reason behind negative stock market reactions to economic support measures is that these measures add uncertainty to the market.[138] Even when the support measures are beneficial for companies, the increased uncertainty can lead to negative correlations between support measures and stock returns.

Concerning the other variables, no real change takes place in comparison to table 2. Similarly, the R^2 are generally small, which is not a problem as long as the F-statistics are significant, which is the case for all models.

The results of this analysis provide evidence that economic support measures generally are beneficial for compa-

[137] See Hale et al. (2021) pp. 22-27.

[138] See Zhang et al. (2020), p. 5; Heyden and Heyden (2021), pp. 3f.

nies and that the market perceives these measures positively. As Zhang et al. (2020) point out, such measures are also necessary to calm stock markets.[139] However, certain policy measures add uncertainty to the market and are therefore possibly not perceived well by investors.

In the following table, the results of regressions using E1 and E2 instead of ESI are presented. Otherwise, the models are exactly the same as in table 3. E1 measures income support given to households negatively affected by the pandemic and E2 measures debt and contract relief for households.[140] As it is possible that E1, E2 and E3 are collinear, I calculate the VIFs for model 3 to exclude the possibility of multicollinearity falsifying the results. As all VIFs are below 10, multicollinearity is not an issue.

The results offer contradicting insights into the relationship between economic support measures and adjusted stock returns. Whereas ESI has a positive and significant coefficient in all models, as shown in table 3, the situation is not so clear for its components E1 and E2. E1 has a positive and significant correlation with the adjusted returns in all models, with an increase of E1 by one SD (1.749) being related to an increase of the adjusted returns by 0.6786 percentage points (0.388*1.749) in model 3. Compared to coefficients of other policy indices, this is relatively high, suggesting that income support can be a policy measure beneficial for companies. For E2, only the coefficient in the first model is significant, showing a negative slope. Addition of control variables and fixed effects therefore takes explanatory power from this variable. In the first model, for an increase of E2 by one SD (0.899), adjusted returns decrease by -0.03506 percentage points (-0.039*0.899). The negative sign of this coefficient indicates that an adverse effect of debt and contract relief on companies might exist. The coefficients and significance levels of E3 are largely unchanged in comparison to table 3.

These results are interesting, as only income support is positively correlated with adjusted returns, but debt relief and other fiscal measures are not. A possible explanation could be the different nature of the policy measures captured by E1 and E2. Whereas income support measures aim at replacing the income of households who lost their income due to the crisis, debt and contract reliefs aim at freezing financial obligations for households, for example by banning evictions or stopping loan repayments.[141] Income support can therefore be beneficial both to households and companies, mitigating the loss of purchasing power of consumers and perhaps even helping companies with paying salaries. Debt and contract reliefs, on the other hand, can have adverse effects on companies having a business model linked to these contracts, for example real estate companies which receive less rent payments when such policy measures are active.

A look on the adjusted R^2 reveals that these values are higher than the corresponding adjusted R^2 in table 3. All adjusted R^2 are still small but using the individual indices E1 and E2 leads to the models explaining more variance in the adjusted returns. This is most likely due to ESI capturing the positive correlation of E1 and the negative or insignificant correlation of E2 in one index, resulting in a lower overall correlation compared to the individual indices.

The other variables have not changed dramatically compared to table 3.

Generally, economic support measures do not have a clear effect on adjusted stock returns. While the correlation as a whole, using the Economic Support Index, is positive and significant, some individual measures have negative or insignificant correlations. This is in line with the results of Heyden and Heyden (2021), finding ambivalent relationships between economic support measures and stock returns.[142] Income support measures show the strongest positive correlation with adjusted stock returns, providing evidence that this policy measure can be especially beneficial.

5.3. Hypothesis 3

Hypothesis 3 investigates the relationship between stringency measures and adjusted stock returns for specific sets of industries regarded as being severely or positively affected by the crisis, where H3a investigates the severely affected industries and H3b investigates the positively affected industries. A list of industries regarded as being severely or positively affected in the literature and which industries I classify as being severely or positively affected can be found in Appendix 2.

Table 5 reports the results of the analysis of hypothesis 3a. The models are similar to the ones previously applied, using the same variables in the same order as in table 2. The only difference is the absence of industry fixed effects, as their inclusion does not make sense when considering a subset of specific industries.

The results of this analysis contradict hypothesis 3a, assuming a negative correlation between stringency measures and adjusted stock returns for companies belonging to severely affected industries. In all models, the coefficients for SI are positive and significant, suggesting that, although the companies belong to severely affected industries, their adjusted stock returns are not severely affected by the stringency measures. Comparing these results to the results presented in table 2, using the entire sample, the coefficients and significance levels for SI are almost the same, with only its coefficient in the fourth model being slightly smaller in table 5 (by 0.001). This means that the correlation between SI and the adjusted returns is close to identical for companies on average and companies belonging to severely affected industries.

While this sounds counterintuitive, it can be explained by the reasoning Ashraf (2020b) formulates, stating that the positive effect of stringency measures on stock returns stems from stringency measures mitigating the negative effects of COVID-19 itself, while the direct effects of stringency measures on the economy are adverse.[143] If the market perceives

[139] See Zhang et al. (2020), p. 5.
[140] See Hale et al. (2021), p. 22.
[141] See Hale et al. (2021), p. 22.
[142] See Heyden and Heyden (2021), pp. 3f.
[143] See Ashraf (2020b), p. 7.

Table 4: Further analyses for the effect of economic support measures on adjusted returns

This table shows the regression results of analyses on the effect of individual economic support measures, using E1 and E2 instead of ESI, on adjusted returns. Variable definitions and data sources can be found in Appendix 1. Fixed effects are included when stated as such. Robust standard errors clustered by company are denoted in parentheses. ***, ** and * report statistical significance levels at 1%, 5% and 10%, respectively, using clustered robust standard errors.

	Dependent variable: AdjustedReturn			
	(1)	(2)	(3)	(4)
E1	0.199***	0.400***	0.388***	0.397***
	(0.016)	(0.069)	(0.071)	(0.070)
E2	-0.039***	0.013	0.016	0.018
	(0.011)	(0.016)	(0.017)	(0.016)
E3	-10.513***	-9.709***	-9.505***	-9.478***
	(3.303)	(3.321)	(3.406)	(3.316)
SI		0.008***	0.009***	0.008***
		(0.001)	(0.001)	(0.001)
Size			-0.024***	
			(0.006)	
Leverage			-0.0001	
			(0.001)	
CashByAssets			0.001	
			(0.001)	
ROA			0.0003	
			(0.001)	
BookToMarket			0.011***	
			(0.001)	
Attention		-0.010***	-0.010***	-0.010***
		(0.001)	(0.001)	(0.001)
AdjustedCases		-0.416***	-0.423***	-0.435***
		(0.081)	(0.084)	(0.079)
essential		-0.021	0.010	
		(0.024)	(0.026)	
Industry FE	No	Yes	Yes	Yes
Country FE	No	Yes	Yes	Yes
Weekday FE	No	Yes	Yes	Yes
Company FE	No	No	No	Yes
Observations	117,936	117,936	114,440	117,936
Adj. R squared	0.00156	0.00428	0.00459	0.00034
F Statistic	52.907***	58.185***	55.936***	28.926***
	(df = 3)	(df = 33)	(df = 38)	(df = 10)

these mitigating effects to be more important than the economically adverse effects, SI can be positively correlated with the adjusted stock returns. This is especially interesting for companies belonging to industries severely affected by the crisis, where such a perception would not be expected to the same extent as for companies on average. The findings, however, show that this can be the case.

Concerning economic support measures, similar results can be observed. In both models containing ESI as a variable, the coefficient of ESI is significant and positive and has exactly the same value as in table 2. In the third model, for an increase of ESI by one SD (30.962), adjusted returns increase by 0.1238 percentage points (30.962*0.004) on average. This suggests that the effect of economic support measures on adjusted stock returns is very similar for companies on average and companies belonging to sectors severely affected by the pandemic. The results for SI and ESI in this analysis generally imply that the effects of policy measures are beneficial even on companies severely affected by the pandemic.

The control variables offer more diversity. The first observation here is a loss in significance for Size and BookToMarket. This means that no company financial performance indicator has significant explanatory power any more for this subset of companies. These variables are therefore unfit to estimate adjusted stock returns for companies belonging to

Table 5: Effect of stringency measures on adjusted stock returns for companies belonging to sectors severely affected by the pandemic

This table shows the regression results of how adjusted returns of companies belonging to sectors regarded as being severely affected by the pandemic react to measures captured in the Oxford Stringency Index while controlling for economic support measures, company financial performance indicators, attention to COVID-19, COVID-19 cases and whether the company is classified as an essential business. Variable definitions and data sources can be found in Appendix 1. Which industries are classified as being severely affected can be seen in Table A.5. Fixed effects are included when stated as such. Robust standard errors clustered by company are denoted in parentheses. ***, ** and * report statistical significance levels at 1%, 5% and 10%, respectively, using clustered robust standard errors.

	Dependent variable: AdjustedReturn			
Variable	(1)	(2)	(3)	(4)
SI	0.006***	0.009***	0.009***	0.008***
	(0.001)	(0.002)	(0.002)	(0.002)
ESI			0.004***	0.004***
			(0.001)	(0.001)
Size			-0.013	
			(0.010)	
Leverage			0.001	
			(0.001)	
CashByAssets			0.002	
			(0.001)	
ROA			-0.0002	
			(0.003)	
BookToMarket			-0.001	
			(0.024)	
Attention		-0.002*	-0.005***	-0.005***
		(0.001)	(0.002)	(0.002)
AdjustedCases		-0.427***	-0.420***	-0.433***
		(0.130)	(0.128)	(0.128)
essential		-0.025	0.008	
		(0.026)	(0.033)	
Country FE	No	Yes	Yes	Yes
Weekday FE	No	Yes	Yes	Yes
Company FE	No	No	No	Yes
Observations	35,968	35,968	35,968	35,968
Adj. R squared	0.00146	0.00349	0.00399	-0.00007
F Statistic	59.549***	8.6739***	6.4718***	11.069***
	(df = 1)	(df = 11)	(df = 17)	(df = 8)

sectors severely affected by the pandemic. In model 2, the significance of Attention is slightly decreased compared to table 2, but the coefficient is not changed. Interestingly, the slope of COVID-19 cases is significant and of greater negative magnitude in table 5 than in table 2 for all models, implying that companies belonging to sectors regarded as being severely affected by the pandemic really are affected more severely by the pandemic than companies on average.

Table 6 reports the results of the analysis of hypothesis 3b. The models use the same variables and fixed effects as in table 5 in the same order.

In contrast to the previous analysis, the result of this analysis supports hypothesis 3b. Looking at SI, all models have a significant and positive slope. The magnitude of these slopes is very similar to the magnitudes in the previous findings, but a bit higher in model 2,3 and 4 of table 5 compared to table 2. This suggests that the mitigating effect of the stringency measures on adjusted stock returns is similar or slightly increased for companies belonging to sectors positively affected by the pandemic in comparison to companies on average.

For ESI, all coefficients are the same as in table 2, but the significance is slightly decreased. As both coefficients are still significant at 5%, this is not a problem. The coefficients for ESI suggest that the influence of economic support measures on adjusted stock returns is similar for companies belonging to sectors positively affected by the pandemic and companies on average.

Considering the control variables, Size and BookToMarket and, for the first time, ROA are significant at 5%. While the coefficients of Size and BookToMarket again suggest that smaller companies and companies with more book equity in comparison to market equity are preferred by investors during the crisis, the significant and positive slope of ROA implies that investors also prefer more profitable companies in these industries. This is in line with the findings of Ding et al. (2021), who also find companies with larger profits to be more resilient to the crisis, although they come to this conclusion investigating companies from all industries.[144] The other company financial performance indicators are again not significant at 10%, making Leverage and CashByAssets insignificant in every analysis. All coefficients for attention are significant at 1% and slightly more negative than in table 2. However, no real economic reason for this very small effect exists and it might be due to Attention only having meaningful values at the beginning of the pandemic, when stock market volatility was especially high.[145]

The COVID-19 cases should be given special attention, as they are not significant at 10% in any model they are included in. This is a major contrast to all other analyses, where COVID-19 cases are always significant at 1%. However, this does not come unexpectedly when analyzing companies belonging to sectors regarded as being positively affected by the pandemic, implying that the analyzed companies really are less affected by the pandemic than companies on average. When looking at the coefficients, although they are not significant, all slopes are less negative than in table 2, further supporting the conclusion that these companies are less affected by the pandemic.

In general, this analysis provides support for hypothesis 3b. It suggests that the companies belonging to sectors regarded as positively affected by the pandemic really are affected less by the pandemic. This analysis further implies that, for these companies, economic support measures are beneficial and stringency measures are mitigating the effects of COVID-19. As the effect of the pandemic itself is assumed to be small, at least for some companies, the stringency measures might be beneficial for certain firms, for example supporting the business model of IT corporations. These results are generally to be expected for companies belonging to positively affected industries. As the coefficients for SI are partly higher than in table 2, the positive or mitigating effects of stringency measures are possibly increased for companies belonging to positively affected industries. It is noteworthy that the slopes of ESI are the same in table 2, 5 and 6, suggesting that all companies profit similarly from economic support measures.

6. Discussion

In this section, I present limitations of my used methods and data and critically discuss my methodology and results.

6.1. Limitations

Several biases and factors left out of consideration can limit the validity of my results. For a start, I cannot rule out other factors having influenced stock returns during the observation period. Events like the ongoing Brexit, the US presidential elections, or drastic developments in the oil market occurred during the observation period and potentially had an influence on stock returns, as pointed out by Ramelli and Wagner (2020).[146] As these events could have affected certain sectors or companies especially, they might exert unseen influence on the results.

Another factor possibly influencing the findings is the choice of companies in this sample. Only companies listed on stock markets are considered, leaving many companies, especially small and medium-sized firms, out of the analyses.[147] Many restaurants, barbers or other small enterprises are not considered, although they might be affected by the policy measures. Therefore, the sample does not exactly represent the economies of the countries. However, as most of the large companies are dependent on smaller companies through various links[148] and the listed companies represent a large portion of the economies, this restriction does not overly affect the validity of the results.

Taking companies with their headquarters being located in a certain country as a sample incurs another limitation, as the operations of a company might not be conducted at the place of the headquarter. The sites of operations could be in other countries and can have varying influences on the company as a whole. In extreme cases, all operations might be conducted abroad with only the headquarters being located in a country. Different pandemic developments and policy measures in other countries can therefore be an unconsidered factor influencing the stock returns of these companies. Considering foreign sales in the robustness checks addresses the international orientation of a company in general and does not cover this issue.

Apart from the stringency measures aimed at slowing the spread of COVID-19, some companies and individuals adopt voluntary social distancing measures, reducing their economic activities. As Baker et al. (2020) conclude, these measures have an important effect on the economy, especially on service-oriented companies.[149] The only approximation for this effect in my models is H1 public information campaigns, a constituent of the Stringency Index, which measures information campaigns raising awareness of the pandemic.[150] These campaigns potentially result in more voluntary social distancing.

Checking the regression assumptions in section 4.5 also reveals limitations of the used models: The residuals are not normally distributed, leading to the t- and F-tests not being fully valid.[151] Large Cook's distance values suggest that some influential observations exist.[152] Endogeneity can also not be ruled out.

[144]See Ding et al. (2021), pp. 14f.
[145]See Baker et al. (2020), p. 743.
[146]See Ramelli and Wagner (2020), pp. 630f.
[147]See Lin and Halk (2021), p. 15.
[148]See Lin and Halk (2021), p. 15.
[149]See Baker et al. (2020), p. 756.
[150]See Hale et al. (2021), pp. 23-27.
[151]See University of California, Los Angeles (2021).
[152]See University of California, Los Angeles (2021).

Table 6: Effect of stringency measures on adjusted stock returns for companies belonging to sectors positively affected by the pandemic

This table shows the regression results of how adjusted returns of companies belonging to sectors regarded as being positively affected by the pandemic react to measures captured in the Oxford Stringency Index while controlling for economic support measures, company financial performance indicators, attention to COVID-19, COVID-19 cases and whether the company is classified as an essential business. Variable definitions and data sources can be found in Appendix 1. Which industries are classified as being positively affected can be seen in Table A.6. Fixed effects are included when stated as such. Robust standard errors clustered by company are denoted in parentheses. ***, ** and * report statistical significance levels at 1%, 5% and 10%, respectively, using clustered robust standard errors.

	Dependent variable: AdjustedReturn			
Variable	(1)	(2)	(3)	(4)
SI	0.006***	0.010***	0.010***	0.011***
	(0.001)	(0.002)	(0.002)	(0.002)
ESI			0.004**	0.004**
			(0.002)	(0.002)
Size			-0.037**	
			(0.015)	
Leverage			0.001	
			(0.001)	
CashByAssets			0.001	
			(0.001)	
ROA			0.004**	
			(0.002)	
BookToMarket			0.128**	
			(0.065)	
Attention		-0.003***	-0.006***	-0.006***
		(0.001)	(0.002)	(0.002)
AdjustedCases		-0.246	-0.219	-0.239
		(0.202)	(0.200)	(0.200)
essential		-0.100**	-0.054	
		(0.046)	(0.046)	
Country FE	No	Yes	Yes	Yes
Weekday FE	No	Yes	Yes	Yes
Company FE	No	No	No	Yes
Observations	16,504	16,504	16,504	16,504
Adj. R squared	0.00152	0.0036	0.00472	-0.00021
F Statistic	35.17***	6.1055***	8.169***	6.7943***
	(df = 1)	(df = 11)	(df = 17)	(df = 8)

Using Fama-French three factor model-adjusted returns also incurs some limitations. As the adjusted returns are excess returns over the predicted returns, including the market excess return times market beta,[153] movements of the entire market can hardly be observed. An influence affecting the entire European market is therefore less visible than an influence affecting only certain industries. Furthermore, as Schmidt et al. (2019) point out, the Fama-French three factor model leaves out some influences on stock returns, for example momentum.[154] These influences can also explain parts of the variance of stock returns but are too complicated to be included here.

[153] See Fama and French (1993), p. 5.
[154] See Schmidt et al. (2019), p. 214.

6.2. Critical discussion of methodology and results

The limitations section above shows some boundaries to the validity of my results. To assess further constraining factors, I perform several robustness checks on the main model (the formula is given in section 3.2). Applying robustness checks on other models, being variations of this one or applied to a subset of the data, is not necessary. I check the robustness against four influences and changes: First, I replace testing-adjusted cases with testing-unadjusted cases to assess how they change the results, similar to Ding et al. (2021).[155] Second, I include foreign sales to estimate the influence they exert on the results. Third, I exclude data from April 2020 and before in order to estimate whether only this period

[155] See Ding et al. (2021), p. 23.

causes the results, as the market volatility was especially high at that time.[156] Last, I exclude financial companies to check that they are not the main drivers of the results, as they have a different financial structure and are often excluded in financial research.[157] None of the robustness checks changes the main findings, a positive and significant correlation of stringency and economic support measures with adjusted stock returns. The only notable discovery is the coefficient of AdjustedCases changing its sign when excluding April 2020 and before. The negative correlation between COVID-19 cases and adjusted stock returns can therefore only be observed during the early pandemic, implying that coefficients of AdjustedCases should be handled with care. As a negative influence of the pandemic itself on stock returns is found by many researchers,[158] the validity of the main results is not threatened. Detailed results of the robustness checks can be found in Appendix 4.

To mitigate the effects of unknown factors influencing stock returns during the observation period, I include fixed effects in the regressions, controlling for parameters constant within each industry, country, weekday and, in some models, company. Furthermore, considering a long timeframe of over a year of daily observations should reduce the influence of other events on stock returns. Still, these influences can never really be excluded using a panel data structure. Despite having some limitations, panel data analyzed using a similar approach to the one I applied leads to valid results for many researchers investigating stock market reactions to COVID-19.[159] As most of the variables I use are also used successfully by other researchers in the same or a similar way, their effectiveness is empirically tested. Therefore, the methodology has some limitations, but should generally deliver valid results.

When drawing conclusions from the results, the real-world-significance of findings is a major issue to address. Most importantly, correlations do imply causal relationships and statistical significance is no guarantee for real-world-significance. A potential problem in this regard is reverse causality, meaning that not the independent variables explain the dependent variable, but vice versa. From an economic perspective, it seems very unlikely that stock returns of companies affect cases of COVID-19, the classification of essential companies or the financial performance of a company of the previous year. Similarly, stringency measures are probably not influenced by stock returns on the same day and lagging SI ten days into the future as a simultaneity check reveals no signs of a reversely causal relationship. Attention to the pandemic could possibly be caused by attention to volatile stock market movements, but Engelhardt et al. (2020) find news attention having a negative effect on stock returns and not vice versa.[160] Although economic support measures are introduced to counter adverse economic effects of the pandemic,[161] they are hardly affected by stock returns on the same day. Reverse causality is therefore likely to be no issue for all used variables.

I further validate my results by checking them with the literature, as can be seen in chapter 5. All major findings are in line with the results of other researchers and no result contradicts economic reasoning or cannot be explained convincingly. Therefore, my findings should provide sufficient real-world-significance to draw conclusions. Arriving at causal conclusions is still hardly possible in quantitative research and I only make causal statements when they are backed by the literature or in line with previous conclusions.

The last step when investigating the impact of policy measures on companies is inferring from the impact on stock returns to the impact on companies in general. Stock returns do not measure the current performance of companies, but the expectations of the market regarding their future performance, as pointed out by Ramelli and Wagner (2020).[162] Stock returns should therefore be treated with care when drawing conclusions about short-term economic consequences of policy measures but can generally be used as a valid approximation for their economic impacts, especially their future influences. Furthermore, using stock returns when investigating economic consequences of COVID-19 is a common approach in the literature that leads to valid results.[163]

7. Conclusion

In this thesis, I investigate the impact of COVID-19 policy measures on companies in Belgium, The Netherlands, Denmark and Norway. Using a panel data structure, I utilize daily stock returns adjusted by the Fama-French three factor model and the indices developed by the University of Oxford to examine this impact.[164] Controlling for testing-adjusted growth of COVID-19 cases, attention to the pandemic, company financial performance indicators and whether a company is classified as being essential or not, I find both stringency and economic support measures to have a small, positive impact on adjusted stock returns.

While the policy measures have a generally positive influence on stock returns, growth in testing-adjusted cases and attention to the pandemic have a generally negative one in the considered countries, especially during the early phase of the pandemic. The positive impact of stringency measures can be explained by these measures mitigating the economically negative influences of COVID-19 itself, as reasoned by

[156] See Baker et al. (2020), p. 743.
[157] See Ramelli and Wagner (2020), pp. 631f.
[158] See Al-Awadhi et al. (2020), pp. 3f; Heyden and Heyden (2021), pp. 3f; Ashraf (2020c), pp. 4-6; See Ding et al. (2021), pp. 13f.
[159] See Ding et al. (2021), pp. 12-25; Ashraf (2020b), pp. 5-7; Chen et al. (2020), pp. 4-6; Al-Awadhi et al. (2020), pp. 2-4.
[160] See Engelhardt et al. (2020), p. 10.
[161] See Ramelli and Wagner (2020), pp. 650f; Heyden and Heyden (2021), p. 1.
[162] See Ramelli and Wagner (2020), p. 623.
[163] See Ashraf (2020b), p. 1f; Al-Awadhi et al. (2020), pp. 1f; Ding et al. (2021), pp. 2f; Chen et al. (2020), p. 2.
[164] See Hale et al. (2021), pp. 20-27.

Ashraf (2020b).[165] Although these measures have adverse economic effects, the market perceives them to be overall beneficial, as the pandemic would be worse otherwise. The robustness checks, such as excluding financial companies and using testing-unadjusted COVID-19 cases do not limit the validity of the main findings.

When looking specifically at economic support measures, I find income support for households to have a strong positive impact on adjusted stock returns. Debt and contract relief have no impact when controlling for the pandemic and other fiscal measures have a negative influence on adjusted stock returns. The negative effect of fiscal measures can be explained by the uncertainty they add to the market, as pointed out by Zhang et al. (2020) and Heyden and Heyden (2021).[166] When using the Economic Support Index, support measures have a small, positive influence on adjusted stock returns. This leads to the conclusion that economic support measures are generally beneficial for companies but can also increase uncertainty in the market.

Considering companies belonging to severely affected sectors, I find these companies to be more negatively affected by the pandemic itself but find both stringency measures and economic support measures to have a positive influence on adjusted stock returns. The magnitude of these effects is similar for these companies and companies on average. Interestingly, stringency measures therefore have a positive influence even on severely affected companies, as do economic support measures. When investigating companies belonging to positively affected sectors, I also find stringency and economic support measures positively affecting adjusted stock returns, while the pandemic itself has no significant impact on these companies. Stringency measures have a more positive influence on positively affected companies than on companies on average while economic support measures have a positive effect of similar magnitude.

Many questions regarding the influence of COVID-19 policy measures on companies are still unanswered, leaving room for future research. For a start, different phases of the pandemic could be investigated, as I only look at the entire timeframe of over a year in my analyses. Furthermore, looking at different stringency measures and their effect on companies could be interesting, as could be a more detailed investigation of different sectors. I mainly consider absolute values of indices, but the influence of changes of indices could be interesting as well. Finally, the anticipation of policy measures and the effects of anticipated policy measures might reveal noteworthy insights.

[165] See Ashraf (2020b), p. 7.
[166] See Zhang et al. (2020), p. 5; Heyden and Heyden (2021), pp. 3f.

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