Online-Appendix zu

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

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Appendix 1: Definition of variables

Table A.1

Definition of variables

This table shows the definition of the variables used in my analyses and their data sources.

Variable	Definition	Data Source
AdjustedReturn	Daily excess stock returns of companies over the returns predicted by the Fama-French three Factor Model	Raw returns: Refinitiv Datastream (2021) Fama-French-model-data: Kenneth French´s website (2021), using European daily 3-factor-data[167]
SI	COVID-19 Stringency Index developed by the University of Oxford. Measures multiple policies aiming at preventing the spread of COVID-19 (e.g., school closures, workspace closures, travel restrictions) on a unified scale	Oxford COVID-19 Government Response Tracker[168]
ESI	COVID-19 Economic Support Index developed by the University of Oxford. Measures policies aiming at financially supporting households and companies (income support and debt relief) on a unified scale	Oxford COVID-19 Government Response Tracker[169]
E1	Income support, meaning replacement of salaries lost due to the pandemic developed by the University of Oxford. Variable is 0 if no income support is given, 1 if <50% and 2 if at least 50% of the salary is replaced	Oxford COVID-19 Government Response Tracker[170]
E2	Debt and contract relief for households developed by the University of Oxford. Measures freezing of financial obligations (e.g., banning evictions, stopping loan repayments). Variable is 0 when no relief is granted, 1 for narrow reliefs and 2 for broad reliefs	Oxford COVID-19 Government Response Tracker[171]
E3	Measurement of other fiscal stimuli (spending and tax cuts) developed by the University of Oxford. Divided by the country´s GDP of 2019 to account for economic differences between countries	Raw E3-values: Oxford COVID-19 Government Response Tracker[172] GDP: World Bank (2021)[173]
AdjustedCases	Daily testing-Adjusted daily growth of COVID-19 cases. Measures change in the ratio of positive test results	Foundation for Innovative New Diagnostics (2021)[174]

[167] See French (2021)
[168] See Blavatnik School of Government, University of Oxford (2021).
[169] See Blavatnik School of Government, University of Oxford (2021).
[170] See Blavatnik School of Government, University of Oxford (2021).
[171] See Blavatnik School of Government, University of Oxford (2021).
[172] See Blavatnik School of Government, University of Oxford (2021).
[173] See World Bank (2021).
[174] See Foundation for Innovative New Diagnostics (2021).

UnadjustedCases	Daily growth of CoVID-19 cases not adjusted for tests. Measures growth of confirmed cases	Foundation for Innovative New Diagnostics (2021)[175]
Attention	Value of the Google Search Volume Index for "corona" in each country until this index reaches 100. Afterwards, the value remains 100 as I assume the attention remains roughly on that level	Google LLC (2021): Google Trends[176]
Size	Natural logarithm of a company´s total assets. Accounting data from the latest available fiscal year at the time of the observation is used	Refinitiv Worldscope (2021), Orbis (2021)
Leverage	Total debt divided by total assets. Accounting data from the latest available fiscal year at the time of the observation is used	Refinitiv Worldscope (2021), Orbis (2021)
CashByAssets	Cash and short-term investments divided by total assets. Accounting data from the latest available fiscal year at the time of the observation is used	Refinitiv Worldscope (2021), Orbis (2021)
ROA	Net income before extraordinary items divided by total assets. Accounting data from the latest available fiscal year at the time of the observation is used	Refinitiv Worldscope (2021), Orbis (2021)
BookToMarket	Book value of equity divided by market value of equity. Accounting data from the latest available fiscal year at the time of the observation is used. The market value is measured on the 31st of December of the fiscal year preceding the observation	Refinitiv Worldscope (2021), Refinitiv Datastream (2021), Orbis (2021)
ForeignSales	Foreign sales as a percentage of total sales to measure the international orientation of a company. Data of the latest available fiscal year at the time of the observation is used	Refinitiv Worldscope (2021)
essential	Dummy which equals one if the company is classified as essential by the US Cybersecurity and Infrastructure Agency. Classification is done using the SIC codes	Essential classification: Wales (2020)[177] SIC codes: SIC-NAICS LLC (2021)[178]
severelyAffected	Dummy which is one if the company belongs to a sector regarded as being severely affected by the pandemic. Classification is done using the SIC codes	Affected classification: Various papers[179] SIC codes: SIC-NAICS LLC (2021)[180]
positivelyAffected	Dummy which is one if the company belongs to a sector regarded as being positively affected by the pandemic. Classification is done using the SIC codes	Affected classification: Various papers[181] SIC codes: SIC-NAICS LLC (2021)[182]

[175] See Foundation for Innovative New Diagnostics (2021).
[176] Google LLC (2021).
[177] See Wales (2020), pp. 7-23.
[178] See SIC-NAICS LLC (2021).
[179] See Baker et al. (2020), p. 752; Ramelli/Wagner (2020), p. 633; Xiong et al. (2020), p. 2236; He et al. (2020), p. 2206.
[180] See SIC-NAICS LLC (2021).
[181] See Ramelli/Wagner (2020), p. 633; He et al. (2020), p. 2206.
[182] See SIC-NAICS LLC (2021).

Appendix 2: Data preparation

This appendix extends the data section of the thesis with more detailed data preparation steps when needed.

Adjusted stock returns

For the time period from the 26th of January 2018 to the 26th of February 2021, I download the return index (RI) for the entire sample of companies from Refinitiv Datastream (2021) in the currency Euro. I choose this currency because two of the four countries in the sample (Belgium and The Netherlands) have the Euro, this currency is a common measurement in Europe and most readers of this thesis will be familiar with the Euro as a currency. In addition to the return index values, I include the company name and the Datastream Identifier (DSCD code) in the download. The number of companies in the original sample is 2139 companies. The full list of the data can be found in Attachment 2.

The sample is already cleaned by Hanauer/Windmüller (2020),[183] but as these researchers conduct research for a different purpose using a different timeframe, some static screens are still necessary. Additionally, I apply several dynamic screens. All screens are shown in the following table:

Table A.2

Data cleaning for return data

This table shows the steps I take to clean the return data. The dynamic screens are based on papers by Hanauer/Windmüller (2020) and Schmidt et al. (2019).[184] Screens indicated with "HW" in the screen name are mainly based on Hanauer/Windmüller (2020), Screens indicated with "S" in the screen name are mainly based on Schmidt et al. (2019).

Screen name	Description
Delete Errors	I delete all companies showing error messages. A list of all errors and the actions I took regarding them can be found in Table A.3. This screen deletes 323 companies
Delete inactive companies	I delete all companies having a sum of all raw returns of zero for the entire observation period, as these companies are very likely to be dead. This screen removes 369 companies
Delete dead companies	I delete all companies marked as being dead (DEAD or SUSP) before the start of the observation period using the company name provided by Refinitiv (2021). When the delisting date is not shown or is unclear, I do not delete the company to ensure no survivorship bias arises. This screen deletes 485 companies
Delete return spikes (HW3)	I remove all returns larger than 200% or smaller than -200%. In contrast to Hanauer/Windmüller (2020), I also delete strong negative returns to ensure no outliers heavily influence the results later on. This is the first dynamic screen. Beginning with this screen, all data preparation steps can be found in the R file of the data preparation, Attachment 14

[183] See Hanauer/Windmüller (2020), pp. 61-63.
[184] See Hanauer/Windmüller (2020), p. 64; Schmidt et al. (2019), Online Appendix p. 19.

Delete strong return reversals (HW4)	I remove all returns in case of strong return reversals. Formula: $r_{i,t}\ or\ r_{i,t-1} \geq 1.0\ and\ (1 + r_{i,t}) * (1 + r_{i,t-1}) - 1 < 0{,}2$ (5) where $r_{i,t}$ is the (raw) return of company i on day t. If the formula is fulfilled, I remove both $r_{i,t}$ and $r_{i,t-1}$
Delete zero returns (HW1)	I delete zero returns at the end of the observation period as they are the returns of delisted companies. For all companies where the last ten returns (two trading weeks) contain only zero values, I delete all returns after the last non-zero return. I choose ten days as a threshold, as it is unlikely that a company is active if the return index does not change for two weeks
Delete abnormally low prices (S8)	I delete all returns where the corresponding unadjusted prices (UP) are lower than 1 US Dollar. If an unadjusted price is not available, I also delete the corresponding return, which seldomly happens. I use US Dollars to exactly replicate the screen from the literature and to avoid issues of different valuations in local currencies (e.g., if a price below one is completely normal in the local currency)
Delete abnormally high prices (HW2)	I delete all returns where the corresponding unadjusted prices (UP) are larger than one million US Dollars. I use US Dollars for the same reason as in the prior screen
Delete returns of holydays (S2)	I delete the returns of all stocks of a country on a day if over 95% of all stocks in that country have a return of zero or no data on that day. This is the last dynamic screen I apply
Liquidity screen	I delete all companies having less than 50 non-zero or non-missing observations before the observation period to ensure having sufficient data when calculating the betas of the Fama-French three factor model. This screen removes 114 companies
Delete delisted companies	I delete all companies with a dead date (DEADDT) before the observation period. To apply this screen, I download the dead date (DEADDT) for the companies in the sample after the Liquidity screen from Refinitiv Datastream (2021). Applying this screen after calculating the adjusted returns is uncommon but makes no difference for the results. This screen deletes 123 companies, resulting in a final sample size of 455 companies

Further outlier elimination, e.g. by winsorizing is not necessary, as abnormal returns are removed by the screens and further outlier treatment is not done by Hanauer/Windmüller (2020) and Schmidt et al. (2019).[185]

The screens explicitly aim at not deleting any company that died during the observation period, only deleting those that died before that period to exclude the possibility of survivorship bias.

After the first screen, I calculate the (raw) returns for each company and each day using the following formula:

$$r_{i,t} = \frac{RI_{i,t} - RI_{i,t-1}}{RI_{i,t-1}} \tag{6}$$

where $r_{i,t}$ is the raw return of company i on day t and $RI_{i,t}$ is the value of the return index for company i on day t.

[185] See Hanauer/Windmüller (2020), p. 64; Schmidt et al. (2019), Online Appendix p. 19.

Table A.3

Error messages when downloading return data

This table shows all error messages that occurred when I downloaded return data from Refinitiv Datastream (2021) and the actions I took regarding the errors.

Error message	Action Taken
"2380, no data in requested period"	I delete the companies
"2381, no data available"	I delete the companies
"2382, no dividends"	I search for the unadjusted prices (UP) to check these companies; either no data is available for the unadjusted prices, or they do not change at all; I delete the companies
"2308, no data to return"	I search for unadjusted prices, but they do not change at all; I delete the companies
"2390, dividend value too big"	I search for unadjusted prices, but they do not change at all; I delete the companies
"0904, no data available"	I delete the companies
"2386, invalid base date"	I search for unadjusted prices, but they do not change during the observation period; I delete the company (this error occurred only once)
"E100, invalid code or expression entered"	I search for unadjusted prices, but they do not change at all; I delete the companies
"E100, access denied"	I search for unadjusted prices, but they do not change at all; I delete the companies
"#NV" for some values	No data exist for the RI of these individual days; if all values of the observation period show this message, I remove the company

I download the factors for the Fama-French three factor model from Kenneth French´s website (2021).[186] The data can be found in Attachment 4 and consists of the 3 factors of the model (market return, HML, SMB) and the risk-free interest rate for Europe on a daily basis. HML stands for high minus low and accounts for the influence of the book-to-market ratio on stock returns, SMB stands for small minus big and accounts for the influence of company size on stock returns.[187] I delete the data for all timepoints before the beta-calculating period, divide all factors by 100 to match them with the returns and set all values of -99.99 to missing. The last should not delete any data at all, as I do not find any such values when looking for them manually. I calculate daily excess returns over the risk-free interest rate by subtracting the risk-free return from this dataset from the raw return for each company for each day. To estimate the betas, I run the regression of the Fama-French three factor model over the beta-calculating-period for each company (the formula of this regression can be seen in section 4.1). I drop the intercept and store the three regression coefficients as the betas for each company. Using the stored betas, I calculate excess returns over the returns predicted by the Fama-French three factor model utilizing the formula of this model,

186 See French (2021).
187 See Fama/French (1993), p. 9.

repositioned to calculate the intercepts for each company and each day, these being the adjusted returns. I store the adjusted returns for each company for each day of the observation period as the data used for the analyses and multiply all returns with 100 to better see the results later on. This leads to return values being denoted in percent, similar to the values used by Ramelli/Wagner (2020).[188]

Company-specific financial performance indicators

To calculate the financial performance indicators, I download the following data items from Refinitiv Worldscope (2021) and Refinitiv Datastream (2021) for the sample after the liquidity screens (578 companies): Total assets (WC02999) in Euro, total debt (WC03255) in Euro, cash and short-term investments (WC02001) in Euro, income before extraordinary items (WC01551) in Euro, book value of equity (common equity, WC03501) in Euro[189] and the market value of equity (MVC) in Euro for the years 2019 and 2020. Furthermore, I download the end date of the fiscal year 2020 for all of these companies. If the data for 2020 is yet unavailable but the data for 2019 is existing, I use the 2019 data for 2020 as well. In case one or more values are missing for both years, I use data from Orbis (2021) additionally. I used the following Orbis (2021) data: TOAS is used as total assets, NCLI+CULI is used as total debt, CASH is used as cash and short-term investments, PL is used as net income before extraordinary items, SHFD is used as book equity.[190] As market value is a Refinitiv Datastream (2021) item, this data is generally very complete. Of course, the data from Orbis (2021) does not represent exactly the same items as the data from Refinitiv Datastream (2021) but comes close enough. I always use the most recent data from Orbis (2021) both for 2019 and 2020, as the data mostly stems from 2019. 2020 values were not yet available for any company. For Danish and Norwegian companies, I convert the values to Euro using the exchange rates of the 31st of December 2019 which I download from Refinitiv Datastream (2021). For Danish companies, I divide the original value by 7.4725 and for Norwegian companies, I divide the original value by 9.86375 to obtain Euro values. I then divide all values obtained from Orbis (2021) by 100 to match with the Refinitiv Datastream (2021) data, a value I find by comparing data present in both databases. I multiply all market values by one million and all accounting data by 1000 to obtain the values in full Euros.

I calculate the financial performance indicators using the formulas given in the data section. Looking at missing data, one company has no values for any performance indicator at all, 12 further companies lack CashToAssets values and in total 3 lack

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188 See Ramelli/Wagner (2020), p. 636.
189 See Thomson Reuters (2018), pp. 98-102.
190 See Bureau van Dijk (2018), pp. 638-640.

Leverage values. I keep all companies in the sample, as they are just disregarded when using the financial performance indicators as control variables.

I remove extreme Leverage values and winsorize the data, as described in the data section. To match the financial performance indicators to the dates, I use the performance indicators for 2019 until the end of the fiscal year 2020, that day included. After that day, I used the indicators for 2020 until the end of the time period. If the end date of the fiscal year is unavailable, I use the 31st of December 2020 as the end date of the fiscal year 2020. This date is also used by a large majority of 387 companies, whereas only 36 companies have a different fiscal year end date and 31 have no data. If a company lacks data for 2020, I use the data of 2019 for the entire time period, as described above.

Industry classifications

Table A.4

Essential industries

This table shows the industries and their SIC codes which I classify as essential according to Wales (2020).[191] The SIC codes are the SIC2 or SIC3 codes, respectively. I use a website containing an overview over SIC codes to find the codes for essential business sectors.[192] If a sector is classified as essential as a whole, I do not explicitly mention its subsectors as being essential.

Essential business	SIC codes
Healthcare/public health	80, 283
Law enforcement/public safety	92
Education	82
Food and agriculture	01, 02, 07, 09, 20, 51, 53, 54, 58
Energy	13, 29, 46, 49, 361, 554
Water and wastewater	494, 495 (already included)
Transportation and logistics	40, 41, 42, 43, 44, 45, 47, 50
Public work and infrastructure support services	734
Communications and IT	48, 357, 366
Other government- or community-based essential functions	866, 91, 93, 94, 95, 96, 97, 99
Critical manufacturing	08, 10, 12, 14, 24, 25, 26, 33, 37
Hazardous materials	
Financial services	60, 61, 62, 64, 872
Chemical industry	28
Defense industrial base	
Commercial facilities	15, 16, 17
Shelter facilities and real estate	65, 734
Hygiene products	721

[191] See Wales (2020), pp. 7-23.
[192] See SIC-NAICS LLC (2021).

Multiple researchers find industries to be severely affected by the pandemic or the COVID-19-related policy measures: Ramelli/Wagner (2020) show that the CAPM-adjusted stock returns of energy, consumer services, real estate and consumer durables & apparel suffer most severely during the crisis.[193] Baker et al. (2020) suggest that industries of the service sector and sectors connected to international travel (tourism and hospitality) are severely hit by the lockdown measures.[194] Xiong et al. (2020) suggest that the industries transportation, food and beverage retail, hotel and tourism, postal warehouse, real estate, video entertainment and construction are most vulnerable to the pandemic in China.[195] He et al. (2020) show that the pandemic has a severely negative impact on mining, agriculture, education, health and real estate.[196]

Table A.5

Severely affected industries

This table shows the industries and their SIC codes which I classify as being severely affected by the crisis according to the literature described above. The SIC codes are the SIC2 or SIC3 codes, respectively. I use a website containing an overview over SIC codes to find the codes for severely affected business sectors.[197] If a sector is classified as severely affected as a whole, I do not explicitly mention its subsectors as being severely affected.

Severely affected sector	SIC codes
Consumer services	72, 75, 76, 78, 79, 82, 83, 84, 86
Tourism and hospitality	70
Real estate	65
Energy	13, 29, 46, 49, 361
Consumer durables and apparel	22, 23, 50, 52, 55, 56, 67, 363, 364, 365
Transportation	40, 41, 42, 43, 44, 45, 47, 37
Construction	15, 16, 17

Various researchers find industries to be positively affected by the pandemic or the policy measures: Ramelli/Wagner (2020) show that telecom, pharma/biotech, semiconductor, software companies and food & staples retailing have positive returns during the crisis.[198] He et al. (2020) find that the pandemic has a strong positive impact on public management, information technology and sports & entertainment in China.[199]

[193] See Ramelli/Wagner (2020), p. 633.
[194] See Baker et al. (2020), p. 752.
[195] See Xiong et al. (2020), p. 2236.
[196] See He et al. (2020), p. 2206.
[197] See SIC-NAICS LLC (2021).
[198] See Ramelli/Wagner (2020), p. 633.
[199] See He et al. (2020), p. 2206.

Table A.6

Positively affected industries

This table shows the industries and their SIC codes which I classify as being positively affected by the crisis according to the literature described above. The SIC codes are the SIC2, SIC3 or SIC4 codes, respectively. I use a website containing an overview over SIC codes to find the codes for positively affected business sectors.[200] If a sector is classified as positively affected as a whole, I do not explicitly mention its subsectors as being positively affected.

Positively affected sector	SIC codes
Telecommunications	48, 336
Pharma/Biotech	283
Semiconductor	3674
Software	737
Food and Staples retailing	51, 53, 54

Both the severely affected classification and the positively affected classification is not comprehensive. I do not include sectors mentioned in the literature if they can hardly be separated from other sectors or are very small. Retail is classified as being severely affected by Xiong et al. (2020) and as being positively affected by Ramelli/Wagner (2020).[201] I classify it as being positively affected by the crisis, as the paper by Xiong et al. (2020) covers China, whereas the paper by Ramelli/Wagner (2020) covers the United States,[202] which I consider to be more similar to Europe.

[200] See SIC-NAICS LLC (2021).
[201] See Ramelli/Wagner (2020), p. 633; Xiong et al. (2020), p. 2236.
[202] See Ramelli/Wagner (2020), p. 631; Xiong et al. (2020), p. 2231.

Appendix 3: Regression diagnostics plots

Figure A.1

Residuals vs Fitted plot

This figure displays the residuals vs fitted plot to check the linearity assumption of the regression diagnostics.

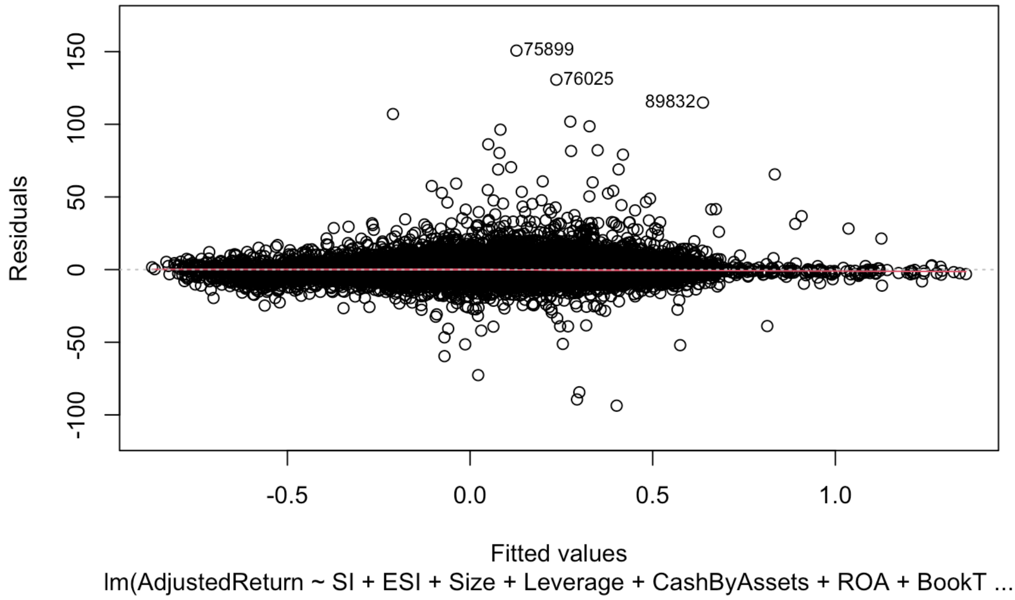


Figure A.2

Normal Q-Q plot

This figure displays the normal Q-Q plot to check the normality assumption of the regression diagnostics.

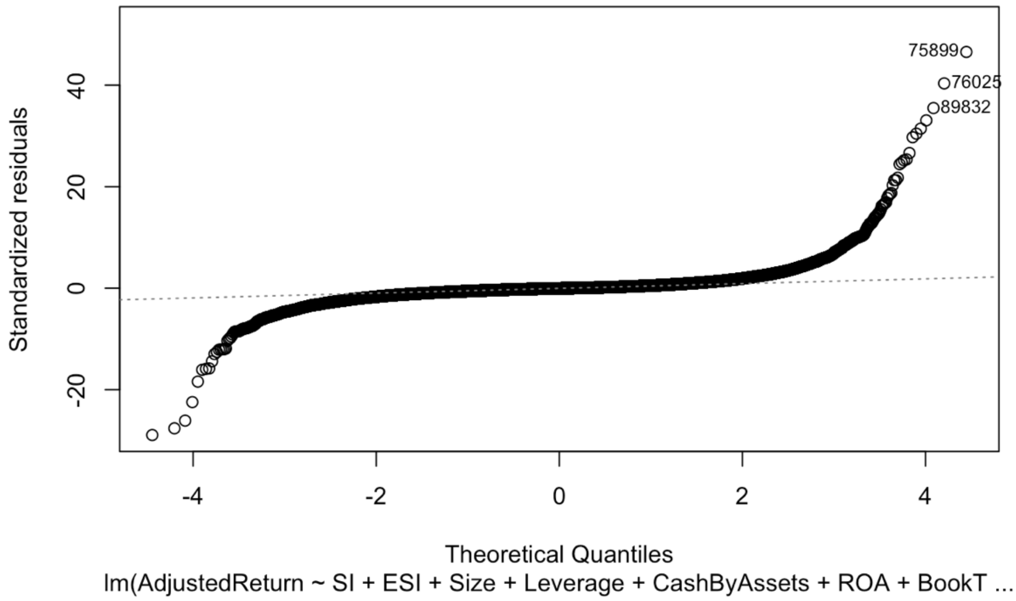


Figure A.3

Scale-Location plot

This figure displays the scale-location plot to check the homoscedasticity assumption of the regression diagnostics.

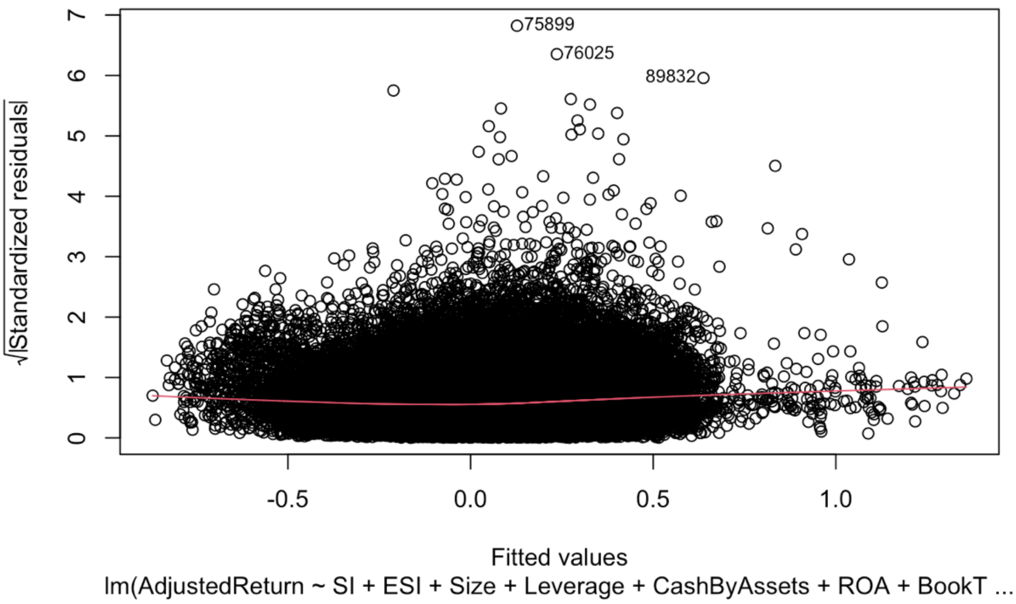


Figure A.4

Residuals vs Leverage plot

This figure displays the residuals vs leverage plot to check for influential values in the regression.

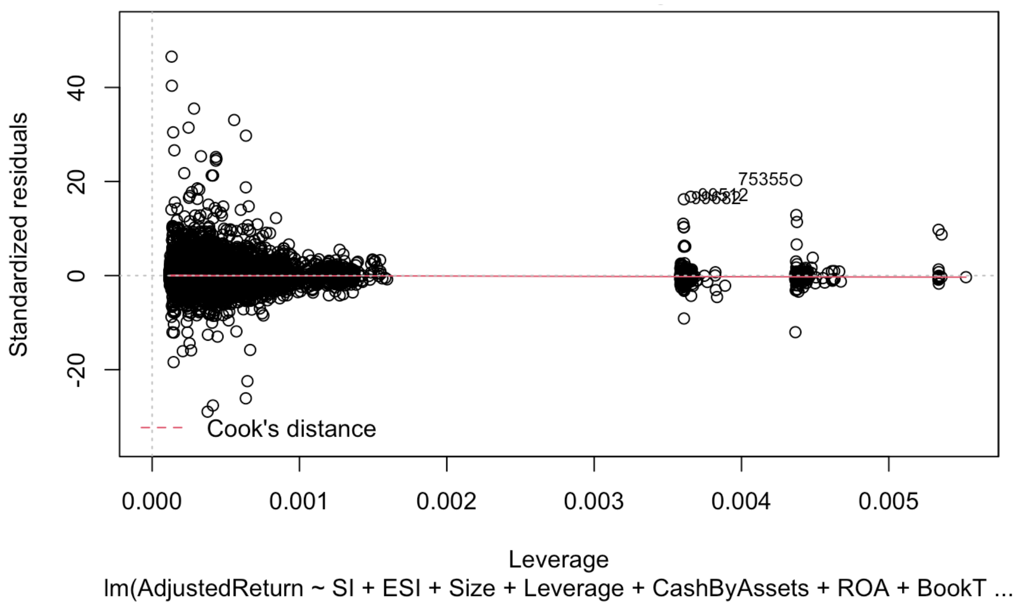
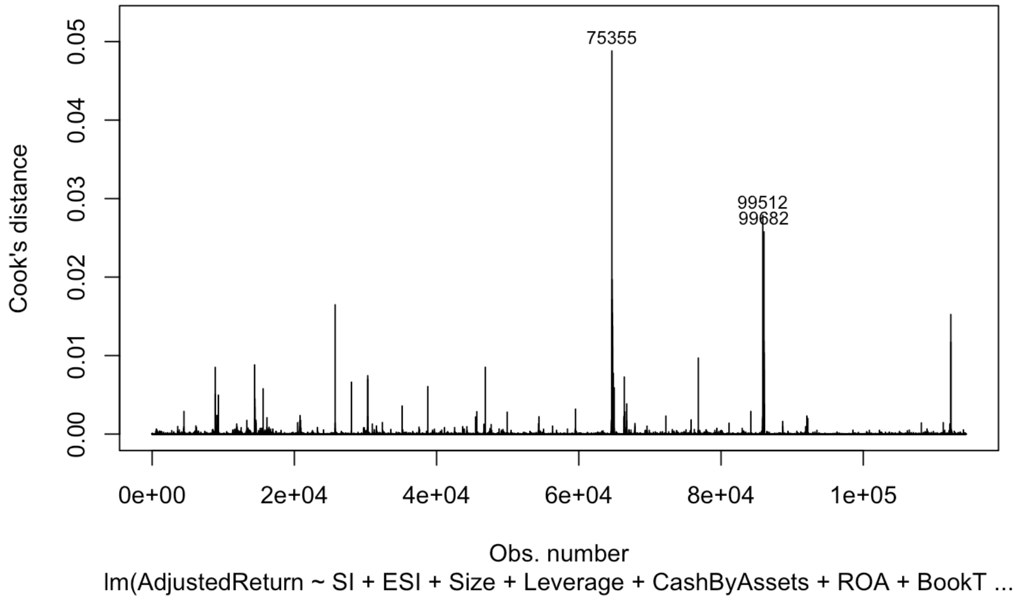


Figure A.5

Cook´s distance plot

This figure displays the Cook´s distance plot to check for influential values in the regression.



Appendix 4: Robustness checks

Table A.7

Robustness checks

This table shows the regression results of the robustness checks. The influence of using UnadjustedCases, ForeignSales, excluding data from April 2020 and before and excluding financial companies is investigated. I identify financial companies using SIC2 codes: 60, 61, 62, 63, 64, 65, 67, utilizing the same website as above for classifying SIC codes.[203] Variable definitions and data sources can be found in Appendix 1. All models include Country, Industry and Weekday fixed effects. 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)
SI	0.009***	0.009***	0.007***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
ESI	0.001*	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Size	-0.024***	-0.017***	-0.030***	-0.025***
	(0.005)	(0.006)	(0.006)	(0.005)
Leverage	-0.0001	0.0002	0.0002	-0.0001
	(0.001)	(0.0005)	(0.001)	(0.001)
CashByAssets	0.001	0.0002	0.00004	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
ROA	0.0004	0.001	0.0004	0.0004
	(0.001)	(0.001)	(0.001)	(0.001)
BookToMarket	0.011***	0.032**	0.015***	0.012***
	(0.001)	(0.014)	(0.001)	(0.001)
ForeignSales		0.0003		
		(0.0002)		
Attention	-0.004***	-0.004***		-0.005***
	(0.001)	(0.001)		(0.001)
UnadjustedCases	-0.021***			
	(0.002)			
AdjustedCases		-0.462***	0.514***	-0.395***
		(0.091)	(0.116)	(0.085)
essential	0.010	0.002	0.005	0.013
	(0.026)	(0.023)	(0.032)	(0.026)
Observations	114,440	75,526	87,303	105,258
Adj. R squared	0.0057	0.00517	0.00195	0.00405
F Statistic	59.438***	23.394***	103.23***	971,522***
	(df = 36)	(df = 36)	(df = 35)	(df = 36)

[203] See SIC-NAICS LLC (2021).

Noteworthy findings of the robustness checks:

In robustness check 1, the slope and significance of ESI is lowered in comparison to table 2. It is still positive and significant at 10%, but UnadjustedCases seems to reduce the influence and explanatory power of that variable, although not alarmingly so. The coefficient of UnadjustedCases itself is negative and significant at 1%, similar to the coefficient of AdjustedCases in table 2. An increase of UnadjustedCases by 1 SD (7.718) relates to a decrease of the adjusted returns by 0.1621 percentage points (-0.021*7.718) on average, a more negative relationship than for AdjustedCases, where that number is 0.05831. However, it has to be kept in mind that both indicators are calculated using very different formulas. The real-world-significance of this difference is therefore limited. The R^2 of this robustness check is slightly higher than the R^2 in table 2, but still below 1%. In general, this robustness check does not alter the main findings.

In robustness check 2, no major changes compared to table 2 can be observed. ForeignSales is not significant at 10% and its inclusion does not alter the other slopes significantly. It therefore does not appear to be an important and influential variable. The sample size, however, is greatly reduced, deleting valuable variation of the data. The R^2 of this robustness check is slightly higher than in table 2, but not larger than 1%. A possible reason for this can be found in effects stemming from the reduced sample size. This robustness check does not alter the main results as well.

In robustness check 3, the slope of SI is slightly lower than in table 2, but still highly significant and positive. The results are overall very similar, apart from one major difference: AdjustedCases has a positive and significant coefficient in this robustness check. The negative correlation of COVID-19 cases and adjusted stock returns therefore seems to mainly stem from the early phase of COVID-19 when the pandemic was a novel and shocking crisis. Although the slope is positive, it does not seem economically reasonable to assume a positive influence of COVID-19-cases on stock returns as it appears unrealistic that more infections have beneficial effects on the economy. This result might rather be due to general market volatility being much lower after April 2020 than in the early phase of the pandemic.[204] Furthermore, stock markets regenerated from the initial shock after April 2020, generally showing positive returns.[205] Another possible explanation is provided by Alfaro et al. (2020), explaining that the predicted number of cases influences stock returns.[206] If the predicted number of cases decreases, the number of actual cases might have a positive correlation with stock returns, as the

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[204] See Baker et al. (2020), p. 743.
[205] See Ding et al. (2021), p. 7.
[206] See Alfaro et al. (2020), p. 1.

market beliefs that the high number of infections will soon decrease. Despite the potential explanations, this is a constraining factor, meaning that the effect of COVID-19 cases on stock returns should be handled with care. In this robustness check, R^2 is lower than in table 2, but not to a large extent. As the coefficients of SI and ESI are not significantly changed, the main results for these variables are not altered.

In robustness check 4, no noteworthy changes can be observed. Excluding financial companies therefore does not alter the main results.