Impact of Covid-19 on Stock Prices in the United States. *

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Covid-19 pandemic caused unexpected hardship on the economy in 2020. To understand how stock prices were impacted due to this pandemic, this paper measures the impacts of weekly Covid-19 fatalities and enforced stay home order on stock prices in the United States. Starting from OLS estimation on stock prices and pandemic development, then with further controlled variables on industries and balance sheet items. Later, in order to amplify the effect of Covid-19, the analysis considers instrumental variable and the two stage least square method with society age and insurance structure. It is discovered, that Covid-19 significantly impacts the companies stock prices in the underlying data, even though the impact of Covid-19 is remarkably low. The regression is also controlled for factors common to all companies, when the panel approach is used. Results from company and time fixed effects manifest, that stock prices are not changed to a large extent.

Keywords: Stock Prices; Covid Shock; Company Structure; Instrumental Variables; Politics; Fixed effects

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1 Introduction

Covid-19 spread caused hardship on global markets in 2020. In January 2020, the pandemic impacted only China, but the disease rapidly spread and became a global pandemic in February and March, which started the market turmoil, when disease control policies were first enforced. Covid-19 was considered as an unexpected short term shock in the early months of 2020, however during the summer months the Covid-19 influence weakened, but then a second pandemic spread followed in mid-October, while the third wave is currently ongoing.

Since the market disturbance caused by Covid-19 was considered to be short term in early months of 2020, then turned into a long-lasting shock, this paper is about how financial markets responded to this first unexpected, then seemingly endless shock. In other words, this paper analyzes the "Impacts of Covid-19 on companies stock prices"? The underlying analysis focuses on responses of stock prices due to Covid-19 related fatalities and the imposed health policies. The analyses is using an OLS approach to identify the impact of weekly fatalities on stock prices, then adding instrumental variables to avoid endogeinity and causality, and fixed effects are added as well. The used research approach will be more closely examined in the methodology section.

Compared to the Great Depression or Global Financial Crisis, stock prices by pandemic development around the world declined, however not economically significant according to Capelle-Blancard and Desroziers. This trend is mostly identified in wealthy countries, which is also the case in this paper, as Covid-19 fatalities and stock prices are considered for the United States [1]. The pandemic situation is one thing that surely draws an influence on stock prices, but was not the only reason why stock prices overall dropped in early 2020. One reason raised by Fahlenbrach et al. was that the firm's flexibility, namely a more equity-oriented company could lower its impact when there is a shock, espcially during the Covid-19 shock in 2020 [2]. Identification of firm structure and potential causal effects will be discussed when using control variables and instrumental variables.

As Covid raged, health policies of Covid-19 were made, including health and financial policies, where our paper focuses on health policies, which people in general are more informed about anyway. Health policies were enforced on a state level instead of federal level and issued at different times. Businesses showed positive or negative growth due to these local pandemic developments, respective policies and its company structure. Upon lots of policies, the "stay home order" is chosen as our measurement of policies, because staying at home directly influences all the businesses.

By measuring the stock prices in 2020 and the fatalities of Covid-19 and its policies, effects to the business environment and industrial characteristics are to be understood.

2 Methodology

2.1 Data

To answer the research question "Impacts of Covid-19 on companies stock prices", the underlying analysis considers United States company and stock market data from January 2019 to November 2020. Daily stock data as well as companies balance sheet information was obtained from WRDS North America. More precisely, stock market data was gathered on a daily basis from the S&P Compstat-Security Daily and the balance sheet data was available on a quartely basis from Compstat Index Fundamentals. Regarding Covid-19, data on fatalities and cases was collected from the US Center for Disease Control and Prevention. Important characteristics of data and the cleaning process are described in more detail in the following.

Stock. The Compstat data set includes daily data on opening and closing stock prices, as well as on earnings per share and minimum and maximum prices each day. This paper, as analysis is undertaken on a weekly basis, considers opening stock price averages within a week (Monday-Friday). Figure 1 and 2 show the distribution of stock prices in the collected data and some descriptive statistics are visualized in Table 3. It is evident, that the data is skewed to the right and there are a few very large outliers, whereas 75% of data observations are around the mean. This distribution is very similar to the original data distribution, before weekly averages were created.

Balance Sheet Data. Companies balance sheet data has an equivalent distribution (Figure 4 - 8). As for the subsequent analysis data on assets, debt, cash and firm classifications is used, Table 3 shows descriptive statistics for those variables as well. Regarding total assets, cash and long-term debt the skewness and kurtosis indicate, that it is far from normal distribution, with data being dense within the first quartile and showing large spreads in the upper range of observations. Standard deviation is larger than the mean of values, which confirms that there is high variances within the data, hence in this analysis the log values of the variables are used.

The data cleaning approach can be viewed in detail in the underlying STATA file. It is worth mentioning though, that since some companies have a lack of observations, we exclude companies where data is only available for less than 70 weeks, which leaves a total of 1731 companies with 158100 observations. Since the Compstat Index Fundamentals data is only available quarterly, the company finance data is identical for twelve weeks, which limits the analysis of the companies financial variables.

Covid-19 related data. For the identification of the severity of Covid-19, Covid-19 weekly fatalities per state are taken. This analysis considers weekly fatalities due to Covid-19 instead of the weekly sum of infection cases, since they depend less on testing capacities. The Covid-19 death and cases are taken as a weekly sum from Wednesday to Wednesday. Hawaii is excluded since there was no Covid-19 infection data available in the used data set. Also, due to lack of company data observations for US territories like Palau, those are dropped as well. In the following undertaken regressions, we include additional data, which is listed in the data part of the appendix.

2.2 Models

To identify the financial market response due to Covid-19, OLS is first used where stock prices of firms were aggregated and there development over time was not taken into account. A right sided skewed distribution of the models residuals indicates, that the stock price should be expressed with log values. To avoid negative log data values, stocks with a price below one Dollar, the so called penny stocks, are dropped for the subsequent analysis. Since that financial stability has been considered an important element in stock prices, further balance sheet items were added to the setup. Also, to measure the effectiveness and the impacts of health policies on businesses, the stay home order is considered in the analysis as a proxy for the imposed local restrictions. As we argue, the stay home order discussed in this paper, is directly influencing business rules, so that using this variable, further analysis on policy and stock price trends are made.

To further identify the issue of measurement error, endogeneity and its causality, additional regressions with several instrumental variables, namely state political attitude, household and age structure, and percentage of people without health insurance are to be measured with the weekly fatalities and the health policies. These instrumental variables are chosen for the following reasons:

Political Attitude. Political attitude is observed in two ways: the senate representation and the previous election outcome. Political attitude can directly influence the Covid-19 policies, where states represented by the democratic party seem more keen on health policies and people are supportive for these policies, which is influencing the weekly death count and its enforcement of lockdown. It has to be mentioned, that the political orientation of a state could also influence the other independent variables, like the size of companies in the respective state. However, we argue that the causality is rather reversed and use the political attitude as an instrument.

Age Structure. The most vulnerable group of people, that are more likely to be severely infected by the Corona virus, are elderly citizens. Hence, a higher percentage of households with elders, that are more than 65 years old, in this concern, are more likely to be infected and develop severe symptoms, which leads to more fatalities and hence impacts the stock prices.

Health Insurance. Whether having enough health care resources is one of the reason why politicians need or not need specific health policies. When the health care is up to the limit due to high cases or malfunction of disease spread prevention, lockdown policies are more likely to be enforced. Fatalities development is also determined by availability and coverage of the healthcare system. The more people without health insurance, the more likely lockdown policies have to come into place. Health insurance contracts are usually long-term, which should not change all of a sudden and that healthcare issue does not influence overall market, so we considered percentage of uninsured people uncorrelated to 2020 stock prices, except for influencing the fatalities due to Covid-19.

To take care of identification development overtime and to account for individual characteristics of companies, a Panel is created to facilitate the impact of Covid weekly death at time t to the company i's stock price at time t, as the Regression 9 in the Appendix visualises. Also, as business environment varies due to state-wide regulations, fixed effects are included in order to gain a deeper understanding of the Covid-19 relation to stock prices of a single company. Furthermore, policies and firms responded more on its local and time development, hence the fixed effects of states and time were measured in the following analysis.

3 Results

3.1 OLS Regressions

First we run the basic OLS regression as visualized in Regression 1. The regression shows that weekly Covid-19 fatalities are significantly impacting average stock prices. With weekly fatalities increasing by one, the stock price on average declines by 0.0002233% (see Table 5). As expected, the relation between the Covid-19 variable and the log stock price is negative, albeit the economic significance of the finding has to be questioned. In fact, all else equal, a weekly sum of fatalities of 1000 in the respective state is associated with an average stock price decline of less than a quarter of one percent. Hence, the explanatory power of the Covid-19 variable on stock price fluctuations is very low. In the following part the baseline regression is modified in order to gain a better understanding of the Covid-19 impact to different groups of companies. This aims to find out which groups were especially vulnerable to the Covid-19 shock and concomitant possible explanations for that are discussed. Of special interest are the effects in different industry sectors, states and time frames. The analysis will start with the latter.

3.2 Pandemic Waves in 2020

In this section, we aim to compare the impact of Covid-19 in different time clusters, especially the comparison of the first wave and second wave is relevant. Fatalities occurring until the end of June form the first wave, while the second wave is starting in the mid of October, that is week 42. The analysis is undertaken to examine whether the negative impact is higher in the first wave, when general stock market reactions were the largest [5]. This is based on the argumentation that businesses achieved a quick adjustment, by offering remote work or implementing a comprehensive hygienic concept, so that the company stocks recovered rapidly. Further, it is expected that both infection waves are associated with a negative effect on the stock prices.

Indeed, the regression shows that overall, the stock prices declined during the first wave, while the contrary is observable after week 41, as seen in Table 6. It is evident, that rising weekly death are associated with shrinking stock prices (when not first wave), while in the first wave (compared to the rest) the influence of every increase in death on stock prices is slightly positive. A positive Covid-19 sensitivity of stock prices during the first wave of infections is unexpected, therefore the following part is presenting possible explanations for the results. The first Covid-19 related fatalities occurred in week nine, that is the last week of February. At that time the S&P 500 already showed historically large course declines, even though deaths due to Covid-19 were zero. Also, even in week 11 only five states have reported Covid-19 deaths and other states joined within the next two-three weeks. Hence, it can be argued, that in the used approach, the first stock price declines, at least in February and for numerous states also in early March, are unrelated to Covid-19 fatalities, which explains the Interaction term coefficient and the outcome of the regression. To account for that, we check the impact of weekly cases in the first wave, as they arise some weeks before fatalities. In this case, as can be seen in Table 7, there is a negative sensitivity to Covid-19 cases during the first wave, which confirms the above declared rationale.

It is further argued, that regression outcome for the second wave is negligible, because it includes data from only 16 companies with a total of 44 observations in 2020, which cant be considered as a sufficient data coverage. Sorted by weeks, the regression displays a similar result for the second wave, but not so for the first wave of Covid-19 related deaths. There is a significant negative impact of rising fatalities in weeks 12-21 and a positive significant effect for the weeks 41-48 (see Table 8 & 9). The largest coefficient can be found in week 12 (mid of April, Table 9), but even then the economic influence of Covid-19 is considerably little. Ceteris Paribus, when deaths increase by the amount of about 110 in week 12, the average stock price declines by one percent. With the highest death amount being 68 (Washington State) in the respective week, this still has low explanatory power. Albeit there are a lot of significant weeks between the first and the second wave, some don't show a significant influence. This seems only reasonable, because of the lack of experience in dealing with a global pandemic and protection measures when the disease hit the United States and the fast gain in experience that followed the weeks afterwards especially in businesses that developed hygiene concepts or went into home-office. Also, the approval of vaccination, which was followed by stock market reactions, has to be take into consideration as a cause for insignificant effects of increasing weekly fatalities in the late summer months.

3.3 Industrial Categories

Further we created an industry categorical variable based on the sic industry classification code used in the Compstat data. One would assume, that companies that had to close down again for disease control measures after the first lockdown period were heavily impacted, with consumption moving to online substitutes or declining because of overall uncertainty of the further economic development during the pandemic. It is hence presumed that retail, service and in the first wave also manufacturing were negatively impacted. The argument is based on the outcomes of Mirza et al., where it is found that in Europe manufacturing, wholesale trade and retail are more vulnerable sectors than others [6]. Also, Posen argues, in person retail and service is hit hard by the crisis [7]. This is in line with Goodell and Huynh, whose results display negative returns in services [3].

The baseline regression clustered by sic industry sectors indicates that weekly fatalities are negatively influencing agriculture, mining and transport, communication and energy, while it is moreover found that the coefficient for the construction industry is positive (see Table 10). Surprisingly, there is a positive coefficient in service evident as well. For retail, manufacturing and wholesale trade as well as finance and real estate the impact of weekly death is not significant, which is again unexpected at least for retail, manufacturing and wholesale trade. It is worth mentioning, that the data set contains only 93 corporations in the sic retail classification and 61 in wholesale trade. Figure 9 & 8 visualizes the industry distribution of observations. Regarding the retail sector, 93 companies make up for a total of 8387 observations, that is enough data coverage for a closer analysis of the retail industry. As we argue, the composition of the sic sectors could explain the unexpected insignificance in retail or manufacturing as it is due to conversely impacted companies within the manufacturing cluster group.

Indeed, a analysis only focused on the first wave sheds light on the diverse impacts within the retail industry sector. It is found, that grocery and food companies stock prices grow when weekly fatalities increase, while the opposite can be found for gasoline stations and car supply corporations (Table 11). The economic significance in even lower than in the baseline regression, which favors the overall retail insignificance. However, the argument made, that the outcome is due to the SIC composition, is undermined when not just the first wave, but the whole data is considered. Home-building retail and the just mentioned car-supply and food retail show a slight positive influence when weekly fatalities increase, which is negligible as the coefficient is comparably small. Yet, the retail industry includes only 93 very large corporations for example Amazon. The drugstores within this data are i.e. Walmart and Target, which were forced to close stores temporarily but had an existing well-established E-Commerce infrastructure to absorb the effect of the disease control restrictions. We assume equivalent for the food suppliers like Dominos Pizza or Del Taco, where it can be presumed that a lot of consumers used their delivery service when smaller restaurants without online services had to close. This could further help to explain the non-existing relation between Covid-19 and the considered companies in the retail sector.

Dividing the manufacturing industry into six groups, reveals that the heavy industries like glass, metal and steel production show declining stock prices when Covid-19 fatalities rise (however very slightly, Table 12). The same result was achieved in Goddell and Huynh, where they gain the result, that with increasing public focus on Covid-19, the returns in heavy industries are negatively affected. The outcome is rationalized with the assumption, that these industries suffered from the supply chain disruptions in China leading to supply shortage in the United States [3]. It is also evident, that electronic office supplies, computers and computer equipment are positively impacted and chemicals, pharmaceuticals are so too. As a result, the effects of Covid-19 on the manufacturing companies differ for the subgroups of companies. However, all the results show even less economic significance than before.

Next, the service sector is considered. As Posen concludes, it is the in person service that is preliminary hit by the Covid-19 crisis [7]. The service sector in our data however, covers large holdings, consultancies, legal and health service providers or computer data analysts rather than the service companies one might think to be most impacted like local hairdressers, event management or cleaning companies. This data in the service industry instead consists of large corporations such as Netflix, PayPal, Twitter, ebay or Adobe which quickly recovered after the stock price decline in March increasing its stock price extensively afterwards. Furthermore, we rationalize the outcome, by stating that also the other service companies in the data were not heavily impacted by both the supply chain disruptions in February, March and April or by the enforced shutting down of businesses, as home office is easier to implement compared to the manufacturing industry.

3.4 State and Local Stay Home Order Policies

The state analysis is of special interest, because it allows for a more precise analysis of the impact of local disease control restrictions. Unfortunately, the data includes less than ten firms for a lot of states. To ensure the explanatory character of the analysis, we will only examine states with more than 3000 observations, which accompany for approximately 30 companies. Out of the 14 states that are left, a total of 11 including California, Texas or Illinois show significant influence with the log stock price regression (See Table 13 & 14), with California being the only state where rising weekly death are related to a stock price boost. Unfortunately, the coefficients for all regressions are lower than before, indicating a barely noticeable influence. There are several feasible rationales for a economically not significant stock price reaction in the respective state, for example the industries settled down or the local and federal disease prevention policies, which are closer examined in the subsequent part.

Those states that show a significance influence of weekly death on stock prices, are in fact, to a higher fraction (2 Republican, 6 Democratic and 3 both parties) states where senate representatives have democratic party affiliation. It has to be questioned, whether companies within states ruled by the democrats exhibit a higher stock price reaction, because stricter disease prevention measures are enforced. In fact, a recent study speaks in favor of this. Gusmano et al. conclude that democratic senators were more likely to impose stay home restrictions and did so faster [4] . Yet, in our analysis the regression on the influence of the party representation to the stay home order confirms the contrary. With republican senators the average stay home order is 0.06697 points higher. However, there were only two republican governed states considered in the collection of stay home policies whereas six states have senate representation by the democratic party. As a result, the impact of party affiliation on stay home order remains for further research.

There are several other factors, though, that might influence the duration and intensity of the stay home order. Table 15 & 16 visualise the outcome of the regressions using instrumental variable on the stay home order. It is evident, that the stock price reaction increases when the senate representation during the pandemic is considered as an Instrument. Using polit_check as an instrument demonstrates, that a jump in stay home policies from zero to one on average causes a stock price decline of 7.280 % when the same independent variables as before are used. This result hints towards an influence of partisanship on stock prices. However, it is needed to mention, that the political representation is highly impacting the companies sales or size as well and the only republican states included in this analysis are Texas and Florida. Both questions the suitability of the variable as an Instrument for the stay home order. Further, the outcome of the last senate election in November is used as an Instrument. One could interpret, that a republican voter in Novembers election might want the restrictions to be loosen and a democratic voter might favor more drastic limitations. The recent election results can among other factors be interpreted as the contentment of the population with the Covid-19 policies that were taken. Notably, the election results in November do not only represent the voters contentment of the governments handling with the Covid-19 crisis, but the interpretation of the election outcome is more complex, which considerably restricts the suitability of the November election variable. Share of households with members over 65, is not suited as an instrumental variable since a weak identification problem is encountered. Lastly, the stock price on average declines by 0.79% with an increase by one unit of the stay home order, when the uninsured percentage was used as an instrumental variable. For all cases, using instruments increases the influence of the stay home order on stock prices by a large extend. It is left for further research to increase the states for which information on policies was collected as well as taking county and city policies into consideration, in order to confirm the trends that were visible in this analysis.

3.5 Consideration of Firm Balance Sheet Structure

Next, other independent variables are added (see Regression 2 - 5). The sector industry classification is used as a control variable. As one would have predicted, the explanatory character of the model is low. Companies sales should have an impact on the price of the stock and the correlation as well as regression confirms that. The regression result is seen in Table 17. When sales are added, the underlying model explains more of the changes in stock prices. It is also evident though, that influence of Covid-19 drops, as sales show a very large impact on the stock prices compared to the used Covid-19 variable. An increase in weekly fatalities by one leads to a stock price decline of 0.0000964%. The effect of Covid-19 on companies stock performance is seemingly little, so that we argue, that there is no substantial effect of Covid-19 with this model setup. Comparing the sales and Covid-19 coefficient confirms the stated argument. A 1% increase in sales is ceteris paribus followed by a average stock price increase of 0.3451% and this is more than 30 times higher than the influence on stock prices if weekly death would rise by 1%.

To account for the differences in stock prices that arise due to companies size, the total assets are included as an indicator for that. Since in times of crisis, there is a particular need for financial flexibility, cash is added next. Fortunately, the t-value and thereby the effect of Covid-19 on stock prices increases with the additional independent variables. We rationalize that with multicollinearity between sales, assets and cash. High assets correlate with a higher value of cash available and sales are very likely to increase with company size as well. In fact, the Vif Value for assets is critical and hence the company size variable is dropped from the regression. The last line of the regression table shows the setup with leverage (debt/assets), as an additional independent variable. This model explains 36% of average log stock price fluctuations. In this final model setup the Covid-19 variable has relative low capability to explain stock price changes. In order to achieve a more influential result, instrumental variables are introduced (see Table 18 and 19). The potential instrumental variable are the share of uninsured, population density and household over 65 percentage (described closer in methodology). Unfortunately, population density shows no significant influence on weekly death, but shows a significant relation to the companies sales and leverage. Hence it is not suited as an instrumental variable.

Share of households with at least one member over 65 is very significantly related to the weekly fatalities within the respective state, showing a decrease by 0.00227 and in fact, tests confirms that it is suited as an IV, but one needs to be warned about the significant effect of the variable to sales, cash and industry. Using this IV, the impact of Covid-19 on stock prices increases. An even larger influence is visible when using the percentage of uninsured, which decreases the Covid-19 coefficient to approximately 0.0047 (see Table 19).

The age structure variable is significant as well, however, the coefficient is lower compared to the household age variable. In the following, the underlying results are compared to the outcomes of the IV regressions of the stay home orders, that is the other channel through which stocks are influenced by the pandemic (see Methodology). Table 18 and 19 show that an increase of stay home policies is related with a average drop of stock prices by 0.79% (with IV Uninsured), while the sum of weekly death all else equal has to rise by 168 deaths in order to achieve an equivalent stock reaction. Considering this, it is concluded that the weekly death variable is able to cause greater stock price fluctuations.

3.6 Panel Analysis

In the subsequent part the outcomes of the panel regressions (Regression 9- 15) are to be analyzed. Industry is not included in the panel regression, because it is time-invariant. The Covid-19 fatalities variable is statistically significant in all regressions and the coefficient changes only slightly. If weekly death at time t for company i within a certain state rise, the company i stock price at time t decreases. Event though the z-value of the Covid-19 variable is the second highest, the economic influence remains very low. In order to achieve a 1% decline in the stock prices of company i, the weekly death at time t would have to increase by more than 8000, which is more than 30 times the mean of weekly death in 2020. Ceteris Paribus, a 4% change in the log-sales however, change the stock price of company i at time t by more than 1% and also a 50% increase in cash hold could achieve the same. Yes, the impact is also low, but comparable to weekly death considerable.

One might wonder about the low z-value of some other independent variables compared to the OLS-estimation , especially for cash and leverage. This could arise because those variables are only attainable on a quarterly basis and therefore show no variation for a total of 12 weeks, but remain constant within the quarter (all results see Table 20) .

With this setup we check for company fixed-effects. There are some variables like the companies rating, the operating industry or the location that, in our data set, remain constant over the time frame. However, they don't have to stay time-invariant, when a longer time period would be considered. There are omitted variables, that are constant over time as well. An example would be the companies experience measured with the founding date of the company (that would not change over time). Again, in this case, the penny stocks remain excluded leaving a total of 1574 companies. Table 21 shows the results when considering company (individual) fixed effects. Covid-19 still has significant impact. The same is evident for the other variables. Altogether the coefficient changes only marginally. Sales remain the most relevant variable associated with stock price reactions, the Covid-19 variable is following afterwards. An increase of Covid-19 weekly death in the state at time t, leads to a reduction of the companies stock price at time t of 0.000117%.

Further, we control for macroeconomic factors common to all companies using time fixed-effects. Both individual (company) and time fixed-effects are included. In this setup Covid-19 fatalities have no statistically significant impact on the stock prices, whereas the other variables are statistically significant. It can hence be formulated, that when accounting for different endowments of companies, that do not change like state, rating or experience and also controlling for the macro development, the company i stock prices at time t are not related to the respective weekly deaths due to Covid-19.

4 Summary and Conclusion

4.1 Summary

This paper analyzes "Impacts of Covid-19 on companies stock prices". Using simple OLS, it is found that an increase in weekly fatalities is associated with an average stock price decline. However, weekly fatalities only show very little influence on the stock prices. It hence can be concluded, that despite the statistically significance of weekly death on stock prices, the economic significance has to be fairly questioned. The same result is achieved when other independent variables are included. Overall, the used model explains 36% of stock price fluctuations. Further, the OLS analysis reveals that during the first wave of infections the prices of stocks increase with the amount of weekly fatalities. This shows one shortcoming of the underlying approach, as the stock market crash in February is not covered in the analysis, because the first deaths occurred at a later point in time and the stock market recovered when weekly fatalities first increased. Regarding different industries, it is evident, that in some industries such as manufacturing, retail or finance stock price reactions are not significantly related to weekly fatalities, while it is found that service, agriculture or transport and communication present a significant influence of Covid-19. Further, it is find, that the imposed local stay home order depends on the party affiliation of the senate representatives and the percentage of uninsured citizens within the state. The problem of the factors also influencing other exogenous variables has to be considered, and could effect causality and thereby the stated results, which however remains for further research. There is also a significant impact of weekly death on stock prices when a Panel analysis is undertaken. Higher weekly death at time t, lead to a stock price decline of company i at time t. Also, in the panel setting, the impact is very low and when accounting for company and time fixed effects there is no significant influence. Considering the latter, it is concluded, that Covid-19 is impacting the companies performance to a small extend. The impact of Covid-19 is conditional on the operating industry, the local politics and Covid-19 regulations in the respective state. Once it is controlled for the current macro development affecting all companies, the Covid-19 impact vanishes.

4.2 Contribution and Potential Problem

There are several shortcomings of the approach in this paper, which remain for further research. Most importantly, the stock price is an imperfect measure of companies performance during the Covid-19 crisis, since only large corporations instead of small companies with low liquidity, that are supposedly more impacted especially by closed stores, are considered. Moreover, the used policy approach has to be extended to the county or city level in every state to gain a deeper understanding of the impact of party affiliations of local politicians on the disease control and prevention policies. Including the local Covid-19 policies on businesses is crucial for the analysis as well, which would have exceeded the scope of this analysis. Even though, stock prices did show a decline, it was not as worse as the reaction of the whole business environment, where government financial measurement, which was not measured here, pulled up the market trend. FED issued a drop in federal funds rate in March, remained this rate for the rest of 2020 and expanded purchase of treasury securities to stabilise the economy. Overall, the stabilising effect of the fiscal and monetary policy on stock prices has to be evaluated closely in further research.

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Appendix: Who wrote which part?

Main contribution to each part, but overall discussed and written together.

Mi-Yun

1.Introduction
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Sophie

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Appendix Robustness Check

Appendix: Robustness Checks

In the following the underlying relation between Covid-19 and stock prices is tested. The first robustness test considers the amount of deaths due to Covid-19 relative to the population count in the considered state, as 1000 deaths in California represent a different level of infectious spreading within the population than 1000 dead people in Montana. By looking at Table 22, one can verify the validity of the Covid-19 impact, as there is significance with a negative coefficient when the independent variables are added for both aggregate effect and panel data. For the main model, the Covid variable loses explanatory value, while all the other t-values remain almost identical.

Moreover, as noted before, the firm balance sheet and stock price data is skewed to the right. To absorb the effect of the largest companies we drop the top 10% of companies assets (as that determines the size). The effect of Covid-19 stays nearly the same, while as can be seen in Table 23 the industry is of less importance and the other variables change slightly. It is hence evident, that even without the largest companies, the model predictions hold. However, when the companies with the highest market values (or best performance) are excluded, that are the top 10% of market value, the result differs moderately (Table 24). With less independent variables, the Covid-19 effect is more negative than seen before. However that balances out, as the model widens. Notably, the industry sector as well as the cash hold are less determining of the stock prices. The result gained in the main section are hence confirmed, as the model predictions hold.

Appendix: Data Sources

Several variables are added into the gathered Compstat data that was merged, the respective data source can be found in the subsequent part. Firstly, the population count for any state of 2019 is merged with the other data. The data is gathered from the US Census Bureau. Secondly, the share of the households that have at least one member over the age of 65 is used. Furthermore, the percentage of uninsured households is used in the IV part. Another variable used in the IV section is the population density, for which the total land area in square kilometers is needed. Also, an indicator variable for political representation in the state is necessary for further analysis. The variable "polit" identifies the Senate representation in the 116 Congress of the United States, with 1 denoting Republican Senate Representation and 0 showing Democratic Senate Representation. If the variables takes on the value of 2, the respective state is represented by a Senator of both parties or one independent and one party representative. This is the case in Vermont (Democratic and Independent) and Maine (Republican and Independent). The "polit_ check" variable does not include states with mixed representation, but only focuses on the states that have Representatives of a single party leaving a total of 136949 observations from 38 states. Additionally, we created "polit_ last" with the outcomes of the Senate election in November 2020. For those states that had no election at that time, the result of the presidential election was taken.

One part of the analysis evaluates the effect of the stay_home_order to stock prices. The stay home order is a variable that accounts for the statewide Covid-19 restrictions created by local policy makers, which was created for the nine federal states with the most observations. Those states are California (CA), New York State and New York City (NY), Texas (TX), Illinois (IL), Colorado (CO), Pennsylvania (PA), Massachusetts (MA), Florida (FL), and New Jersey (NJ). There are other policies such as business close down and mandatory masks regulation in each states, but business policies coincide with stay-home policy and masks regulation does not directly influence company operation. A value of two suggest that there was a curfew in place, while O indicates there was no stay home order and 1 indicating anything in between especially when limitations of public gatherings are legally enforced. We gathered information about the stay home policies, using the Covid-19 page of the New York Times and the web pages of the state health institutions or local governments websites in general. By using archive.org we checked the policies in former weeks. With the information available on the web pages the stay home order variable was created manually.

1. Covid-Daily Covid death and case data by state: Centers for Disease Control and Prevention. Available under https://data.cdc.gov/Case-Surveillance/COVID-19-Case-Surveillance-Public-Use-Data/vbim-akqf. Last visited 01/10/2021.
2. Population of states: United States Census Bureau. Data downloaded: Annual

Estimates of the Resident Population for the United States, Regions, States, and Puerto Rico: April 1, 2010 to July 1, 2019. Used data is 2019 data. Available under https://www.census.gov/data/datasets/time-series/demo/popest/2010s-state-total.html#par_textimage_500989927. Last visited 01/10/2021.

3. Age structure: Population Reference Bureau using data of the United States Census Bureau https://www.prb.org/which-us-states-are-the-oldest/. Last visited 25/01/2021.

4. Households with a member over 65: US Bureau of Covid19 site - US Census Bureau. Available under https://covid19.census.gov/datasets/households-by-type-states/data?geometry=126.351%2C-16.868%2C-125.720%2C72.108&selectedAttribute=B25044_004M. Last visited 01/10/2021.

5. Square kilometers within a state: State Area Measurements and Internal Point Coordinates - US Census Bureau. Available under https://www.census.gov/geographies/reference-files/2010/geo/state-area.html. Last visited 01/10/2021.

6. Percentage of Uninsured households (Health Insurance in the United States: 2019): Health Insurance in the United States: 2019 - Tables- US Census Bureau. Available under https://www.census.gov/data/tables/2020/demo/health-insurance/p60-271.html. Last visited 01/10/2021.

Appendix: Figures

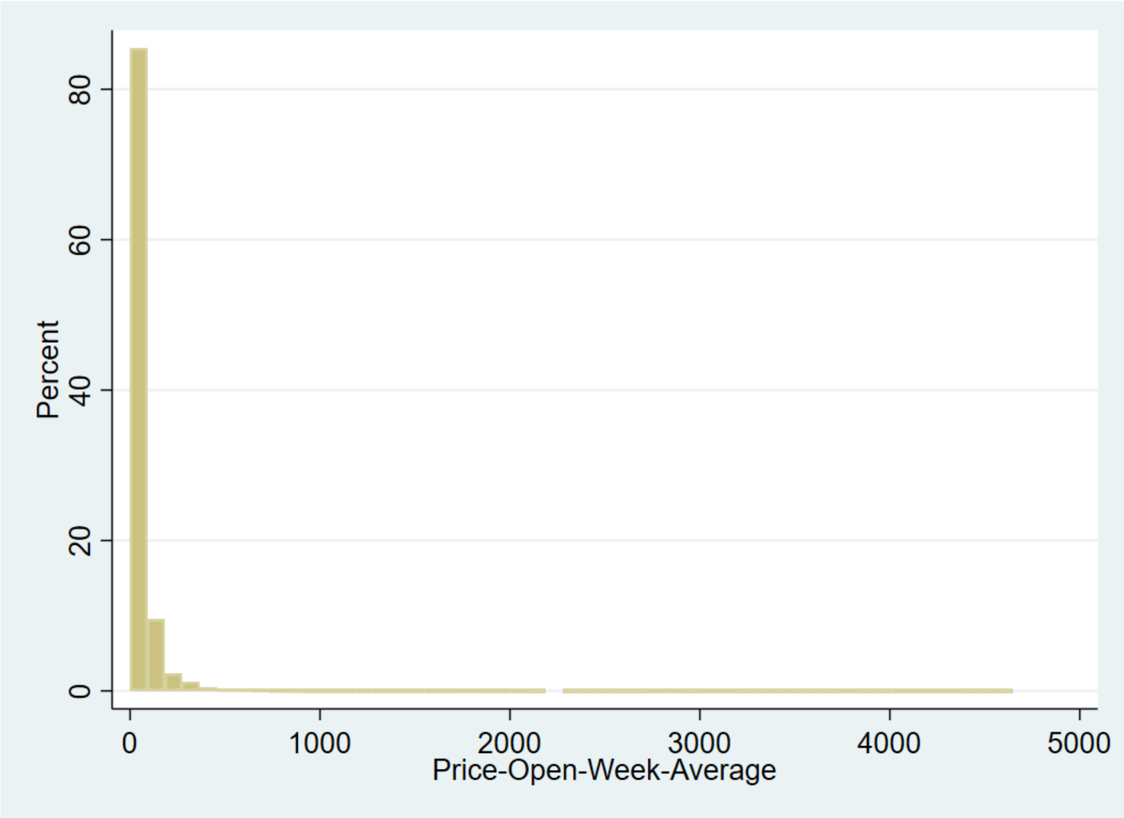

Figure 1: Distributions of Stock Prices

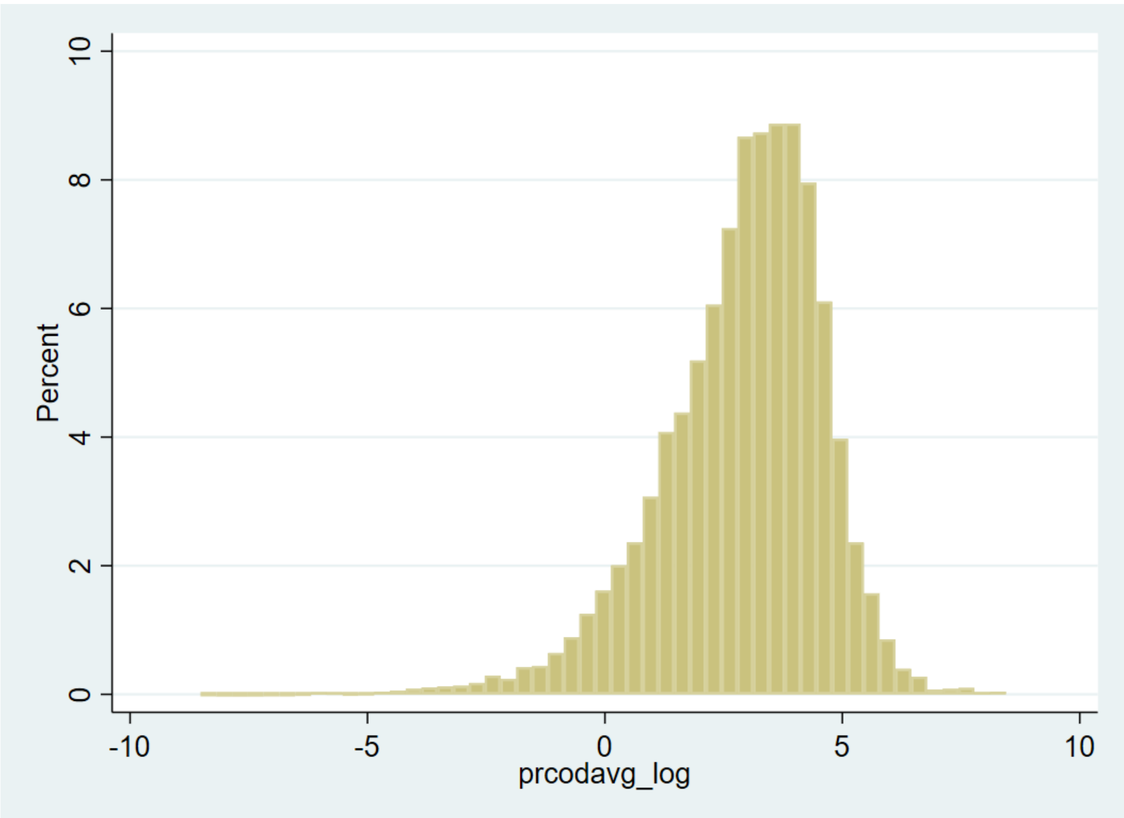

Figure 2: Distribution of log of Stock Price

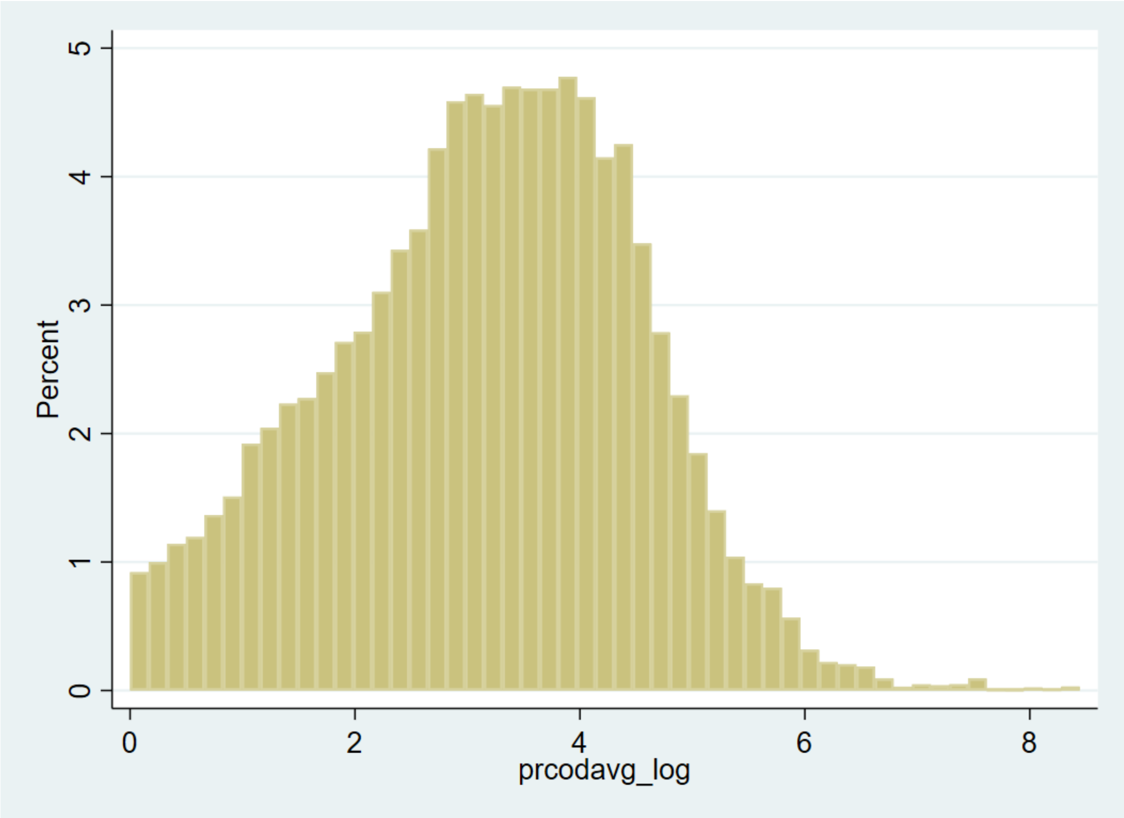

Figure 3: Log of Stock Price penny

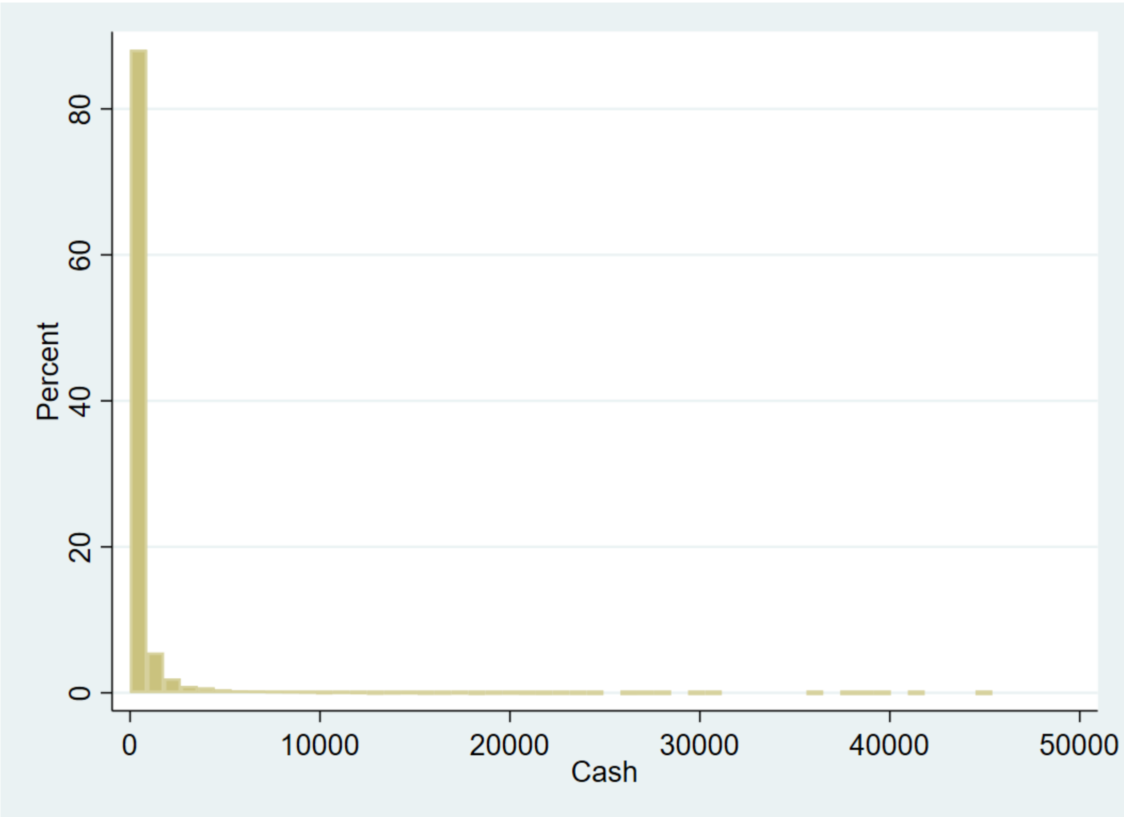

Figure 4: Cash

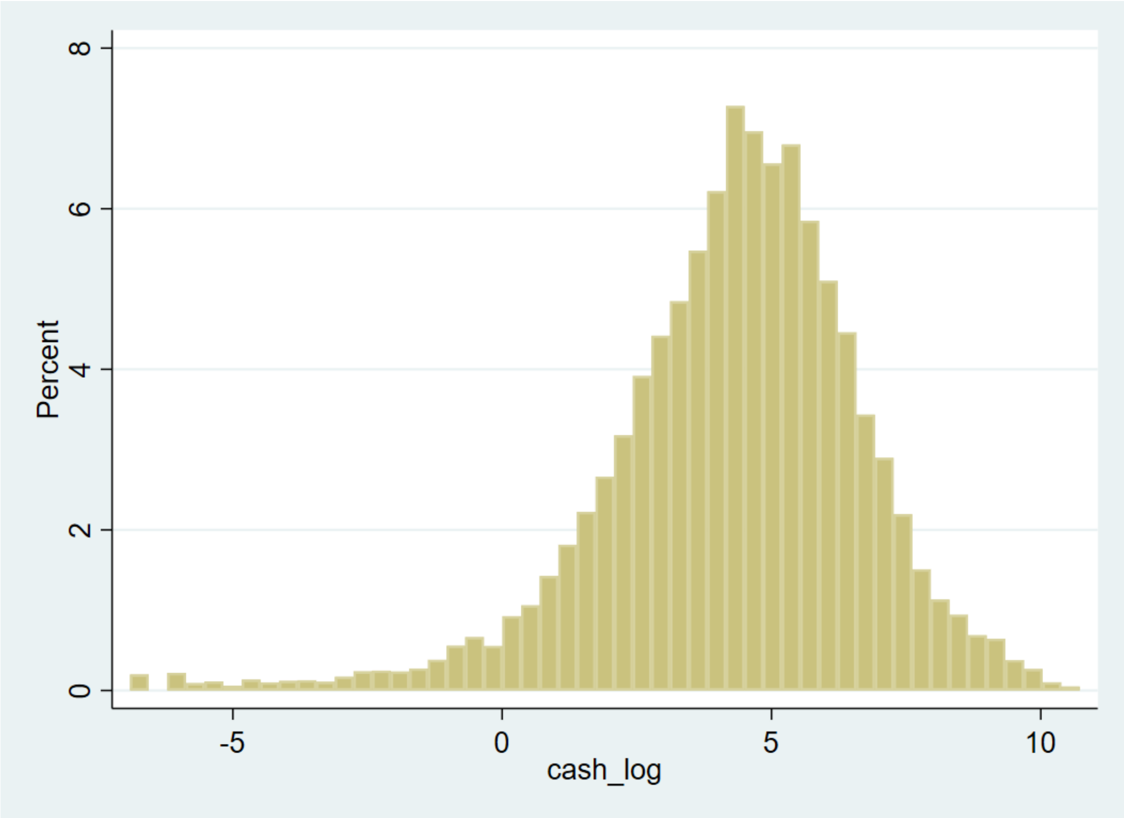

Figure 5: log of cash

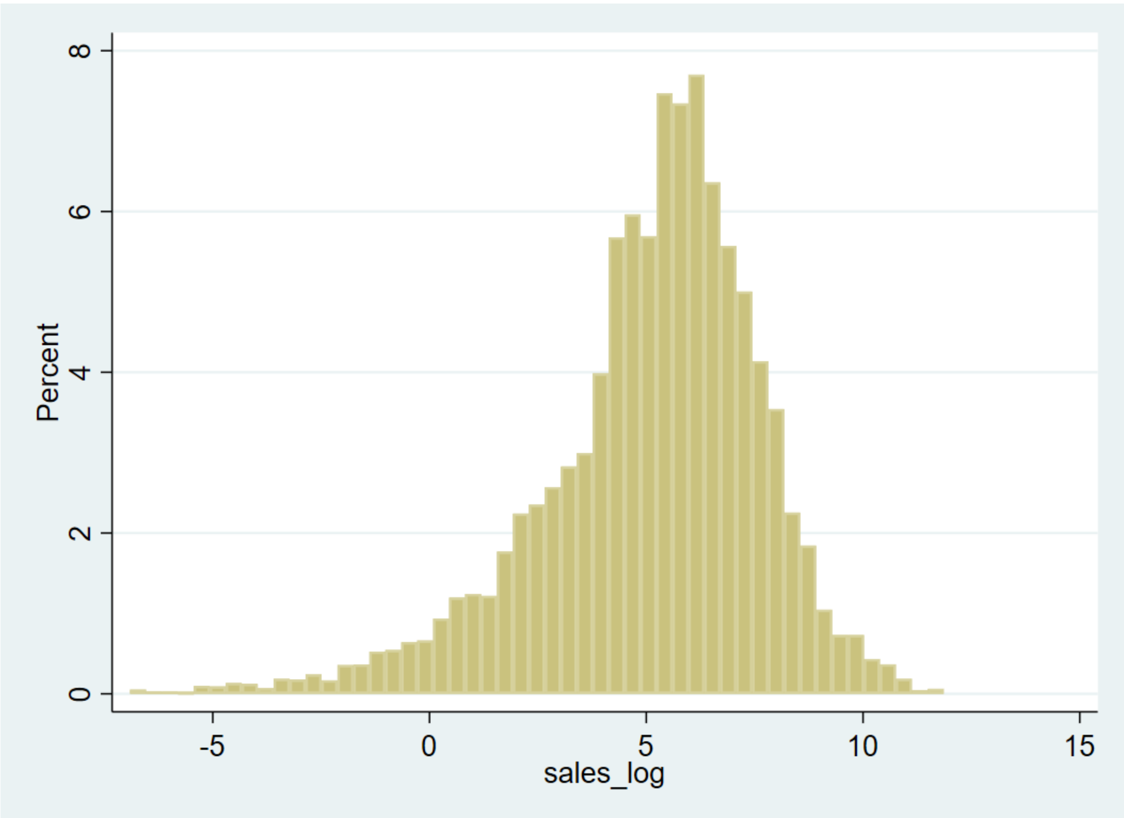

Figure 6: Log of sales

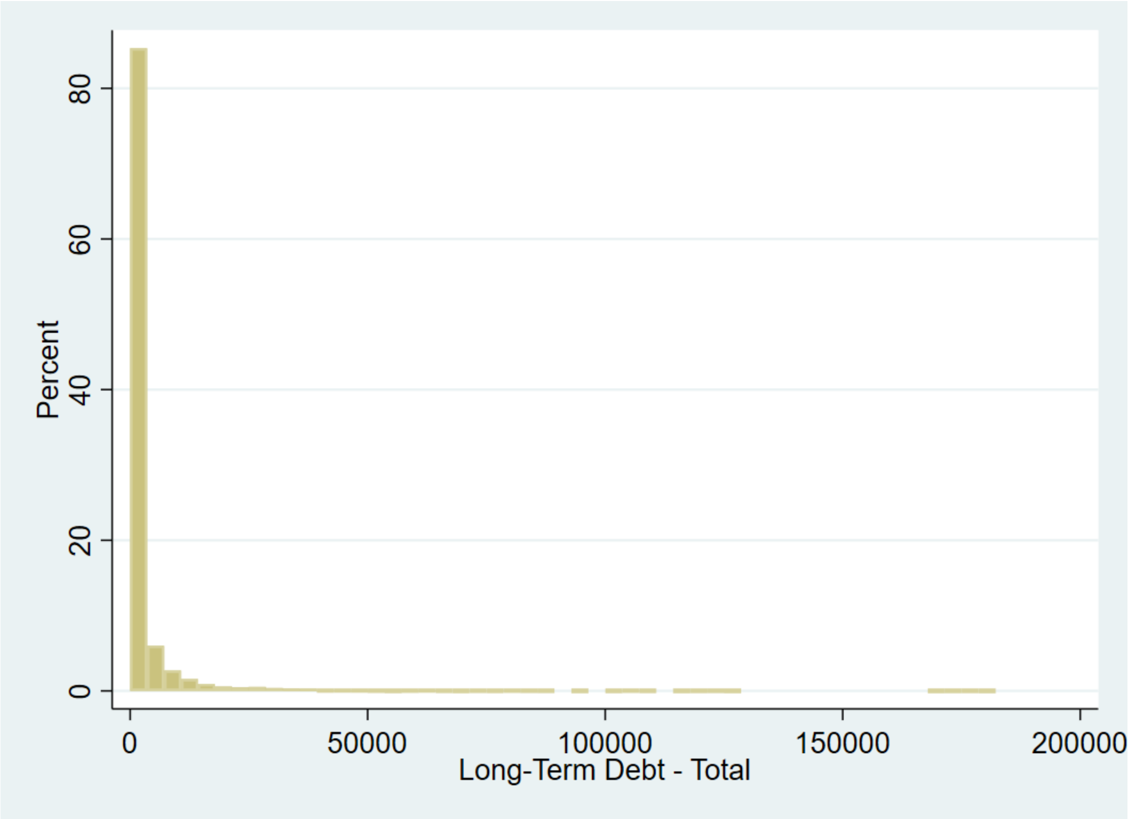

Figure 7: Long Term Debt

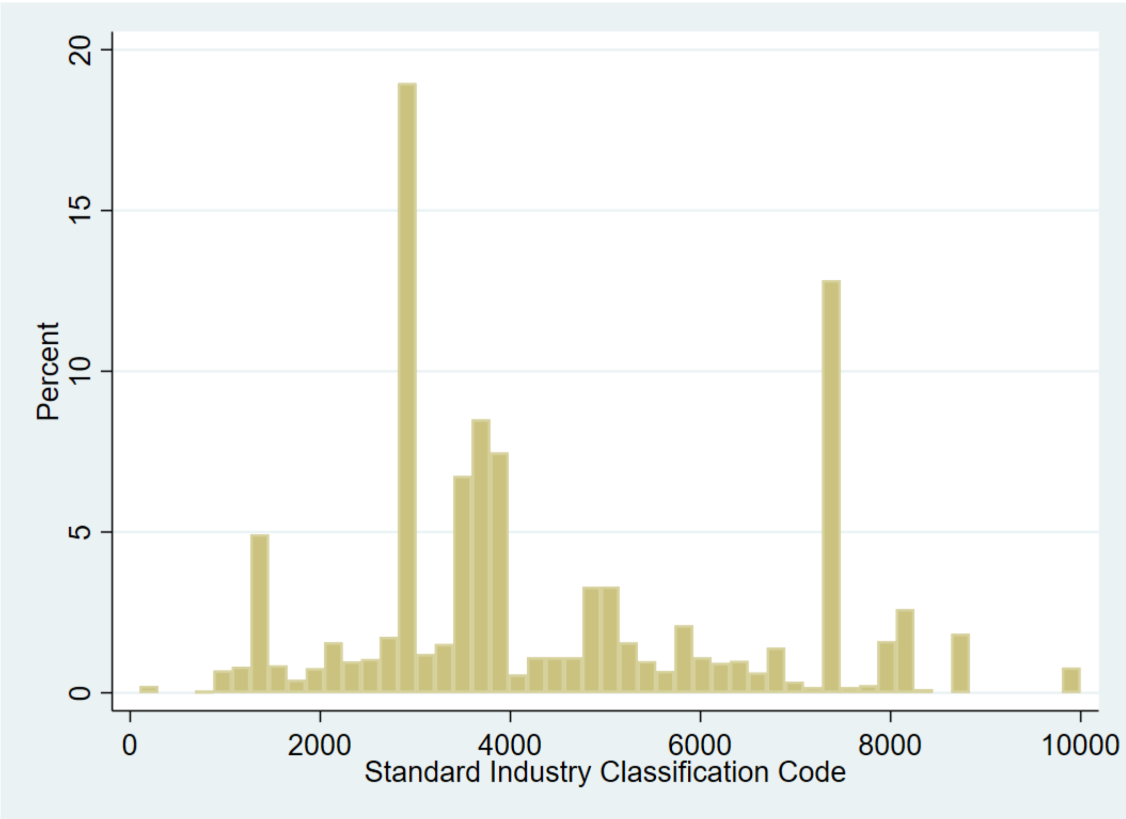

Figure 8: Industry

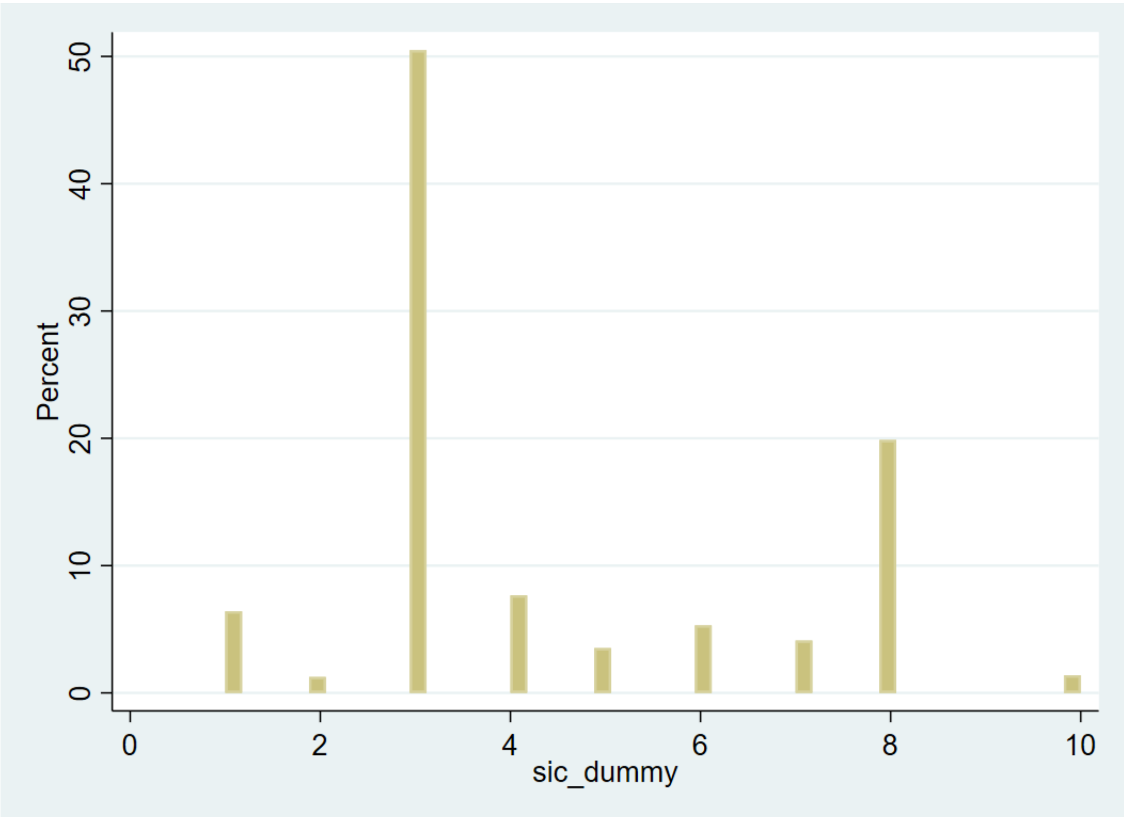

Figure 9: SIC industries

Appendix: Regressions

Baseline Regressions

OLS regression on log of stock prices (*STOCKPRICELOG*) and weekly death count (*COVID*).

$$STOCKPRICELOG = \beta_0 + \beta_1 COVID \tag{1}$$

For further analysis, control variables are added respectively, first industry categories (*INDUSTRY*), then on balance sheet structures, log of sale (*SALESLOG*, log of cash (*CASHLOG*), company leverage (*LEVERAGE*).

$$STOCKPRICELOG = \beta_0 + \beta_1 COVID + \beta_2 INDUSTRY \tag{2}$$

$$STOCKPRICELOG = \beta_0 + \beta_1 COVID + \beta_2 INDUSTRY + \beta_3 SALESLOG \tag{3}$$

$$\begin{aligned} STOCKPRICELOG = \beta_0 + \beta_1 COVID + \beta_2 INDUSTRY + \beta_3 SALESLOG \\ + \beta_4 CASHLOG \end{aligned} \tag{4}$$

$$\begin{aligned} STOCKPRICELOG = \beta_0 + \beta_1 COVID + \beta_2 INDUSTRY + \beta_3 SALESLOG \\ + \beta_4 CASHLOG + \beta_5 LEVERAGE \end{aligned} \tag{5}$$

Instrumental Variables on Covid-19 development and Policies

For more influential results, instrumental variables with two stage least square method is introduced. With the following regression, several instrumental variables (IV) are measured and compared, hat values shows the first stage estimations. These instrumental variables (IV) are Household with one or more members over 65 years old, people without health insurance, and age structure of states. Detailed results can be seen in table 18 - 19.

$$\begin{aligned} CO\hat{V}ID = \beta_0 + \beta_1 IV \\ STOCKPRICELOG = \beta_0 + \beta_1 CO\hat{V}ID \\ \text{or} \\ STOCKPRICELOG = \beta_0 + \beta_1 CO\hat{V}ID + \beta_2 INDUSTRY + \beta_3 SALESLOG \\ + \beta_4 CASHLOG + \beta_5 DEBTtoASSETS \end{aligned} \tag{6}$$

Further interpretation on policies:
(1): Impact of hygienic policy when people are not enforced (*STAYHOME* $= 0$),
suggested (*STAYHOME* $= 1$) or mandatory (*STAYHOME* $= 2$) on log of stock prices (*STOCKPRICELOG*).

$$STOCKPRICELOG = \beta_0 + \beta_1 STAYHOMEPOLICY \tag{7}$$

(2): Method of two stage least square estimation is introduced for our instrumental variable model. Several instrumental variables (IV) are measured and compared respectively, they are Senate party representation, results of the latest election, people without health insurance, and household structure with members over 65.

$$\begin{aligned} STAY\hat{HOME} &= \beta_0 + \beta_1 IV \\ STOCKPRICELOG &= \beta_0 + \beta_1 STAY\hat{HOME} \\ &\text{or} \\ STOCKPRICELOG &= \beta_0 + \beta_1 STAY\hat{HOME} + \beta_2 INDUSTRY \\ &+ \beta_3 SALESLOG + \beta_4 CASHLOG + \beta_5 DEBTtoASSETS \end{aligned} \tag{8}$$

Baseline regression on Covid and its impacts to financial stability expressed as Panel:

For panel analysis, setup are similar as baseline OLS estimations, only that each company are seperately identified at different time t.

$$STOCKPRICELOG_{i,t} = \beta_0 + \beta_1 COVID_{i,t} \tag{9}$$

$$STOCKPRICELOG_{i,t} = \beta_0 + \beta_1 COVID_{i,t} + \beta_2 INDUSTRY_{i,t} \tag{10}$$

$$STOCKPRICELOG_{i,t} = \beta_0 + \beta_1 COVID_{i,t} + \beta_2 INDUSTRY_{i,t} + \beta_3 SALESLOG_{i,t} \tag{11}$$

$$\begin{aligned} STOCKPRICELOG_{i,t} = \beta_0 + \beta_1 COVID_{i,t} + \beta_2 INDUSTRY_{i,t} + \beta_3 SALESLOG_{i,t} \\ + \beta_4 SIZELOG_{i,t} \end{aligned} \tag{12}$$

$$\begin{aligned} STOCKPRICELOG_{i,t} = \beta_0 + \beta_1 COVID_{i,t} + \beta_2 INDUSTRY_{i,t} + \beta_3 SALESLOG_{i,t} \\ + \beta_4 SIZELOG_{i,t} + \beta_5 CASHLOG_{i,t} \end{aligned} \tag{13}$$

$$STOCKPRICELOG_{i,t} = \beta_0 + \beta_1 COVID_{i,t} + \beta_2 INDUSTRY_{i,t} + \beta_3 SALESLOG_{i,t} + \beta_4 SIZELOG_{i,t} + \beta_5 CASHLOG_{i,t} + \beta_6 LEVERAGE_{i,t} \tag{14}$$

Final Regression considered for the subsequent part

$$STOCKPRICELOG_{i,t} = \beta_0 + \beta_1 COVID_{i,t} + \beta_2 INDUSTRY_{i,t} + \beta_3 SALESLOG_{i,t} + \beta_4 CASHLOG_{i,t} + \beta_5 LEVERAGE_{i,t} \tag{15}$$

Appendix: Tables

Table 1 and 2 indicate all variable names and their descriptions, whereas table 3 and 4 shows their descriptive statistics on original level and logs respectively. Tables following on are estimate tables mentioned in the paper.

Table 1: Variable Descriptions (1)

Variable name	Description
Stock Prices (source: WRDS North American)	
prcodavg	Opening Stock Prices Average taken on a weekly basis.
prcodavg_log	Log levels of Opening Stock Prices Average taken on a weekly basis.
time	Weeks in 2020.
Balance Sheet Features (source: Compstat)	
sale	Net quarterly sales.
sales_log	Log of net quarterly sales.
chq	Amount of available cash in company's balance sheet quarterly basis.
cash_log	Log of available cash
atq	Total assets (quarterly) of the company
assets_log	Log of total assets (quarterly)
debt.to.assets	Ratio debt to total assets in a company's balance sheet.
sic	Standard Industrial Classification (SIC) for industrial classification
Covid-19 Related Data	
weekly_death	Sum of weekly death cases due to Covid-19 within a state
weekly_death_log	Log value of sum of weekly death within a state
stay_home_order	Health policies issuing people to stay at home, 0 = not stay home order, 1 = suggested to stay at home, 2 = forced to stay at home

Table 2: Variable Descriptions (2)

Variable name	Description
Further variables	
time_check	Timing variable
polit	Political State Representation in the 116 Congress of the United States. 0-suggest that the state is only represented by democratic party members in the Senate, 1-indicating that the state is only represented by Republicans in the Senate, 2-indicating that there are Representatives of both party in the Senate for that state
polit_check	Political representation that only considers only Democratic or Republican representation in the 116 Congress on the United States, mixed representation is not considered. 0-suggest Democratic Party, 1-indicating Republican Party
polit_last	Outcome of the election in November for the Senate representation of the states. If there was no election in November, the outcomes of the presidential election are considered
time_check	Dummy variable to compare the two infection waves of Covid-19. 0-baseline, 1-Week 1-27 in 2020 considered only, 2-Week 42 and the following weeks of 2020
sic_dummy	Dummy variable to compare the impact of Covid-19 oh stock prices in different industries. Generated from the sic industry classification of the original Compstat data. 1-Mining, 2-Construction, 3-Manufacturing, 4-Transport, Communication and Energy, 5-Wholesale Trade, 6-Retail Trade, 7-Finance, Insurance and Real Estate, 8-Services, 9-Public Administration (no observations), 10-Agriculture, Foresty and Fishing
retail_dummy	Dummy variable for the subgroups within the retail industry. 1-Grocery and Food, 2-Clothing, 3-Eating and drinking places, 4-Auto supply and gasoline stations, 5-Computer parts (no observations), 6-Home building materials
manu_dummy	Dummy variable for further clustering of the manufacturing industry. 1-Aircraft, 2-Electronic, Computer Parts, TV, Radio and Semiconductors, 3-Metal, Steel and Glass, 4-Cigarette's and Tobacco, 5-Food and Alcohol
time_variable	Panel time variable. Week 1-52 in 2019 and for 2020 the weeks 52+

Table 3: Descriptive statistics for original values

	mean	p50	p25	p75	
Price-Open-Week-Average	54.81835	22.96775	7.05675	58.74675	
Sales/Turnover (Net)	1393.42	204.727	26.701	780.4	
Assets - Total	8352.478	1183.194	233.736	4642.58	
Observations	157571				

	min	max	sd	skewness	kurtosis
Price-Open-Week-Average	.0002	4648.298	144.3768	14.95384	334.406
Sales/Turnover (Net)	-33.688	141671	5701.765	12.37232	219.2506
Assets - Total	0	551669	29284.47	8.779847	109.5376

This table visualises the descriptive statistics for the original values of data, with mean, median (p50), 25th percentile (p25), 75th percentile (p75), minimum, maximum, standard deviation (sd), skewness, and kutosis.

Price-Open-Week-Average indicates weekly opening stock price average, whereas sales and assets are balance sheet items.

Table 4: Descriptive statistics for log values

	mean	p50	p25	p75	
prcodavg_log	2.898068	3.134091	1.953985	4.073236	
weekly_death	102.0519	0	0	50	
sales_log	5.100199	5.48193	3.879169	6.772737	
assets_log	6.826088	7.077675	5.461724	8.44481	
debt_to_assets	.3175959	.2583957	.0842344	.4181624	
Observations	157571				

	min	max	sd	skewness	kurtosis
prcodavg_log	-8.517193	8.444257	1.715849	-.8991966	4.850931
weekly_death	0	1934	250.1067	3.339187	15.49622
sales_log	-6.907755	11.86126	2.558768	-.8952791	4.493462
assets_log	-6.907755	13.2207	2.489068	-.8969193	5.666613
debt_to_assets	0	144	1.545856	76.63965	6635.234

This table manifests the descriptive statistics for the log values of data, with mean, median (p50), 25th percentile (p25), 75th percentile (p75), minimum, maximum, standard deviation (sd), skewness, and kurtosis.

Variable names were indicated in table 1 on page IX

Table 5: Simple Regressions on Covid Death Cases

	(1) prcodavg	(2) prcodavg_log	(3) prcodavg_log
weekly_death	-0.00530***		-0.000223***
	(0.00111)		(0.0000147)
weekly_death_log		-0.0157***	
		(0.00441)	
_cons	55.36***	3.167***	3.185***
	(0.400)	(0.0229)	(0.00381)
N	156444	47122	147093

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(1): OLS on index weekly fatalities on index stock prices;
(2): OLS on log value of weekly death and log stock prices;
(3): OLS on the impact of weekly fatalities on stock prices expressed as logs- this is used text

Table 6: Regression using Interaction terms to compare the two waves with Death Cases

	(1) prcodavg_log	(2) prcodavg_log
weekly_death	-0.000259***	-0.000173***
	(0.0000236)	(0.0000166)
1.time_check	-0.147***	
	(0.0153)	
1.time_check × weekly_death	0.0000857*	
	(0.0000346)	
2.time_check		0.438
		(0.364)
2.time_check × weekly_death		0.00320*
		(0.00159)
_cons	3.257***	3.148***
	(0.0130)	(0.00676)
N	64125	64125

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS to compare the impact of increasing weekly fatalities when infection cases. First rose and when they started to increase considerable in autumn, that is the second wave.
(1): OLS using Interaction terms. Time check has the value 1 for week 1-27 in 2020. (2): OLS using Interaction terms: Time check is has the value 2 for week 42-50 in 2020.

Table 7: Regression using Interaction terms to compare the two waves with fatalities

	(1)	(2)
	prcodavg_log	prcodavg_log
weekly_cases	-0.00000383***	-0.00000279***
	(0.000000542)	(0.000000420)
1.time_check	-0.113***	
	(0.0154)	
1.time_check × weekly_cases	-0.00000354***	
	(0.00000105)	
2.time_check		0.243
		(0.288)
2.time_check × weekly_cases		0.0000473***
		(0.00000998)
_cons	3.228***	3.131***
	(0.0132)	(0.00659)
N	64125	64125

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS to check for the impact of weekly cases on stock prices in the two waves.

(1): OLS using Interaction terms. Time check has the value 1 for week 1-27 in 2020. (2): OLS using Interaction terms: Time check is has the value 2 for week 42-50 in 2020.

Table 8: Regression Week First Wave

	(1) week_12	(2) week_13	(3) week_14	(4) week_15	(5) week_16	(6) week_17	(7) week_18	(8) week_19	(9) week_20	(10) week_21
weekly_death	-0.00900***	-0.00219***	-0.000705***	-0.000371***	-0.000290***	-0.000274***	-0.000260***	-0.000222***	-0.000311***	-0.000206+
	(0.00234)	(0.000552)	(0.000132)	(0.0000792)	(0.0000638)	(0.0000674)	(0.0000672)	(0.0000657)	(0.0000898)	(0.000110)
_cons	3.091***	3.121***	3.133***	3.166***	3.167***	3.186***	3.196***	3.182***	3.178***	3.163***
	(0.0280)	(0.0281)	(0.0270)	(0.0272)	(0.0279)	(0.0278)	(0.0280)	(0.0280)	(0.0286)	(0.0291)
N	3117	3179	3170	3185	3187	3182	3198	3210	3204	3215

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS to compare the impact of weekly fatalities on log stock prices for different weeks during the first wave of infections. Considered are (1): Week 12; (2):Week 13; (3): Week 14; (4): Week 15; (5): Week 16; (6): Week 17; (7): Week 18; (8): Week 19; (9): Week 20; (10): Week 21

Table 9: Regression Week Second Wave

	(1) week_41	(2) week_42	(3) week_43	(4) week_44	(5) week_45	(6) week_46	(7) week_47	(8) week_48
weekly_death	0.00273+	0.00308+	0.00295+	0.00500*	0.00982***	0.0103***	0.00638***	0.00716***
	(0.00159)	(0.00168)	(0.00167)	(0.00254)	(0.000112)	(0.000120)	(0.0000749)	(0.0000837)
_cons	3.132***	3.160***	3.176***	3.179***	3.192***	3.188***	3.184***	3.195***
	(0.0340)	(0.0340)	(0.0340)	(0.0342)	(0.0342)	(0.0344)	(0.0347)	(0.0347)
N	1629	1621	1619	1618	1609	1611	1610	1614

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS to compare the impact of weekly fatalities on log stock prices during the second wave of infections. Considered are (1): Week 41; (2): Week 42; (3): Week 43; (4): Week 44; (5): Week 45; (6): Week 46; (7): Week 47; (8): Week 48

Table 10: Impact on stock prices in different industries

	Dependent Variable: Stock Price				
sic	1	2	3	4	5
Industries	Mining	Construction	Manufacturing	Transport_Communication	Wholesale_trade
weekly_death	-0.000253***	-0.000300***	-0.000307***	-0.000272***	-0.000294***
	(0.0000182)	(0.0000179)	(0.0000250)	(0.0000186)	(0.0000182)
sic_dummy	-1.009***	-0.0267	-0.157***	0.193***	-0.0668**
	(-0.0191)	(-0.0306)	(-0.0093)	(-0.0156)	(-0.0249)
sic_dummy × weekly_death	-0.000410***	0.000513***	0.0000375	-0.000236***	0.000066
	(-0.0000664)	(-0.0000918)	(-0.0000355)	(-0.0000607)	(-0.0000727)
Constant	2.992***	2.928***	3.007***	2.913***	2.930***
	(0.00476)	(0.00470)	(0.00667)	(0.00489)	(0.00474)
Observations	156444	156444	156444	156444	156444

	Continuation - Dependent Variable: Stock Price			
sic	6	7	8	10
Industries	Retail	Finance_Insurance	Service	Agriculture_Fishing_Foresty
weekly_death	-0.000288***	-0.000290***	-0.000342***	-0.000289***
	(0.0000183)	(0.0000182)	(0.0000193)	(0.0000179)
sic_dummy	0.372***	0.899***	0.212***	-0.124*
	(-0.0177)	(-0.0187)	(-0.0122)	(-0.0561)
sic_dummy × weekly_death	-0.00000327	-0.0000934	0.000278***	-0.000369***
	(-0.0000651)	(-0.0000709)	(-0.0000478)	(-0.000103)
Constant	2.908***	2.891***	2.885***	2.929***
	(0.00482)	(0.00476)	(0.00512)	(0.00467)
Observations	156444	156444	156444	156444

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS to compare the sensitivity to weekly death in industries. Weekly death measures the impact of increasing death, if the respective sic_dummy is zero. sic_dummy shows the impact of a industry on companies stock price when weekly death are zero. And the last row visualizes the impact of weekly death in the considered industry (if that sic_dummy is 1). (1): Mining; (2): Construction; (3): Manufacturing; (4): Transport and Communication; (5): Wholesale Trade; (6): Retail; (7): Finance, Insurance and Real Estate; (8): Service; (9): Agriculture, Fishing and Forestry.

Table 11: Impact on Retail Companies

	(1) prcodavg_log	(2) prcodavg_log
weekly_death	-0.000289***	-0.000176***
	(0.0000181)	(0.0000300)
retail_dummy=0	0	0
	(.)	(.)
retail_dummy=1	0.499***	0.535***
	(0.0230)	(0.0445)
retail_dummy=2	0.696***	0.717***
	(0.0263)	(0.0582)
retail_dummy=3	0.263***	0.176**
	(0.0299)	(0.0621)
retail_dummy=4	0.978***	1.231***
	(0.0379)	(0.0740)
retail_dummy=6	1.027***	1.136***
	(0.0508)	(0.111)
retail_dummy=0 × weekly_death	0	0
	(.)	(.)
retail_dummy=1 × weekly_death	0.000869***	0.00103***
	(0.000108)	(0.000152)
retail_dummy=2 × weekly_death	0.000486***	0.000223
	(0.000131)	(0.000143)
retail_dummy=3 × weekly_death	0.0000346	0.000213
	(0.000116)	(0.000243)
retail_dummy=4 × weekly_death	-0.0000492	-0.00198***
	(0.000116)	(0.000338)
retail_dummy=6 × weekly_death	0.00217***	0.000633
	(0.000413)	(0.00111)
Constant	2.908***	2.795***
	(0.00476)	(0.00988)
Observations	156444	46379

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS further clustered using Interaction terms to check the effects to different retail companies. Weekly Death shows the effect to log stock prices when the respective Retail subgroup is not considered (the variable is zero), retail_dummy shows the log stock price reaction, when weekly death are zero. And the Interaction term shows the sensitivity of stock prices to weekly death in the respective retail cluster group. Retail_dummy=1: Baseline, all other sectors; Retail_dummy=1: Grocery and Food; Retail_dummy=2: Clothing; Retail_dummy=3: Eating and Drinking places; Retail_dummy=4: Auto Supply and Gasoline; Retail_dummy=6: Home Building materials

Table 12: Impact on Manufacturing companies

	(1)
	prcodavg_log
weekly_death	-0.000254***
	(0.0000165)
0.manu_dummy	0
	(.)
1.manu_dummy	0.914***
	(0.0463)
2.manu_dummy	-0.362***
	(0.0189)
3.manu_dummy	-0.116***
	(0.0318)
4.manu_dummy	-0.788***
	(0.0109)
5.manu_dummy	0.552***
	(0.0276)
6.manu_dummy	0.194***
	(0.0475)
0.manu_dummy × weekly_death	0
	(.)
1.manu_dummy × weekly_death	-0.000226
	(0.000138)
2.manu_dummy × weekly_death	0.000251***
	(0.0000702)
3.manu_dummy × weekly_death	-0.000647**
	(0.000241)
4.manu_dummy × weekly_death	0.000335***
	(0.0000391)
5.manu_dummy × weekly_death	0.000565***
	(0.0000620)
6.manu_dummy × weekly_death	0.000482*
	(0.000200)
_cons	3.306***
	(0.00417)
N	147095

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
OLS taking log stock price clustered for Manufacturing industry using Interaction terms.

Weekly death shows the effect of increasing weekly death on log stock prices when the manu_dummy=0. The dummy variables show the impact on stock prices if the respective industry is zero (not considered). And the Interaction term displays the sensitivity in the respective manufacturing cluster for weekly death. Manu_dummy=0: Baseline- all other sectors considered; Manu_dummy=1: Aircraft; Manu_dummy=2: Electronics, Computer supply, TV and radio, Semiconductors; Manu_dummy=3: Metal, Steel and Glass; Manu_dummy=4: Chemicals and Pharmaceuticals; Manu_dummy=5: Cigarette's and Tobacco; Manu_dummy=6: Food and Alcohol

Table 13: Impact on States (1)

	(1) california	(2) colorado	(3) texas	(4) florida	(5) pennsylvania	(6) georgia	(7) illinois
weekly_death	0.000171***	-0.00117**	-0.000232***	-0.0000682	-0.000200*	-0.000289*	-0.000356***
	(0.0000317)	(0.000382)	(0.0000253)	(0.0000507)	(0.0000796)	(0.000129)	(0.0000773)
_cons	3.139***	2.613***	2.876***	3.001***	3.088***	3.379***	3.478***
	(0.0104)	(0.0194)	(0.0101)	(0.0181)	(0.0176)	(0.0191)	(0.0162)
N	25279	5069	17837	6295	6784	4840	7649

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS impacts of weekly deaths on stock prices in different states. (1): California; (2): Colorado; (3): Texas; (4): Florida; (5): Pennsylvania; (6): Georgia; (7): Illinois

Table 14: Impact on States (2)

	(1) new_york	(2) connecticut	(3) massachusetts	(4) north_carolina	(5) new_jersey	(6) ohio	(7) virginia
weekly_death	-0.000130*	-0.000285	-0.000140**	-0.0000882	-0.000105*	-0.00101***	-0.000987*
	(0.0000531)	(0.000175)	(0.0000541)	(0.000339)	(0.0000519)	(0.000214)	(0.000395)
_cons	2.938***	3.645***	3.140***	3.614***	2.724***	3.274***	3.798***
	(0.0152)	(0.0265)	(0.0140)	(0.0259)	(0.0222)	(0.0211)	(0.0276)
N	9474	3160	11385	3442	4603	4492	3268

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS impacts of weekly deaths on stock prices in different states. (1): New York; (2): Connecticut; (3): Massachusetts; (4): North Carolina; (5): New Jersey; (6): Ohio; (7): Virginia

Table 15: IV for Stay Home Order Policy with log Prices

Dependent Variable: procdavg_log					
	(1) OLS	(2)	(3)	(4)	(5)
Instrumental Variables		Polit_main	Polit_last_election	Uninsured	HH_over_65
Stay-home-order	-0.0306***	-3.554***	-2.329***	-0.161***	-0.553***
	(0.00757)	(0.275)	(0.169)	(0.0130)	(0.0277)
Constant	3.053***	5.746***	4.759***	3.149***	3.441***
	(0.00712)	(0.208)	(0.125)	(0.0107)	(0.0211)
N	94057	82231	94057	94057	94057
IV_stage_1	.	0.0682 ***	0.0854 ***	-23.42 ***	0.0328 ***
IV_st1_p_value	.	0	0	0	0
F_stage_1	.	245.9	374.7	47232.9	7890.0

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS with Dependent Variable log of Stock Prices using Instrumental Variables on Stay Home Order with two stage least square method. First stage estimation coefficients are shown IV_stage_1 and IV_st1_p_value its respective pvalue. F_stage_1 shows the Fvalue of the first stage result. All instruments are significant in the first stage estimation.

Following are explanations for each instrumental variables. (1): Senate Representation in the 116 Congress: 0 is only democratic party representation, 1 only republican party representation, mixed represented states are not considered. (2): Using the outcomes of the Senate Representation in the 117 Congress election in November 2020, if not yet elected take the presidential election result. 0 represents Democratic Party and 1 Republican Party. (3): Percentage of uninsured households. (4): Share of households with at least one member over 65.

Table 16: IV Regression Stay Home Order

Dependent Variable: procdavg_log	(1)	(2)	(3)	(4)
Instrumental Variables	Polit_main	Polit_last_election	Uninsured	HH_over_65
stay_home_order	-7.280***	-4.027***	-0.791***	-0.171***
	(0.931)	(0.328)	(0.0244)	(0.0106)
sic	-0.0000267+	0.0000206***	0.0000567***	0.0000636***
	(0.0000145)	(0.00000558)	(0.00000190)	(0.00000177)
sales_log	0.316***	0.243***	0.218***	0.213***
	(0.0187)	(0.00604)	(0.00246)	(0.00230)
cash_log	0.228***	0.224***	0.222***	0.222***
	(0.0102)	(0.00532)	(0.00238)	(0.00223)
debt_to_assets	-0.890***	-0.642***	-0.700***	-0.711***
	(0.0721)	(0.0377)	(0.0166)	(0.0156)
_cons	6.430***	3.964***	1.514***	1.045***
	(0.715)	(0.250)	(0.0230)	(0.0152)
N	73490	84305	84305	84305

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS with Dependent Variable log of Stock Prices using Instrumental Variables on Stay Home Order with other independent variables, those are the operating industry, the log sales of the company, the log cash held, leverage of the company. The columns show impact of stay home order on stock prices with different Instrumental Variables. Following are explanations for each instrumental variables
(1): Senate Representation in the 116 Congress: 0 is only democratic party representation, 1 only republican party representation, mixed represented states are not considered. (2): Using the outcomes of the Senate Representation in the 117 Congress election in November 2020, if not yet elected take the presidential election result. 0 represents Democratic Party and 1 Republican Party. (3): Percentage of uninsured households. (4): Share of households with at least one member over 65.

Table 17: Further Regression with Balance Sheet Structure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	prcodavg_log	prcodavg_log	prcodavg_log	prcodavg_log	prcodavg_log	prcodavg_log	prcodavg_log
weekly_death	-0.000223***	-0.000218***	-0.0000964***	-0.000165***	-0.000259***	-0.000249***	-0.000239***
	(0.0000147)	(0.0000145)	(0.0000131)	(0.0000127)	(0.0000124)	(0.0000122)	(0.0000123)
sic		0.0000940***	0.0000710***	0.0000818***	0.0000726***	0.0000825***	0.0000741***
		(0.00000178)	(0.00000151)	(0.00000149)	(0.00000147)	(0.00000145)	(0.00000145)
sales_log			0.345***	0.0979***	0.115***	0.108***	0.234***
			(0.00150)	(0.00347)	(0.00346)	(0.00339)	(0.00195)
assets_log				0.282***	0.137***	0.180***	
				(0.00368)	(0.00413)	(0.00434)	
cash_log					0.166***	0.147***	0.190***
					(0.00213)	(0.00214)	(0.00197)
debt_to_assets						-0.693***	-0.602***
						(0.0195)	(0.0173)
_cons	3.185***	2.766***	1.053***	0.294***	0.550***	0.526***	0.965***
	(0.00381)	(0.00851)	(0.0114)	(0.0145)	(0.0147)	(0.0146)	(0.0110)
N	147093	147093	135997	135984	135610	134791	134804

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS on impacts of following variables: Covid-19 weekly death, Industry, Sales expressed as logs, Assets (Firm Size) log, log cash available and leverage on the log stock prices.

Table 18: IV for Weekly Death Cases with log Prices

Dependent Variable: procdavg_log				
	(1)Baseline	(2)	(3)	(4)
Instrumental Variables		Households_over_65	Uninsured	Age_Structure
weekly_death	-0.000223***	-0.00284***	-0.00487***	-0.00117***
	(0.0000147)	(0.000178)	(0.000223)	(0.000208)
Constant	3.185***	3.448***	3.653***	3.280***
	(0.00381)	(0.0184)	(0.0229)	(0.0213)
N	147095	147095	147095	147095
IV_stage_1	.	-1675.6***	4.785***	-8.255***
IV_st1_p_value	.	0	0	0
F_stage_1	.	1176.0	1051.1	722.5

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS with Dependent Variable log of Stock Prices using Instrumental Variables on weekly death using two stage least square method. Results of first stage regression. IV_stage_1 shows the coefficient for the first stage regression and IV_st1_p_value its respective pvalue. F_stage_1 shows the Fvalue of the first stage result. All of our instruments are significant in the first stage regression.

Following are explanations for instrumental variables. (1): Baseline case as used in the last table. (2): IV with Households share with members over 65. (3): Percentage of uninsured households. (4): Age structure in the respective state, that is the percentage of inhabitants over 65.

Table 19: IV Regression Weekly Death

Dependent Variable: procdavg_log				
	(1) Baseline	(2)	(3)	(4)
Instrumental Variables		Households_over_65	Uninsured	Age_Structure
weekly_death	-0.000239***	-0.00227***	-0.00473***	-0.000967***
	(0.0000123)	(0.000149)	(0.000152)	(0.000190)
sic	0.0000741***	0.0000723***	0.0000700***	0.0000734***
	(0.00000145)	(0.00000156)	(0.00000203)	(0.00000143)
sales_log	0.234***	0.198***	0.155***	0.222***
	(0.00195)	(0.00335)	(0.00381)	(0.00387)
cash_log	0.190***	0.226***	0.271***	0.203***
	(0.00197)	(0.00334)	(0.00376)	(0.00389)
debt_to_assets	-0.602***	-0.557***	-0.502***	-0.586***
	(0.0173)	(0.0135)	(0.0173)	(0.0127)
_cons	0.965***	1.189***	1.459***	1.045***
	(0.0110)	(0.0202)	(0.0227)	(0.0235)
N	134804	134804	134804	134804

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS with Dependent Variable log of Stock Prices using Instrumental Variables of weekly death with added independent variables, those are the operating industry, the log sales of the company, the log cash held, leverage of the company. The columns visualize the impact of weekly death on average stock prices if instrumental variables are used. Following are explanations for each instrumental variables.
(1): Baseline case as used in the last table. (2): IV with Households share with members over 65. (3): Percentage of uninsured households. (4): Age structure in the respective state, that is the percentage of inhabitants over 65.

Table 20: Panel Regression

	(1)	(2)	(3)	(4)	(5)
	prcodavg_log	prcodavg_log	prcodavg_log	prcodavg_log	prcodavg_log
weekly_death	-0.000137***	-0.000137***	-0.000116***	-0.000125***	-0.000118***
	(0.0000177)	(0.0000177)	(0.0000166)	(0.0000162)	(0.0000161)
sales_log			0.299***	0.298***	0.281***
			(0.0222)	(0.0221)	(0.0208)
cash_log				0.0172*	0.0188**
				(0.00680)	(0.00684)
debt_to_assets					-0.518***
					(0.0938)
_cons	3.063***	3.063***	1.570***	1.498***	1.741***
	(0.0337)	(0.0337)	(0.124)	(0.130)	(0.126)
N	147093	147093	135997	135623	134804

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel Regression on the impacts of the variables for company i at time t on company i stock price at time t.

Table 21: Time Fixed Effects

Dep. Variable	prcodavg_log	
weekly_death	-0.000117***	0.00000256
	(0.0000161)	(0.0000180)
sales_log	0.276***	0.253***
	(0.0215)	(0.0213)
cash_log	0.0168*	0.0434***
	(0.00693)	(0.00719)
debt_to_assets	-0.521***	-0.429***
	(0.0958)	(0.0958)
1.time_variable		0
		(.)
2.time_variable		0.0612***
		(0.00261)
3.time_variable		0.0717***
		(0.00372)
4.time_variable		0.0820***
		(0.00388)
5.time_variable		0.0988***
		(0.00402)
6.time_variable		0.114***
		(0.00387)
7.time_variable		0.128***
		(0.00468)
8.time_variable		0.154***
		(0.00481)
9.time_variable		0.160***
		(0.00518)
10.time_variable		0.131***
		(0.00591)
11.time_variable		0.136***
		(0.00599)
12.time_variable		0.135***
		(0.00619)
13.time_variable		0.123***
		(0.00707)
14.time_variable		0.132***
		(0.00728)
15.time_variable		0.138***
		(0.00751)

Continued from previous column

Dep. Variable	prcodavg_log
16.time_variable	0.134***
	(0.00740)
17.time_variable	0.138***
	(0.00736)
18.time_variable	0.133***
	(0.00743)
19.time_variable	0.123***
	(0.00760)
20.time_variable	0.101***
	(0.00797)
21.time_variable	0.0894***
	(0.00837)
22.time_variable	0.0587***
	(0.00872)
23.time_variable	0.0717***
	(0.00880)
24.time_variable	0.0803***
	(0.00905)
25.time_variable	0.0980***
	(0.00930)
26.time_variable	0.0997***
	(0.00955)
27.time_variable	0.100***
	(0.00978)
28.time_variable	0.0976***
	(0.00980)
29.time_variable	0.0916***
	(0.00999)
30.time_variable	0.0942***
	(0.0104)
31.time_variable	0.0772***
	(0.0108)
32.time_variable	0.0419***
	(0.0111)
33.time_variable	0.0192+
	(0.0115)
34.time_variable	0.0291*
	(0.0116)
35.time_variable	0.0161
	(0.0118)
36.time_variable	0.0291*

Continued from previous column

Dep. Variable	prcodavg_log
	(0.0117)
37.time_variable	0.0705***
	(0.0111)
38.time_variable	0.0723***
	(0.0113)
39.time_variable	0.0507***
	(0.0114)
40.time_variable	0.00676
	(0.0121)
41.time_variable	0.000527
	(0.0123)
42.time_variable	0.0192
	(0.0124)
43.time_variable	0.0315*
	(0.0123)
44.time_variable	0.0414***
	(0.0123)
45.time_variable	0.0543***
	(0.0124)
46.time_variable	0.0512***
	(0.0127)
47.time_variable	0.0468***
	(0.0130)
48.time_variable	0.0622***
	(0.0131)
49.time_variable	0.0584***
	(0.0130)
50.time_variable	0.0733***
	(0.0129)
51.time_variable	0.0918***
	(0.0128)
52.time_variable	0.0990***
	(0.0127)
53.time_variable	0.108***
	(0.0129)
54.time_variable	0.117***
	(0.0130)
55.time_variable	0.132***
	(0.0132)
56.time_variable	0.114***
	(0.0135)

Continued from previous column

Dep. Variable	prcodavg_log
57.time_variable	0.0960***
	(0.0137)
58.time_variable	0.107***
	(0.0138)
59.time_variable	0.112***
	(0.0141)
60.time_variable	0.103***
	(0.0142)
61.time_variable	0.00292
	(0.0145)
62.time_variable	-0.0620***
	(0.0152)
63.time_variable	-0.266***
	(0.0161)
64.time_variable	-0.394***
	(0.0172)
65.time_variable	-0.302***
	(0.0170)
66.time_variable	-0.301***
	(0.0170)
67.time_variable	-0.203***
	(0.0171)
68.time_variable	-0.205***
	(0.0181)
69.time_variable	-0.170***
	(0.0180)
70.time_variable	-0.117***
	(0.0174)
71.time_variable	-0.111***
	(0.0177)
72.time_variable	-0.131***
	(0.0175)
73.time_variable	-0.0691***
	(0.0170)
74.time_variable	-0.0292+
	(0.0166)
75.time_variable	0.0368*
	(0.0160)
76.time_variable	-0.000434
	(0.0160)
77.time_variable	0.000169

Continued from previous column

Dep. Variable	prcodavg_log
	(0.0164)
78.time_variable	-0.0281^{+}
	(0.0168)
79.time_variable	-0.0445**
	(0.0170)
80.time_variable	-0.0586***
	(0.0175)
81.time_variable	-0.0194
	(0.0173)
82.time_variable	-0.0105
	(0.0180)
83.time_variable	-0.00423
	(0.0182)
84.time_variable	0.0341^{+}
	(0.0180)
85.time_variable	0.0521**
	(0.0178)
86.time_variable	0.0404*
	(0.0179)
87.time_variable	0.0473**
	(0.0177)
88.time_variable	0.0345*
	(0.0174)
89.time_variable	0.0155
	(0.0174)
90.time_variable	0.0167
	(0.0173)
91.time_variable	-0.0119
	(0.0175)
92.time_variable	0.00214
	(0.0178)
93.time_variable	0.133*
	(0.0519)
94.time_variable	0.132*
	(0.0543)
95.time_variable	0.119*
	(0.0552)
96.time_variable	0.206***
	(0.0526)
97.time_variable	0.403***
	(0.0146)

Continued from previous column

Dep. Variable		prcodavg_log
98.time_variable		0.355***
		(0.0145)
99.time_variable		0.353***
		(0.0154)
100.time_variable		0.381***
		(0.0151)
_cons	1.841***	1.771***
	(0.132)	(0.128)
N	134804	134804

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Time fixed effects on log of stock prices is measured in this table.
1.time.variables is the week 1 of 2019 and week 1 of 2020 starts from $52 + 1$
Fixing the time trend, weekly_death does not show significant influence on stock price.
Stock prices, from time 62 to 74, which was in early 2020, first wave Covid-19 shock.
For latter weeks in 2020, stock prices overall are not significantly influenced by Covid-19.

Concluded

Table 22: Robustness Check 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	Panel_1	OLS_2	Panel_2	OLS_3	Panel_3	OLS_4	Panel_4	OLS_5	Panel_5
death_fraction	-19.42***	-20.12***	-18.77***	-20.12***	-5.708**	-18.39***	-24.15***	-18.18***	-21.80***	-17.45***
	(2.040)	(1.844)	(2.025)	(1.844)	(1.826)	(1.743)	(1.743)	(1.659)	(1.717)	(1.648)
sic			0.0000941***	0.0000951***	0.0000710***	0.0000727***	0.0000670***	0.0000684***	0.0000742***	0.0000750***
			(0.00000178)	(0.0000170)	(0.00000151)	(0.0000146)	(0.00000146)	(0.0000139)	(0.00000145)	(0.0000139)
sales_log					0.346***	0.195***	0.216***	0.298***	0.236***	0.280***
					(0.00149)	(0.0205)	(0.00189)	(0.0221)	(0.00194)	(0.0207)
cash_log							0.196***	0.0172*	0.188***	0.0190**
							(0.00197)	(0.00684)	(0.00196)	(0.00689)
debt_to_assets									-0.603***	-0.524***
									(0.0173)	(0.0943)
_cons	3.175***	3.063***	2.756***	2.641***	1.045***	1.794***	0.881***	1.192***	0.953***	1.408***
	(0.00378)	(0.0337)	(0.00850)	(0.0794)	(0.0113)	(0.121)	(0.0107)	(0.142)	(0.0110)	(0.138)
N	147093	147093	147093	147093	135997	139768	135623	135623	134804	134804

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robustness Check OLS and Panel on the impact of the variables on stock prices when the weekly Covid-19 fatalities relative to inhabitants in the state are considered.

Table 23: Robustness Check 2

	(1) OLS	(2) Panel	(3) OLS_2	(4) Panel_2	(5) OLS_3	(6) Panel_3	(7) OLS_4	(8) Panel_4	(9) OLS_5	(10) Panel_5
weekly_death	-0.000281***	-0.000146***	-0.000274***	-0.000146***	-0.000150***	-0.000146***	-0.000346***	-0.000167***	-0.000336***	-0.000167***
	(0.0000185)	(0.0000233)	(0.0000182)	(0.0000233)	(0.0000154)	(0.0000225)	(0.0000142)	(0.0000218)	(0.0000141)	(0.0000220)
sic			0.000109***	0.000102***	0.0000501***	0.0000682***	0.0000497***	0.0000646***	0.0000548***	0.0000671***
			(0.00000230)	(0.0000217)	(0.00000180)	(0.0000181)	(0.00000167)	(0.0000174)	(0.00000166)	(0.0000175)
sales_log					0.412***	0.188***	0.270***	0.193***	0.286***	0.188***
					(0.00189)	(0.0215)	(0.00192)	(0.0217)	(0.00198)	(0.0208)
cash_log							0.279***	0.0410***	0.268***	0.0399***
							(0.00248)	(0.0108)	(0.00247)	(0.0108)
debt_to_assets									-0.489***	-0.103
									(0.0173)	(0.0848)
_cons	2.771***	2.733***	2.286***	2.281***	0.707***	1.657***	0.261***	1.487***	0.354***	1.532***
	(0.00486)	(0.0421)	(0.0111)	(0.102)	(0.0128)	(0.123)	(0.0121)	(0.132)	(0.0124)	(0.132)
N	140682	140682	140682	140682	131332	131332	130942	130942	130142	130142

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robustness Check: OLS and Panel on impact of variables on independent variable stock prices when the largest companies, that are the companies in the top 10% of assets (outliers) are excluded.

Table 24: Robustness Check 3

	(1) OLS	(2) Panel	(3) OLS_2	(4) Panel_2	(5) OLS_3	(6) Panel_3	(7) OLS_4	(8) Panel_4	(9) OLS_5	(10) Panel_5
weekly_death	-0.000324***	-0.000169***	-0.000314***	-0.000169***	-0.000189***	-0.000165***	-0.000359***	-0.000185***	-0.000345***	-0.000184***
	(0.0000178)	(0.0000226)	(0.0000176)	(0.0000226)	(0.0000151)	(0.0000217)	(0.0000141)	(0.0000212)	(0.0000139)	(0.0000213)
sic			0.0000993***	0.0000952***	0.0000476***	0.0000653***	0.0000490***	0.0000627***	0.0000544***	0.0000652***
			(0.00000225)	(0.0000211)	(0.00000177)	(0.0000176)	(0.00000167)	(0.0000170)	(0.00000165)	(0.0000170)
sales_log					0.382***	0.186***	0.254***	0.191***	0.272***	0.186***
					(0.00183)	(0.0207)	(0.00188)	(0.0209)	(0.00195)	(0.0200)
cash_log							0.253***	0.0390***	0.243***	0.0393***
							(0.00245)	(0.0108)	(0.00243)	(0.0106)
debt_to_assets									-0.546***	-0.121
									(0.0189)	(0.0904)
_cons	2.727***	2.710***	2.288***	2.289***	0.796***	1.642***	0.388***	1.475***	0.485***	1.521***
	(0.00475)	(0.0410)	(0.0108)	(0.0996)	(0.0126)	(0.121)	(0.0122)	(0.132)	(0.0124)	(0.132)
N	140507	140507	140507	140507	131156	131156	130721	130721	129949	129949

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robustness Check: OLS and Panel on the impact of the variables on stock prices excluding companies that are in the top 10% of the market value in the data set (outliers).