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The Impact of Corona-News on Investors' Attention to Earnings Announcements

An Empirical Analysis of the Norwegian Stock Market

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Abstract

We use corona-news readership to analyze the short-term effects of investor attention on financial market reactions to earnings announcements in 2020. Our findings show that corona-news does have a distracting effect on other news. As a consequence, we find that investors are less likely to trade when they pay attention to news about corona. On average a one standard deviation increase in corona-news readership reduces the short-term abnormal traded volume by 23% following an earnings announcement. These findings suggest that behavioral effects such as attention does translate to financial market decisions. They are also robust after controlling for other possible explanations. We further investigate if corona-readership has a negative effect on volatility and returns but are not able to establish a significant relationship.

Acknowledgments

We want to thank our supervisor Maximilian Rohrer for his valuable advice and crucial comments throughout this whole process. He provided us with encouragement, suggestions, and constructive criticism that contributed immensely to the paper. Further, we are very grateful to Thomas Ingebretsen and other employees at NRK, who provided us with insights and news data, which made our analysis possible.

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1. Introduction

From its first discovery in Wuhan, China, in December 2019, the coronavirus (COVID-19) has spread rapidly throughout the world. In March 2020, the World Health Organization defined the new coronavirus as a global pandemic (World Health Organization, 2020). The impact of the pandemic has been severe. Almost one year after the virus was first discovered, 67 million people have been infected, and 1.5 million have died (John Hopkins University, 2020). The Norwegian government implemented measures such as limiting large social gatherings, travel restrictions, and widespread lockdowns to control the virus's impact. The government measures vary over time, and people therefore seek out information about allowed activities regularly.

Building on the behavioral economics literature, investors have a limited amount of attention. Stress and other forms of psychological distractions influence attention. Subsequently, an investor stressed about corona might pay extra close attention to news about the coronavirus at the expense of otherwise important information, such as investment opportunities. If enough investors neglect information about the stock market, it can lead to mispricing of stocks and market inefficiency.

We analyze an event in which investors' attention to new information is important, specifically the reaction to earnings announcements. Earnings announcements provide investors with new information about a company's financials and is a unique opportunity for investors to assess whether the company is worth investing in or not. Our main research question is:

"*Has the coronavirus pandemic affected stock market reactions to earnings announcements?*"

If the coronavirus has a distracting effect, we expect the reaction to earnings announcements to be lower for days where attention towards corona is high. On the other hand, if investors are equally attentive, corona should not influence their reaction. We measure the stock market reaction in three key metrics: traded volume, volatility, and return. To test this, we have developed three hypotheses. If it is true that inattention from corona affects the stock market reaction to earnings announcements:

(1) Abnormal volume on the days after an announcement will be less for days with higher corona-news readership than lower.

(2) Abnormal volatility on the days after an announcement will be less for days with higher corona-news readership than lower.

(3) Abnormal return will have a weaker short-term reaction in the direction of the earnings surprise for days with a higher corona-news readership than days with lower.

Our first finding is that corona-news diverts attention from other news. Days with high readership of corona articles have a significantly lower readership of other articles. This result confirms that corona-readership is a suitable proxy to measure distraction. Further, in stock market reactions, we find that: (1) Abnormal volume reactions to earnings announcements have a significant negative relationship with corona-news readership. On average a one standard deviation increase in corona-news readership reduces the short-term reaction by 23%. (2) Abnormal volatility reactions have a negative, but non-significant relationship with pageviews on corona articles. This effect amounts to a 1.54 basis points decrease in abnormal volatility with an increase by one standard deviation in pageviews on corona articles. (3) Similarly for returns, we find a non-significant negative relationship. We find that the market reaction is approximately 12% less sensitive to earnings announcements on days with relatively high readership of corona articles than days with low.

In our analysis, we use readership statistics on corona articles as a proxy for distraction. Readership statistics include pageviews and read time of articles published in our time period. The time period for this analysis is from the beginning of February until the end of September 2020. Readership statistics give a clear and direct indication of how many people are engaged with articles about corona compared to articles on other topics. The data consist of all articles from the second-largest source of corona-news in Norway, NRK. Using the subject specification set by the journalist who wrote the article, we categorize the articles as either a corona article or other article. Our analysis consists of two main parts:

In the first part of our analysis, we investigate if corona news diverts attention away from other news. We do this by running multiple linear regressions on how readership of other news is affected by readership of corona news. To control for seasonal changes in readership, indicator variables for month and day of week are included. The purpose of this part of the analysis is to establish corona-news readership as a suitable proxy for distraction for the second part.

In the second part of our analysis, we look at how the market reacts in the days surrounding an earnings announcement. We investigate the effect of news by looking at the relationship of pageviews on corona-news and daily stock market reactions. We compare how abnormal volume, volatility, and return differ on the days with a higher corona readership and lower. Opportunistic managers might want to publish the announcement on days where attention is lower to hide bad results. Earnings announcements are scheduled events and can therefore, not be strategically published on days with higher readership of corona-news.

Our analysis's primary concern is to measure the effect of investor attention to corona, and not how corona-news affects companies' fundamentals. For example, news about travel-restrictions will undoubtedly have a fundamental effect on the aviation industry. We mitigate this by adjusting for industry-specific effects in our calculations of volume, volatility, and return. Further, our results may be a result of differences in firm characteristics. While it is hard to adjust for all companies' differences, we introduce several control variables to minimize this possibility. Our findings are still robust after the introduction of these variables.

To validate that our results are caused by inattention and not another consequence of the pandemic, we run placebo regressions. The key difference between two close competitors, one publishing an earnings announcement and one not, is the attention to this report's information. In the placebo models, the values for abnormal reactions are swapped with that of their closest competitor. The closest competitor is determined by market capitalization in the same industry on the same day. We thereby remove the element of attention. In the placebo regression, we find no significant relationship between the dependent variables and the amount of corona-news readership. This result further signifies that the effect on trading volume is caused by corona-news having a distracting effect.

Like many papers before, our results confirm that behavioral factors impact stock market reactions. In this case that investor inattention causes underreactions to new information on days with increased distraction from corona-news. Even though we do not identify a significant effect on returns we do identify depressed trading volume. This might suggest that price informativeness has suffered during the pandemic. We believe inexperienced retail investors have carried this cost.

The remaining parts of this paper are structured as follows. In Chapter 2 we discuss related literature. Chapter 3 presents all specifications on how we collected, cleaned, and processed our data. In Chapter 4 we present evidence of how readership of corona-news diverts attention from other articles. In Chapter 5 we build on the findings of the previous chapter to show how corona diverts investor attention away from financial information, by analyzing market reactions to earnings announcements. Chapter 6 explains our findings and discusses alternative explanations. Chapter 7 concludes our paper.

2. Literature Review

Our paper relates to research on corona and attention in relation to the stock market. In this chapter we will discuss how both relate to this paper and what our contributions are.

The effects of corona on stock markets have a small yet growing amount of research devoted to it. Many studies are concerned with explaining the unprecedented amount of volatility and negative returns at the height of the pandemic. Ashraf (2020) finds that countries stock market index fall with the number of confirmed cases and deaths. He, Sun, Zhang and Li (2020) study how the corona pandemic affected different industries' stock returns in China. They find that industries such as tech, healthcare, and education responded well to the pandemic. Other industries such as transportation and mining were hit negatively. These findings further signify the importance of adjusting for industry effects when analyzing the coronavirus' impact on the stock market. Baker et al. (2020) use a news-based approach to explain market reactions during the corona pandemic. In contrast to previous disease outbreaks, including the much deadlier Spanish flu, they find that corona-news can explain large daily moves in the U.S stock market between February through April 2020. They mainly focus on news that contain economic terms in relation to corona. In contrast, our study uses all news related to corona as a measure for attention. As far as we know, there have not yet been any other studies on how the corona-pandemic affected investors' attention.

The theory of investor inattention is part of the growing literature within behavioral finance that tries to explain market anomalies through psychological biases. Behavioral finance contradicts traditional works in finance as it argues that individuals are rational and always use all available information when making a decision. There are several market anomalies that the traditional models struggle to explain. For example, investors tend to sell "winners" and hold on to "losers" (Odean, 1998), the momentum effect in stock prices (Daniel, Hirshleifer, & Subrahmanyam, 1998), or investors' underreaction to newly released information. The latter is what this paper attempts to address; That investors underreact to earnings announcements.

DellaVigna and Pollet (2009) study the response in returns to companies' earnings. They use the weekend as a distraction proxy. Their findings show that earnings released on Fridays have a much lower initial reaction than other days of the week. About 40% of the initial return happens on the first day compared to other weekdays, where the initial reaction is 51%. A result that shows the effect inattention can have on the stock markets.

In another similar study, Hirshleifer, Lim, and Teoh (2009) analyze the effect of the number of competing earnings announcements on the subsequent return and traded volume. They find that both return and volume are negatively affected when investors are distracted by high amounts of competing information. Unlike these studies, we cannot find that corona-news readership as a proxy for distraction has a significant effect on returns. However, we are also able to find an effect on traded volume.

While these papers look at both long- and short-term reactions, in this paper, we only focus on the short term. As corona has caused a lot of market volatility, it would be difficult to separate the delayed effects to the earnings announcement information from reactions to new information in a long-term analysis.

In a more recent study on inattention, Focke, Ruenzi, and Ungehauer (2019) analyze whether advertising has a short-term effect on the stock markets. They hypothesize that advertising could increase attention towards a company and thereby increase their stock returns. They measure attention more directly, by for instance using google search statistics for companies. Similarly to our study, they cannot find a significant effect on either return or volatility.

All the studies on attention mentioned above are of the American stock market. Few studies have analyzed investors' inattention in the Norwegian stock market. Larsen and Thorsrud (2017) study the effect of news in the business newspaper Dagens Næringsliv on the Norwegian stock market returns. While they do not analyze attention, they show how news data can be used to analyze stock returns. Larsen and Thorsrud construct topics and sentiment in the news to estimate the magnitude of the news effect. For example, if many articles about oil are positive, they expect a positive return for oil companies. Their findings show that news can explain stock market returns. Compared to our study, they do not measure the attention to each news article in the form of readership, but rather the number of articles and their content.

This paper contributes to the financial literature firstly by analyzing the corona pandemic. More research is vital to better our understanding if a similar situation were to happen again. Secondly, our research focuses on what information individuals are attentive to and how it can affect stock market reactions during the pandemic in Norway. Lastly, our measurement for attention by using readership statistics on news articles is potentially a more sophisticated and accurate measure than previous studies on inattention.

3. Data and Summary Statistics

3.1 Data

NRK provided us with data on news article readership from the beginning of October 2019 until the end of September 2020. They are government-owned and one of the largest media firms in Norway. Compared to other major news sources in Norway, only *VG.no* had higher readership numbers. This insight was provided to us through a meeting with the online marketing firm, *Kobler*. The readership data from NRK includes the number of pageviews on an article, time spent reading in seconds, date of publication, title, and the article's subject. The subject of the article is set by the journalist who wrote it. By evaluating some articles ourselves, we concluded that this subject reflected the article's content in most cases. In total, NRK published 21.225 articles between October 2019 and September 2020. Out of these articles, 3.780 were categorized as corona articles. At the height of the corona-pandemic in March, approximately 75% of articles had corona as the topic.

Earnings announcement dates are collected from the Oslo Stock Exchange's NewsWeb, a website for company announcements. All companies listed are required by law to publish an earnings report with financial information for each half-year, according to § 5-12 of the Securities Trading Act (Verdipapirhandelloven, 2008). Even though it is not required by law, most companies also publish quarterly reports of their earnings. NewsWeb is a platform used to upload earnings reports as well as other forms of important information such as insider information or dividend payments. This led to several issues in our data collection process. The most common issue is companies mislabeling their quarterly reports as something else. For example, a quarterly report being labeled as "Other Information" or "Annual report", rather than "Half-year/quarterly report". With this in mind, we implement several steps to improve the accuracy of earnings announcement dates:

1. Include dates of earnings announcements uploaded to the wrong category.
2. Exclude dates that include reminders or invitations to the presentation of when their earnings announcements are published.
3. Exclude dates of other irrelevant information published under the "half-year / quarterly earnings" category.
4. Exclude annual report dates if they are published after their Q4-report since it contains no new information.

5. Exclude dates of companies uploading "updated" earnings announcements that only contain small changes or are formatted differently.

After these steps, we are left with 638 earnings announcements from the beginning of February until the end of September 2020. Due to the time-consuming nature of constructing earnings reports, they are usually published with a two-month delay. This results in most reports being published in February, May, August, and November.

For each company earnings announcement, we also collect data on earnings per share (EPS) for the corresponding quarter in 2020 and historic EPS values. Some companies report their earnings in a currency other than NOK. For example, Equinor ASA reports their earnings in USD, or Aega ASA that reports their earnings in EUR. For all instances where earnings are reported in a different currency, their earnings are converted to NOK using their earnings report's corresponding currency.

Out of the 268 companies listed on the Oslo Stock Exchange at the end of September 2020, 34 of them were listed in 2020. Since these companies lack historic earnings data, they are removed from our final dataset. Some of the remaining companies have missing observations and are also removed. The final data set contains 221 unique companies.

We match the remaining earnings announcement dates with the amount of corona-news readership and company-specific stock information for each date. All stock-specific data are collected from the Oslo Stock Exchange homepage and the Bloomberg terminal. For every stock listed on the Oslo Stock Exchange, we collect data on the closing price, trading volume, market capitalization, book-to-market, number of outstanding shares, and number of analysts with a financial analysis of the company uploaded on Bloomberg in the month leading up to the announcement. Stock prices, the book-to-market values, and market-capitalization are in NOK. We drop observations that have missing values in either of our variables. The final dataset contains 595 observations.

3.2 Definitions

Abnormal trading volume, $V_{c,t}$, is calculated using the difference between the log trading volume in NOK (number of trades · stock price), and the normalized trading volume in NOK. Normalized trading volume is the log of the average trading volume in NOK of the last 20 trading days for company c on day t, 10 days before day t:

$$V_{c,t} = \log\left(1 + NOKVolume_{c,t}\right) - \frac{1}{20}\sum_{k=t-31}^{t-10} \log\left(1 + NOKVolume_{c,k}\right) \tag{3.1}$$

We do not include the last two weeks of trading (10 days) because there might be abnormal trading leading up to the earnings announcement. Usually, volume refers to the actual number of trades of a security. However, we use volume measured in NOK, to compare companies of different stock prices and shares outstanding. The logarithm of volume is used to interpret the change in volume as percentages.

To ensure our calculations do not merely capture the market-wide change in traded volume, we also adjust for the market abnormal trading volume. Market reaction is calculated for each industry, with the industry classifications for each company being collected from the Oslo Stock Exchange’s website. Further, a company's trading volume within an industry influences the rest of the industry's market. For example, if Equinor experiences large abnormal trading volume, it makes up such a large part of the Energy sector that the rest of the energy industry market’s abnormal volume is also effected. To adjust for the correlation between a company's abnormal volume and the abnormal volume of the market, we remove each company from the calculation of the comparative market. The same logic applies to our calculations of volatility and return. The markets abnormal trading volume is calculated by taking the mean abnormal trading volume within each industry, less the company it is compared to. Abnormal volume, adjusted for industry is defined as:

$$AV_{c,i,t} = V_{c,i,t} - \frac{1}{N_i - 1}\sum_{d \in C: d \neq c} V_{d,i,t} \tag{3.2}$$

Where, $AV_{c,i,t}$ is the adjusted abnormal volume for company c in industry i on day t, $V_{c,i,t}$ is the unadjusted abnormal volume, N_i is the number of companies in industry i.

We use squared daily returns as a proxy for daily volatility. This measure is also known as the realized variance and is a popular proxy for return volatility. Daily return ($R_{c,t}$) is calculated by taking the log of the fraction of the closing price for company c on day t and the closing price the day before:

$$R_{c,t} = \log\left(\frac{Close_{c,t}}{Close_{c,t-1}}\right) \tag{3.3}$$

$$Volatility_{c,t} = R_{c,t}^2 \tag{3.4}$$

With a measure of daily volatility, we can calculate abnormal volatility. Similar to abnormal volume, we normalize by subtracting the mean daily volatility of the last 20 trading days, 10 days before day t:

$$VOLA_{c,t} = Volatility_{c,t} - \frac{1}{20}\sum_{t=k-31}^{k-10} Volatility_{c,k} \tag{3.5}$$

Further, we adjust for the market's abnormal volatility by subtracting the mean abnormal volatility within each industry, less the company it is compared to:

$$AVOLA_{c,i,t} = VOLA_{c,i,t} - \frac{1}{N_i - 1}\sum_{d\in C:d\neq c} VOLA_{d,i,t} \tag{3.6}$$

To calculate cumulative abnormal returns (CAR) following the earnings announcement date, we use a 2-day time window. The return of a given company is compared to the market return of companies within the same industry. This assumes that the expected return of a company's stock is equal to the expected return of the market it operates in. Values for return are winsorized to limit the impact of outliers. Let $R_{c,i,t}$ be the return for company c in industry i on day t and $MR_{c,i,t}$ be the market return for industry i of company c on day t.

$$CAR[0,1] = \prod_{t=k}^{k+1}(1 + R_{c,i,t}) - \prod_{t=k}^{k+1}(1 + MR_{c,i,t}) \tag{3.7}$$

The market return is defined as the return of the total market capitalization for each industry. This is calculated as the sum of the market capitalization, $Mcap_{d,c,i,t}$ of all companies d in industry i except company c.

$$MR_{c,i,t} = \log\left(\frac{\sum_{d\in C:d\neq c} Mcap_{d,i,t}}{\sum_{d\in C:d\neq c} Mcap_{d,i,t-1}}\right) \tag{3.8}$$

For each earnings announcement we calculate the earnings surprise. An earnings surprise is when a company's reported earnings differ from expectations. We define expected earnings per share using Brown & Kennelly's (1972) model for forecasting earnings:

$$\widehat{EPS_q} = EPS_{q-4} + \delta \tag{3.9}$$

Where, EPS_q is the earnings per share in quarter q, and δ is a drift term. The drift term is equal to the average quarterly change over the available historical data. It is a relatively simple model that assumes a seasonal pattern in earnings. Foster (1977) tested the predictability of the model and found the model to be sufficiently accurate.

Using the estimated earnings values, we calculate the earnings surprise associated with each earnings announcement. Earnings surprise is defined as the difference between the actual EPS and the estimated EPS, normalized by each company's stock price (Kothari, 2001). We define earnings surprise as:

$$ES_{c,t} = \frac{EPS_{c,t} - \widehat{EPS}_{c,t}}{PNormal_c} \tag{3.10}$$

Where $ES_{c,t}$ is the earnings surprise for company c on its earnings announcement date t, $EPS_{c,t}$ is the actual earnings per share, and $\widehat{EPS_{c,t}}$ is the estimated earnings per share to the corresponding earnings date. Moreover, $PNormal_c$ is the share-price for company c on January 31st. The date of January 31st was chosen due to relatively stable market conditions compared to prices during the upcoming corona pandemic.

Further, we divide earnings surprise into five equally sized quintiles from the most negative to the most positive in the sample period. The advantage of using earnings surprise quintiles rather than the actual earnings surprise is to make it more linear. Kothari (2001) documents that the relationship between earnings surprises and stock market reactions are very non-linear, where small changes in the earnings surprise can have a great impact. Using quintiles also limits the effect of huge outliers.

For a complete overview of all variables and their definitions and source, see table A.1 in the appendix.

3.3 Summary Statistics

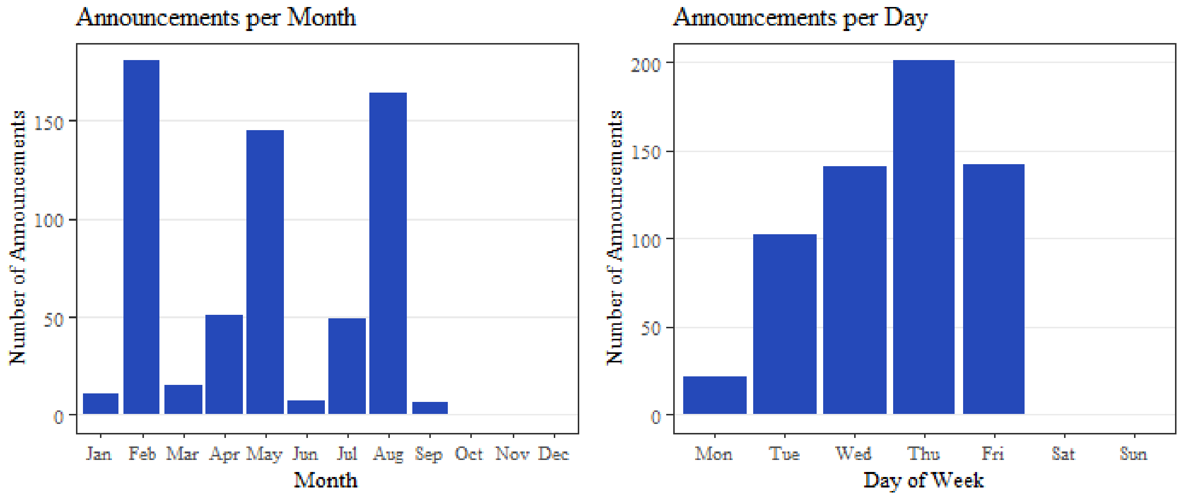

***Figure 3.1**: Shows distribution of earnings announcements throughout the sample period for each month of the year and day of the week. Saturday and Sunday are excluded from the data.*

From Figure 3.1 we find that earnings announcements have a strong seasonal pattern. Most earnings are published with a two-month delay, after the end of each financial quarter. More surprisingly, there seems to be a preference for the day of the week to publish earnings. DellaVigna & Pollet (2009) also document that most earnings are published on either Tuesday, Wednesday, or Thursday. They also find Friday to be the least popular day to publish announcements, contrary to our figure where Monday has the lowest number.

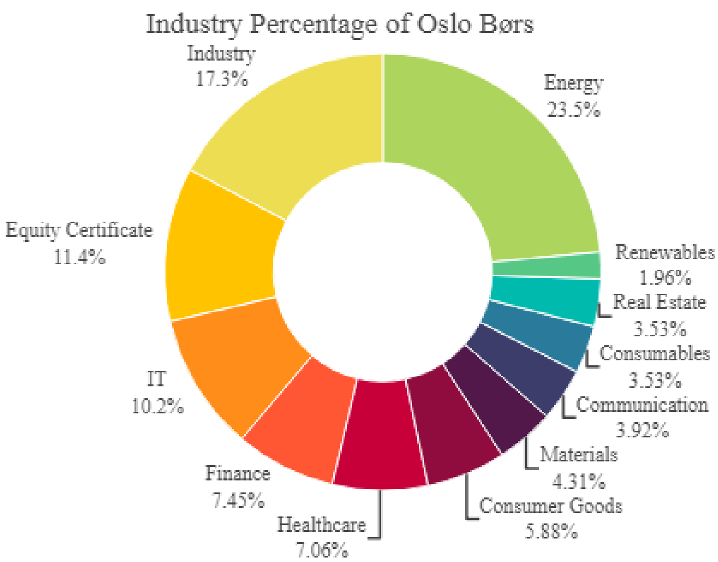

***Figure 3.2:** Shows the percentage share of industries on the Oslo Stock Exchange in 2020.*

Table 3.1:
Summary Statistics of News Readership and Company Data (1)

This table summarizes company-specific financial variables and statistics on the news readership of corona-articles published by NRK. The sample period is from the end of January until the end of September 2020. CNEWS is the number of clicks per article on a given day reported in 1,000's. Earnings surprise is the estimated surprise associated with each earnings announcement. CAR[0,1] is the cumulative abnormal return of the announcement day and the next day after the announcement. AV[0,1] and AVOLA[0,1] is the average abnormal volume and volatility of the day of and day after the earnings announcement. Market cap is market capitalization reported in billion NOK. Nr. of Analyst is the number of analysts with a financial analysis of the company uploaded on Bloomberg, in the month leading up to the announcement. Inst. Ownership is the percentage of institutional ownership of a given company. Book-to-market is the ratio of book value divided by market capitalization. Share turnover is the average number of shares traded divided by the average number of outstanding shares for each month.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
CNEWS (1,000)	595	63.946	28.430	0	54.1	60.5	75.4	166
Earnings Surprise	595	-0.322	2.379	-38.454	-0.038	-0.004	0.009	3.339
CAR[0,1]	595	-0.005	0.058	-0.180	-0.038	-0.004	0.029	0.255
AV[0,1]	595	0.953	1.995	-9.120	0.124	0.885	1.813	9.436
AVOLA[0,1]	595	0.003	0.016	-0.157	-0.001	0.0005	0.003	0.175
Market Cap (BNOK)	595	11.271	42.848	0.017	0.408	1.600	5.546	555.720
Nr. of Analysts	595	4.994	6.032	0	0	3	7	36
Inst. Ownership (%)	595	46.051	25.256	0.000	23.819	44.904	65.666	100.000
Book-to-Market (%)	595	1.312	5.068	-72.825	0.334	0.914	2.026	33.844
Share Turnover (%)	595	0.353	0.627	0.000	0.040	0.149	0.352	5.312

Figure 3.2 shows the percentage share of each industry on the Oslo Stock Exchange in 2020. The size of each industry is not equal. The two largest industries, Energy and Industry, make up over 40% of companies. The smallest industry is Renewables, with a total share of only 1.96 %.

Table 3.1 reports summary statistics for the variables used in our analysis of how corona-news readership affects stock market reactions to earnings announcements. It can give us an indicator of how variables might behave in a regression analysis. Each observation represents an earnings announcement.

Market capitalization is the market value of a company's equity, measured in billion NOK. *Book to market* (B/M) is the total value of a company's assets, or book value, divided by market capitalization. B/M is averaged for each month due to some instances of missing observations. *Institutional ownership* is a measure of how many percent of a company's outstanding shares are owned by institutions. Institutional owners include investment firms, mutual funds, or other companies that invest on other people's behalf. *Number of analysts* is the total number of analysts who with a financial analysis on the given company the last month. *Share turnover* is the average number of shares traded out of the total number of outstanding shares over the last 30 trading days.

From Table 3.1, we can tell that *market capitalization* and the *number of analysts* have values skewed to the right. This means that there are a few observations that severely deviate from the mean. For example, Equinor is an outlier in our data with a market capitalization and number of analysts much greater than the average company on the Oslo Stock exchange. To make these variables more normally distributed, we log-transform their values in our further analysis. The number of analysts is converted as $log(1 + Nr.of\ Analysts)$ due to values of 0.

Table 3.2:
Summary Statistics of News Readership and Company Data (2)

Table 3.2 shows the difference between announcements on days with high amounts of corona-news and days with low amounts. The sample period is from the end of January until the end of September 2020. CNEWS is the number of clicks per article on a given day reported in 1,000's. Earnings surprise is the estimated surprise associated with each earnings announcement. CAR[0,1] is the cumulative abnormal return of the announcement day and the next day after the announcement. AV[0,1] and AVOLA[0,1] is the average abnormal volume and volatility of the day of and day after the earnings announcement. Market cap is market capitalization reported in billion NOK. Nr. of Analyst is the number of analysts with a financial analysis of the company uploaded on Bloomberg. Inst. Ownership is the percentage of institutional ownership of a given company. Book-to-market is the ratio of book value divided by market capitalization. Share turnover is the average number of shares traded divided by the average number of outstanding shares for each month.

	Corona Bottom	Corona Top	Difference	p-value	t-value
CNEWS (1,000)	40.461	98.252	57.791	0	-20.239
Earnings Surprise	-0.367	-0.833	-0.467	0.234	1.195
CAR[0,1]	-0.002	-0.006	-0.004	0.550	0.598
AV[0,1]	0.789	0.572	-0.217	0.271	1.102
AVOLA[0,1]	0.004	0.003	-0.001	0.711	0.370
Market Cap (BNOK)	10.569	9.543	-1.026	0.808	0.243
Book-to-Market (%)	1.221	0.904	-0.318	0.675	0.420
Nr. of Analysts	5.497	4.160	-1.338	0.084	1.732
Inst. Ownership (%)	47.328	40.908	-6.420	0.028	2.209
Share Turnover (%)	0.379	0.323	-0.056	0.397	0.849

Table 3.2 explores any fundamental differences between companies that posted their earnings announcements during days with low amounts of corona-news readership and high amounts. We divide the earnings dates into four equally sized quartiles for each month, depending on how much corona-news readership was present on that day. Corona Bottom represents the bottom quartile, and Corona Top represents the top quartile. We perform a univariate statistical test for each variable to assess a significant difference in mean between the two groups. We find no significant difference between the earnings surprise, market capitalization, book-to-market, or share turnover, between companies posting earnings on days with high amounts of corona-news readership. However, companies posting on low-corona readership days have a greater number of analysts following the company and a higher amount of institutional ownership. These differences are not caused by a few outliers.

4. Corona News

4.1 News Analysis

The fact that there was a lot of news coverage and attention on corona during 2020 is well-known. This is a natural consequence of the high infection rate that led to unprecedented measures such as strict lockdowns worldwide. In Norway, articles about corona have totaled over a billion pageviews between January and September 9th 2020; this amounts to a third of all articles' pageviews in the same period (Jerijervi, 2020). Jerijervi lists the newspapers with the highest numbers as VG.no and Dagbladet.no with 446 million and 156 million, respectively. NRK had 279 million pageviews on articles about corona in the same time period, making it the 2nd most prominent source of corona information in Norway. NRK only publishes their news articles online, meaning that we have access to the total number of times an article was read.

4.1.1 Graphical Evidence

As discussed previously, attention is a limited resource, and we wish to examine whether this increased attention towards corona has resulted in less attention towards other news. Figure 4.1 indicates an increase in pageviews on corona articles coinciding with a decrease in pageviews on other articles.

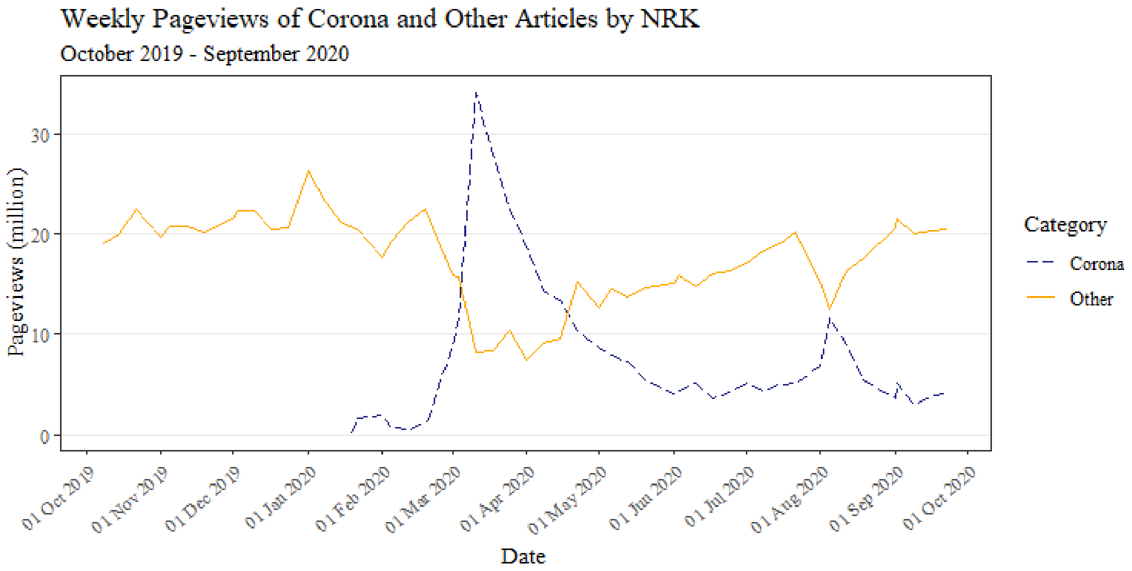

***Figure 4.1**: Shows the pageviews of all articles published by NRK in the categories "Corona" and "Other". Numbers have been aggregated by week to improve interpretability.*

4.1.2 Regression Analysis

We test the effect of corona articles readership on other articles by using data on pageviews per article and seconds read per article. Corona diverts attention if an increase in pageviews or readtime of corona articles has a negative effect on pageviews or readtime of other articles. Otherwise, the effect should be 0.

We normalize the total pageviews in both categories for each day by the total number of articles written in the category ($N_{i,t}$). This ensures that the number of clicks and time read is not just a result of an increase in the number of articles written about a topic. To increase readability, pageviews are converted to 1,000's. The definition for pageviews and readtime per article category i on day t, is shown below:

$$\widetilde{Pageviews}_{i,t} = \frac{\sum Pageviews_{a,i,t}}{N_{i,t}} \cdot \frac{1}{1{,}000} \tag{4.1}$$

$$\widetilde{Readtime}_{i,t} = \log\left(\frac{\sum Readtime_{a,i,t}}{N_{i,t}}\right) \tag{4.2}$$

We run the regression below to identify a causal relationship between our readership variables for corona articles and other articles. In our regression model, equation 4.4, we use the logarithmic transformation of *readtime*, due to the variable being skewed (see appendix Figure A.1). $\widetilde{Pageviews}_O$ is the normalized amount of pageviews in the other category and $\widetilde{Pageviews}_C$ for the corona category. From insights into NRK's historical data and previous analysis, they show a substantial seasonal difference in readership. To ensure our results are not based on seasonal differences, we add indicator variables for the month of year and day of the week.

$$\widetilde{Pageviews}_O = B_0 + B_1\widetilde{Pageviews}_C + C_i \sum_{i=1}^{n} I(month_i) + D_i \sum_{i=1}^{n} I(day_i) + \epsilon \tag{4.3}$$

$$\widetilde{Readtime}_O = B_0 + B_1\widetilde{Readtime}_C + C_i \sum_{i=1}^{n} I(month_i) + D_i \sum_{i=1}^{n} I(day_i) + \epsilon \tag{4.4}$$

Table 4.1:
Linear Regression Models of Corona-Readership Effect on Other-Readership

Using readership data from NRK from the beginning of corona in February until the end of September, we regress the number of clicks and seconds spent reading corona articles on clicks and reading time of other articles. Saturday and Sunday are excluded from the sample in order to capture the effect during trading days. Regression (2) and (5) adjust for monthly fixed effects by using indicator variables for each month in the time period. Regression (3) and (6) also adjusts for within week variation with indicator variables for day of week. Standard errors are adjusted for heteroskedasticity and autocorrelation. Robust t-values are reported in the parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent variable:					
	PageviewsO			ReadtimeO		
	(1)	(2)	(3)	(4)	(5)	(6)
PageviewsC	-0.030	-0.056**	-0.059**			
	(-1.007)	(-2.026)	(-2.164)			
ReadtimeC				-0.010*	-0.011*	-0.015**
				(-1.806)	(-1.693)	(-2.160)
March		1.261	1.182		0.0001	0.005
		(0.319)	(0.315)		(0.001)	(0.067)
April		-1.860	-1.678		0.053	0.063
		(-0.526)	(-0.486)		(0.602)	(0.692)
May		-4.988	-4.865		0.019	0.028
		(-1.464)	(-1.415)		(0.228)	(0.333)
June		-4.774**	-4.954**		-0.107	-0.103
		(-1.988)	(-2.071)		(-1.547)	(-1.554)
July		15.561***	15.832***		0.134**	0.145***
		(4.881)	(5.099)		(2.425)	(2.827)
August		5.214**	5.073**		-0.034	-0.031
		(2.582)	(2.298)		(-0.730)	(-0.627)
September		3.283	3.433		-0.158***	-0.148**
		(1.328)	(1.313)		(-2.754)	(-2.535)
Tuesday			-3.598			-0.083
			(-1.256)			(-1.301)
Wednesday			-7.203***			-0.149**
			(-2.737)			(-2.422)
Thursday			-3.496			-0.057
			(-1.200)			(-0.866)
Friday			-6.352**			-0.129*
			(-2.260)			(-1.943)
Observations	173	173	173	173	173	173
$\bar{R}^2$	-0.001	0.207	0.228	-0.001	0.060	0.077

If corona-news diverts attention, an increase in pageviews or readtime of corona articles has a negative effect on pageviews or readtime of other articles. This means that B_1 should be less than 0.

Table 4.1 shows that $B_1 < 0$ in all regression. Model (1), (2) and (3) reports the regression results for pageviews, and regression (4), (5), and (6) the results for readtime. Corona pageviews are significant at the 5% level in model (2) and (3) at the 5% level after adding control variables for day of week and month. Model (1), without controls, does not provide a significant relationship. Readtime shows similar results. In regression (4), there is a significant negative relationship between readtime spent on corona articles and other articles. This effect is still persistent after introducing control variables for day of week and month in model (5) and (6).

In the models with control variables, we see that attention to news fluctuates over time, both between months and the day of the week. For example, people have more time to read the news during the public holiday of July and are therefore more attentive to news. Our further analysis will use pageviews per corona article as our proxy for attention towards corona. We call this variable CNEWS.

In conclusion, readership of corona articles does have a distracting effect on the readership of other news. While this is a necessary condition for our further analysis, it does not directly indicate that corona readership should affect stock markets. In the next chapter, we will therefore test the influence of corona-readership on investors' reactions to earnings announcements.

5. Stock Market Reaction

Building on the finding in the previous chapter, we test whether news about corona also has a distracting effect on investors' reaction to earnings announcements. Earnings announcements give investors new insights into companies’ financials. Depending on the content of the information, investors decide to buy or sell its stock. If a higher degree of investors is distracted from the new information in the earnings announcement, we expect a lower reaction.

The advantage of using quarterly reports is that they are scheduled events. They are also events which are highly specific for each company. The goal is to investigate the statistical relationship between the number of readers for corona articles and a reduction in absorption of the information from the earnings report. Therefore, it is essential to ensure that no other variable that affects one or both variables causes it to look like there is a connection. Using scheduled reports negates the risk of other variables than attention, such as other information than the earnings, affecting the stock price. When we use scheduled news, this risk is lower because the chance of another event coinciding with this date is much lower.

A control for the size of earnings surprise associated with the announcement is also included. The reaction in the stock market is expected to be proportional to the amount of earnings surprise. We base our estimated earnings on historical earnings of the same quarter. This results in high degrees of negative earnings surprise because many companies’ earnings were affected negatively by the pandemic.

As stated in the introduction, our primary concern is to measure the effect of investor attention to corona, and not how corona-news affects companies’ fundamentals. Outside of firm-specific characteristics, the stock price is affected by market factors. The market reactions to the pandemic have been extreme. Baker et al. (2020) find that post-pandemic volatility levels have remained above normal throughout April. They also find that the middle of March levels was only matched by other major economic events like December 2008 and late 1929. No other disease or pandemic in modern times has ever caused reactions like this. We mitigate extreme market reactions by adjusting the abnormal reactions for industry values. Companies in the same industry generally face the same regulations and market conditions. When faced with new economic conditions, industries' returns are also highly correlated with a strong momentum effect (Moskowitz & Grinblatt, 1999).

In our analysis, we include several control variables to adjust for firm characteristics. We do this to address the concern that the companies publishing their earnings reports on days with high amounts of corona-news readership are fundamentally different from the ones publishing on days with low amounts. Extensive research has been done to assess how investors react to earnings announcements. Size, measured in a firm's market capitalization, is found to be inversely correlated. Meaning smaller firms have a greater reaction than large ones (Atiase, 1985). A higher share of institutional ownership and the number of analysts following the company can lead to less information asymmetry and, therefore, a smaller reaction ((Kim, Krinsky, & Lee, 1997); (Hong, Lim, & Stein, 2000)). Investors react differently to earnings surprises of companies with low book-to-market (growth firms) than companies with high book-to-market (value firms) (Skinner & Sloan, 2002).

NRK is a news source generally concerned with nationwide coverage and not specifically about financial news. Still, we cannot rule out the possibility of some reverse causality. Meaning that there are instances where NRK reports on the movements of stock markets in relation to corona. Out of the 3780 articles about corona, "Børs" which translates to "stock exchange", were mentioned in 15 of the article titles, meaning that most articles are not about stock market movements.

In the following chapters, we provide graphical and statistical analysis of how corona-news readership affects short-term market reactions. Market reactions are measured in three key metrics and presented in the following order:

- Volume
- Volatility
- Return

5.1 Volume Market Reaction

Following hypothesis (1): If it is true that inattention from corona affects the stock market reaction to earnings announcements, abnormal volume on the days after an announcement will be less for days with higher corona-news readership than lower.

First, we present graphical evidence of the effect on volume, comparing announcements with high amounts and low amounts of corona-news readership. Second, we analyze further using regressions of all earnings announcements in our sample.

5.1.1 Graphical Evidence

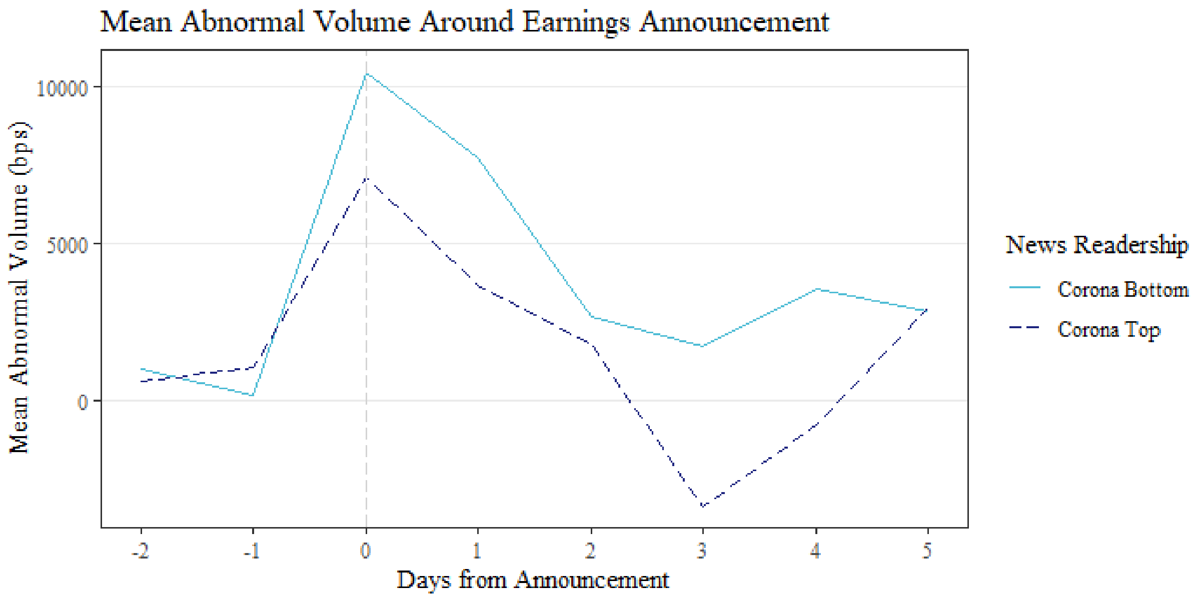

Figure 5.1: *Shows the average abnormal volume in the days around an earnings announcement in basis points. Corona Bottom is the quartile containing the days with the least amount of corona news readership, and Corona Top the days with the most.*

Figure 5.1 shows the initial reaction of average abnormal volume for days with a low degree of corona pageviews and high degree. *Corona Top* represents the days in the top quartile of corona-news readership, and *Corona Bottom* the bottom quartile. Abnormal volume on day t is calculated as the log traded volume in NOK, adjusted by the average traded volume from t-30 to t-10, and the industry average abnormal volume on day t. The full specification of the calculations can be found in Chapter 3.2.

From the figure, we see a considerable spike in abnormal traded volume on the day of the announcement (t=0). The effect of the announcement also continues into the next day. We can explain part of the continued effect by instances where companies publish earnings announcements after trading hours on day 0. The average initial reaction for days with low-amounts of corona-news readership is an abnormal volume increase to about 10,000 bps above normal levels. On the following day of the announcement, the abnormal volume is still higher than normal by about 7,500 bps. Compared to days with high amounts of corona-news readership, the effect is about 6,000 bps above normal levels on the day of the announcement and about 4,000 bps the next day. We interpret this as corona having a distracting effect on investors, resulting in less traded volume. In the days leading up to the announcement, the abnormal traded volume is close to 0. It indicates that the potential pre-leakage of information does not have a large effect. From day 2, after the announcement, through day 5 the initial effect disappears, but low corona-news readership days are still higher than high ones.

5.1.2 Regression Analysis

To further analyze whether our findings though the graphical evidence holds, we perform a regression analysis where we also include several control variables. Our ordinary least squared (OLS) regression specifications are:

$$AV[0,1] = B_0 + B_1 CNEWS + C_i \sum_{i=1}^{n} X_i + D_i \sum_{i=1}^{n} I(AbsES_i) + E_i \sum_{i=1}^{n} I(month_i) + \epsilon \tag{5.1}$$

$AV[0,1]$ is the average abnormal volume of the day of and after an earnings announcement. We average over the two initial days because the plot indicated that most of the effect took place in this time frame. $CNEWS$ is the number of pageviews on corona-articles, adjusted for the number of articles, on each day, equal to calculations of $\widetilde{Pageviews}_C$ in 4.1.2. X_i represents the control variables log(market capitalization), book-to-market, institutional ownership, and log(1+number of analysts). An indicator variable for each absolute earnings surprise quantile ($AbsES$) is added. We use the absolute earnings surprise quantiles because both negative and positive earnings surprises are expected to generate abnormal volume. Lastly, we also include indicator variables for each month of our sample period. Standard errors are adjusted for heteroskedasticity.

Following hypothesis (1), we expect B_1 to be less than 0, meaning that corona-pageviews have a negative impact on the short-term market reaction measured in abnormal volume.

Table 5.1:
Linear Regression Models of Corona-News Readership Effects on Abnormal Volume

Table 5.1 shows the multivariate regression results on how the number of pageviews on corona articles published by NRK affects the abnormal trading volume of stocks publishing an earnings announcement on the same day. Regression (2) includes control variables for firm characteristics, indicator variables for absolute earnings surprise quintiles and month. Coefficients are reported in basis points. Standard errors are adjusted for heteroskedasticity, robust t-values are reported in the parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent variable:	
	AV[0,1]	
	(1)	(2)
CNEWS	-75.523***	-81.736***
	(-2.950)	(-3.252)
log(Market Cap) (BNOK)		-292.681
		(-0.529)
Book-to-Market (%)		17.433
		(0.189)
log(1+Nr. of Analysts)		-1,177.011
		(-1.171)
Inst. Ownership (%)		10.271
		(0.313)
Abs ES Q2		667.718
		(0.316)
Abs ES Q3		4,710.867**
		(2.427)
Abs ES Q4		3,157.293
		(1.396)
Abs ES Q5		-1,845.335
		(-0.757)
March		-8,941.804**
		(-2.266)
April		-5,396.390**
		(-2.569)
May		-5,402.806***
		(-3.004)
June		-9,687.426*
		(-1.661)
July		257.740
		(0.130)
August		-1,270.193
		(-0.741)
September		-3,149.622
		(-0.289)
Observations	595	595
$\bar{R}^2$	0.017	0.047

In Table 5.1, we see that the coefficient to CNEWS (B_1) < 0 and significant at the 1% level in both models. This relationship is still robust after introducing controls for company characteristics and monthly fixed controls in model (2). Using only CNEWS, in model (1), as the explanatory variable 0.017 of the variation of abnormal volume is explained. This value is increased to 0.047 after the introduction of control variables in model (2). These findings indicate that investors' reaction to the earnings announcements, measured in abnormal volume, is negatively affected by the amount of corona-news readership. Using model (2), we interpret the effect as an increase of 1,000 clicks on corona articles, resulting in a 81.736 bps (0.81 %) decrease in investors' reaction to an earnings announcement. Further, a one standard deviation increase in CNEWS would on average, result in a 2,324 bps ($28.43 \cdot 81.736$) or 23% decrease in abnormal volume.

Other variables that significantly affect abnormal volume in *March, April, May,* and *June.* To control that we do not just measure the month-to-month effect, we run a placebo regression to check our findings' robustness.

5.1.3 Placebo Regression

Corona has been restrictive in many ways that have a real impact on all companies' economic development on the Oslo Stock Exchange. Corona has also, as mentioned, brought much uncertainty about financial outcomes. The main difference between two similar companies, one publishing an earnings announcement and one not, is the attention to this report's information. Suppose there is another phenomenon, such as information about restrictions that causes firms on high corona-news readership days to have higher abnormal volume. In that case, this should be equal for all firms on those days, not just the firms publishing an earnings report.

To ensure that the effect we are measuring is inattention and not some other consequence of the pandemic, we run a placebo regressions. In the placebo regressions, the values for abnormal volume are swapped with that of their closest competitor. The closest competitor is the company closest in market capitalization in the same industry on the same day. For example, Equinor, the biggest company in the Energy sector, published its Q2 on 24.07.2020. Equinor’s value for abnormal volume is then replaced by that of Aker Solutions, the second largest company in the same industry.

Table 5.2:
Placebo Linear Regression Models of Corona-News Readership Effects on Abnormal Volume

Table 5.2 shows the multivariate placebo regression results on how the number of pageviews on corona articles published by NRK affects the abnormal trading volume of stocks publishing an earnings announcement on the same day. In this case, the abnormal volume is replaced by the closest competitors abnormal volume in the same industry on the same day. Regression (2) adjust for the control variables log(market capitalization), market-to-book ratio, institutional ownership share, and log(1+number of analysts). Indicator variables for absolute earnings surprise quintiles and month are also included. Coefficients are reported in basis points for better readability. Standard errors are adjusted for heteroskedasticity and robust t-values are reported in the parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent variable:	
	AV[0,1]	
	(1)	(2)
CNEWS	-21.444	-17.269
	(-0.897)	(-0.715)
Company controls		X
Abs ES indicators		X
Month indicators		X
Observations	585	585
$\bar{R}^2$	-0.001	0.003

There should be no difference in reactions on days with high amounts of corona-news readership and days with low amounts to confirm our results. This means that news readership should not have a significant relationship with abnormal volume in the placebo regression. From Table 5.2, we can see that the relationship between abnormal volume and CNEWS is still negative, but these results are not significant. This confirms that our results in Table 5.1 are not caused by fundamental differences between days with high amounts of corona-news readership and days with low amounts.

5.2 Volatility Market Reaction

This section analyzes the effect of corona-news on volatility in the period surrounding an earnings announcement. We hypothesize that: (2) Abnormal volatility on the days after an announcement will be less for days with higher corona-news readership than lower. To calculate abnormal volatility, we normalize for the average value of the last 20 days, with a 10-day lag, as well as the average of all other companies in the same industry. A detailed description of the calculations can be found in Chapter 3.2.

First, we present graphical evidence of the effect on volatility, comparing announcements with high amounts and low amounts of corona-news. Second, we analyze further using regressions of all earnings announcements in our sample.

5.2.1 Graphical Evidence

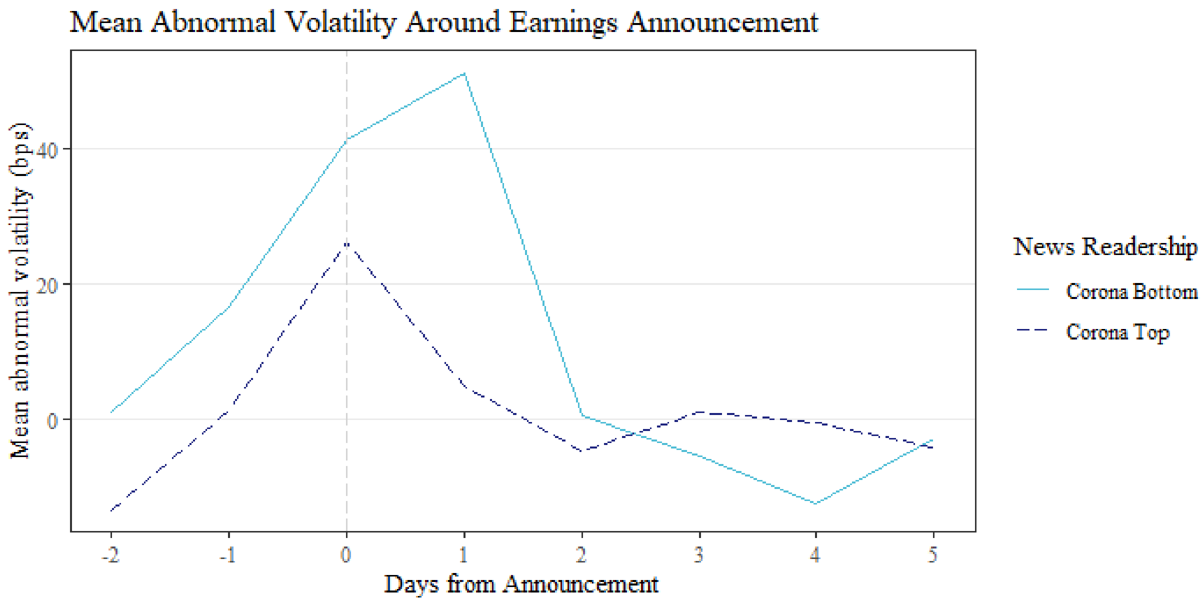

Figure 5.2: *Shows the average abnormal volatility in the days around an earnings announcement in basis points. Corona Bottom is the quartile containing the days with the least amount of corona news readership, and Corona Top the days with the most.*

Figure 5.2 shows the short-term reaction in daily volatility to an earnings announcement. As we can see, there is an increase leading up to and a spike around day zero of publication. Corona bottom spikes one day after the initial announcement, indicating that there is activity after market close on day 0. As shown in the figure, the values normalize around day two as the new information has been incorporated into the stock price. In line with our hypothesis, there is a clear difference in the mean for corona top days and corona bottom days. On the day of the announcement, we can see that corona bottom volatility is 40 bps higher than normal, and the days with the top amount of news readership are 25 bps higher. This would indicate that there is a higher distracting effect on the days with high corona news readership.

5.2.2 Regression Analysis

We test our second hypothesis by running the regression, as seen in equation 5.2. $AVOLA[0,1]$ is the average abnormal volatility for day 0 and 1 of earnings announcement publication. $CNEWS$ is the normalized amount of pageviews of corona-articles.

$$\begin{aligned} AVOLA[0,1] = {} & B_0 + B_1 CNEWS + C_i \sum_{i=1}^{n} X_i + D_i \sum_{i=1}^{n} I(AbsES_i) \\ & + E_i \sum_{i=1}^{n} I(month_i) + \epsilon \end{aligned} \tag{5.2}$$

The specifications are the same for the regression analysis of abnormal volume. The only difference is that the dependent variable is now abnormal volatility instead. X_i represents the control variables, log(market capitalization), book-to-market, institutional ownership, log(1 + number of analysts), and share turnover. Indicators for absolute earnings surprise quintiles ($AbsES$) and month of year is also added.

Following hypothesis (2), we expect B_1 to be less than 0, meaning that corona-readership has a negative impact on the short-term market reaction measured in abnormal volatility.

Table 5.3 shows a negative relationship between abnormal volatility and *CNEWS*. We report the coefficients in basis points for easier interpretation. Holding all other variables constant, a one thousand increase in readership of corona-news, measured in pageviews, would result in a 0.054 basis point or 0.0000054 decrease in volatility. Further, a one standard deviation increase in CNEWS would result in a on average 1.54 bps $(28.43 \cdot 0.054)$ decrease in abnormal volatility.

This effect is insignificantly small with a low economic impact. And we cannot reject the null hypothesis that this relationship is significantly different from zero.

Table 5.3:
Linear Regression Models of Corona-News Readership Effects on Abnormal Volatility

Table 5.3 shows the multivariate regression results on how the number of pageviews on corona articles published by NRK affects the abnormal volatility of stocks publishing an earnings announcement on the same day. Abnormal volatility for each stock is the average abnormal volatility of day 0 and 1. Since volatility is expected to react to both positive and negative earnings surprises, the absolute earnings surprise is used and divided into five quantiles. An indicator variable for each earnings quantile is included. Control variables include indicators for each month, log(market capitalization), market-to-book ratio, institutional ownership share, log(1 + number of analysts), and share turnover. Coefficients are reported in basis points for readability. Standard errors are adjusted for heteroskedasticity, and robust t-values are reported in the parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent variable:	
	AVOLA[0,1]	
	(1)	(2)
CNEWS	-0.011	-0.054
	(-0.077)	(-0.339)
Company controls		X
Abs ES indicators		X
Month indicators		X
Observations	595	595
$\bar{R}^2$	-0.002	0.013

When CNEWS is used as the only independent variable in model (1), it explains almost none of the variation in our data, with $\bar{R}^2$ approximately 0. The introduction of control variables in model (2) increases the $\bar{R}^2$ slightly to 0.013. Regression table for all variable coefficients are presented in appendix Table A.2. Placebo analysis for abnormal volatility can be found in appendix Table A.3. From this table, we can see that abnormal volatility and CNEWS has a non-significant, positive relationship.

In conclusion, the results indicate that we can reject that corona-news readership affects investors' reactions, measured in volatility, to earnings announcements.

5.3 Return Market Reaction

Our last hypothesis is: (3) Abnormal return will have a weaker short-term reaction in the direction of the earnings surprise for days with a higher corona-news readership than days with lower.

Calculation of cumulative abnormal returns is done by aggregating returns and subtracting the market returns in the same industry for the time period; the exact definition can be found in Chapter 3.2.

5.3.1 Graphical Evidence

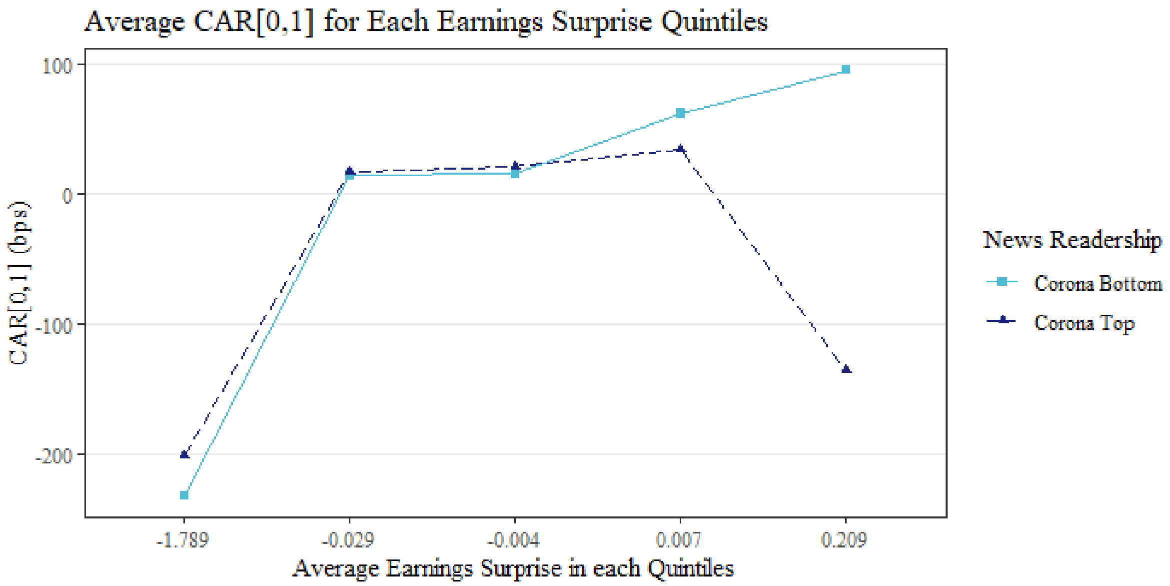

Figure 5.3: *Shows the average cumulative abnormal return in basis points in each earnings surprise quintile. Corona Bottom is the quartile containing the days with the least amount of corona news readership and Corona Top the most.*

Figure 5.3 shows the short-term market reaction, measured in cumulative abnormal returns, to earnings surprise. *Corona Top* represents the days in the top quartile of corona-news readership and *Corona Bottom* the bottom quartile. The earnings announcements in the two middle quartiles are not reflected in the plot. $CAR[0,1]$ is the average cumulative abnormal return from the day of earnings announcement (day 0), to the day after the announcement (day 1).

As we can see, $CAR[0,1]$ increases with the earnings surprise. However, this relationship is not as linear as one would expect. A possible explanation is that our earnings surprise calculations are as presented in Chapter 3.2 based on pre-corona values and can therefore be inaccurate. However, this should cause our earnings surprise values to be more negative as most businesses will report lower numbers than previous quarters. In line with our hypothesis, we observe that the days with the top amount of news readership have slightly less negative reaction for the two most negative earnings surprise quintiles. In the two positive quintiles, Corona Top also show a weaker reaction in the direction of the earnings surprise. The most notable difference is found for the most positive earnings surprises (Q5). There is a difference of over 200 bps in reaction, with Corona Top even having negative abnormal returns. In conclusion, Figure 5.3 shows some indication of corona-readership having a distracting effect on the return reaction.

5.3.2 Regression Analysis

We regress the cumulative abnormal returns on the day of and after an earnings announcement ($CAR[0,1]$), on the number of pageviews on corona-articles ($CNEWS$), the earnings surprise quintile rank (ES), an interaction term between pageviews and the earnings surprise rank ($ES \times Pageviews$). Furthermore, multiple control variables are also interacted with earnings surprise. The control variables are log(market capitalization), book-to-market, institutional ownership, and log(1 + number of analysts), share turnover and month of announcement. The model specification is:

$$\begin{aligned} CAR[0,1] = {} & B_0 + B_1 CNEWS + B_2 ES + B_3 (ES \times CNEWS) + \sum_{i=1}^{n} C_i I(month_i) \\ & + \sum_{i=1}^{n} D_i (ES \times I(month_i)) + \sum_{i=1}^{n} E_i X_i + \sum_{i=1}^{n} F_i (ES \times X_i) + \epsilon \end{aligned} \tag{5.3}$$

All variables are interacted with earnings surprise because the effect of the different variables might change depending on the earnings surprise. This method is, for example, documented in DellaVigna and Pollet (2009), where they find inattention to be greater for very positive earnings news. However, it does make the results slightly less intuitive to interpret.

Following hypothesis (3) we expect B_3 to be < 0, meaning that investors react less to earnings surprises when there are high amounts of corona-news readership than low.

Table 5.4:
Linear Regression Models of Corona-News Readership Effects on Abnormal Returns

Table 5.4 shows the results of the multivariate regression on how the amount of pageviews on corona articles (1,000) published by NRK (CNEWS) affects cumulative abnormal returns of stocks around earnings announcements (CAR[0,1]). Abnormal returns are the returns for each company adjusted for the market return for the industry they are within. Earnings surprises are divided into five quintiles, where the first quintile is the most negative surprise (ES=1) and the fifth quintile the most positive (ES=5). Control variables include indicators for each month, log(market capitalization), market-to-book ratio, institutional ownership share, log(1 + number of analysts), and share turnover the last 30 days. All control variables are interacted with the earning surprise quintiles rank. Regression (3) only includes observations in the most negative and positive earnings surprise quintiles. In regression (3), ES TOP is an indicator variable for the most positive earnings surprise. Coefficients are reported in basis points for better readability. Standard errors are adjusted for heteroskedasticity, and robust t-values are reported in the parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent variable:		
	CAR[0,1]		
	(1)	(2)	(3)
CNEWS	2.860	3.128	5.747
	(1.178)	(1.276)	(1.422)
ES	86.529*	178.307	
	(1.842)	(1.445)	
ES × CNEWS	-0.763	-0.755	
	(-1.051)	(-1.048)	
TOP ES			160.686
			(1.102)
TOP ES × CNEWS			-1.242
			(-1.288)
Controls Interacted		X	X
Observations	595	595	238
$\overline{R}^2$	0.006	0.023	0.046

Using the regression model (2) from Table 5.4, we can measure the abnormal return sensitivity to earnings surprises and corona-news readership. The estimates of the coefficients to earnings surprise (ES) and the interaction term with corona-news readership (ES×CNEWS), imply that abnormal return is less sensitive as CNEWS increases. A one-unit increase in ES, holding all other variables constant, can be expressed as: $B_2 + B_3 CNEWS$.

Since we have no clear definition of a low and high amount of corona-news readership, we use the 25% and 75% cut-off values of CNEWS, respectively, to illustrate the effect. The 25% and 75% cut-off values for CNEWS as presented in the summary statistics Table 3.1 is 54.1 and 75.4 thousand pageviews per article. Using these values and the coefficient estimates from model (2) we get: $178.3 - 0.755 \cdot 54.1 = 137.45$ and $178.3 - 0.755 \cdot 75.4 = 121.37$. This means that market reaction is approximately 12 % ($\frac{121,37}{137,45} - 1$) less sensitive to earnings announcements on days with relatively high amounts of corona-news readership than days with low.

This result can be compared to Hirshleifer et al. (2009) that find market reactions to be 13.3% less sensitive to days with a high number of competing earnings announcements, or DellaVigna and Pollet (2009) that finds 15.8 % less reaction to Friday announcements. However, unlike their findings, we cannot confirm that our difference is significantly different from 0 since our p-value is higher than 0.10.

In model (3) we limit our sample to only earnings announcements with the most positive earnings surprises ($ES = 5$) and the most negative ($ES = 1$). An indicator variable ($TOP\ ES$) is used in this regression and is equal to 1 for the top earnings surprise quintile. We expect the effect to be larger when only using the most extreme surprises. Using the coefficients from model (3) and a similar method for calculations as for model (2) we get: $160.68 - 1.242 \cdot 54.1 = 93.49$ and $160.68 - 1.242 \cdot 75.4 = 67.03$. Meaning the sensitivity is approximately 28% ($\frac{67.03}{93.49} - 1$) lower with a high amount of corona-news readership. However, these results are not significant either. Regression table for all variable coefficients are presented in appendix Table A.4. Placebo analysis for abnormal return can be found in appendix Table A.5 Similarly to Table 5.4, the results show no significance.

In conclusion corona-news readership does not have a significant effect on short-term abnormal return following an earnings announcement.

6. Discussion

Our results are mixed in relation to our hypothesis. In regard to corona-readership, we find a negative significant relationship with abnormal volume and a negative, but not significant, relationship with volatility and returns. It suggests that stockprices are efficient and that their reaction to earnings news is independent of the amount of daily corona-readership. On the contrary, we do identify depressed trading volume that might suggest a lower degree of price informativeness. In this discussion we go through possible explanations for our findings.

Influx of private investors

Volume can be derived from an influx of unprofessional traders that does not affect price movements. Unprofessional investors might be attracted to the stock market since they read about it in the news. An increased talk about economic effects and stock market movement might increase their interest in stocks. And with the extra time that quarantine and temporarily layoffs provide they might decide to spend their time investing. Oslo Stock Exchange saw an increase of 15.5% in private stock ownership during corona (Kampevoll, 2020). Our data does not provide additional insights into what types of investors drive market reactions. Even though we use control variables such as institutional ownership and number of analysts following a company, that serves as a proxy for professional investors, these might not reflect the full picture. Table 3.2 shows that stock that had their earnings announcements in the top quartile of corona-readership has a significantly smaller share of institutional ownership and number of analysts. It could be that new private investors, that are more likely to be distracted, drive the effect in volume, but this does not translate into price movements. Barber & Odean (2007) document that private investors are net buyers on high-attention days and that professional investors' buying behavior is not affected by attention.

Professional traders

Professional traders are paid to make a profit from inefficiencies in the market. This means that they on average, devote considerably more time in searching for information on trades. They often limit their search to a particular industry or certain criteria which also leads to lesser demand on their attention. They also use more tools in their search. DellaVigna & Pollet (2009) and Hirshleifer et al. (2009) show that distraction has an effect on returns. These papers base their findings on data that spans 1984-2006 and 1995-2004, respectively. In the years since traders have developed much more sophisticated trading methods, as well as ways to receive and analyze relevant information. New technology has opened possibilities for data and analytics which can forecast market trends and speed up their investment decisions. As methods for market analysis become more complicated the difference between retail and institutional traders might also increase as fewer retail traders make use of them.

Earnings announcements could be harder to interpret during corona

It is not entirely intuitive that a higher amount of abnormal trading volume should necessarily affect returns and volatility. Investors may find information during the pandemic harder to trade on. If investors find earnings announcements challenging to interpret in the context of corona one would expect a greater dispersion of opinions to the new information. An assumption that builds on the fact that investors are aware of the new information. A greater dispersion of opinion would further lead to a higher traded volume, but without much price change. This explanation is contrary to our findings where we observe a lower traded volume, which furthers the argument that it is indeed caused by inattention to the new information. An alternative explanation could be that when information is more complex investors might abstain from buying stocks altogether. Instead of investing, they might decide to keep their money in a savings account if they do not feel confident in their investment decision. This would mean the effect is not driven by inattention to the earnings announcements, but rather that the information is more difficult to trade on. It is difficult to control for this effect, but since we limit our study to February through September information should almost be equally complicated.

7. Conclusion

Individuals must be attentive to the unprecedented government restrictions and consequences of coronavirus. We test whether news about corona diverts attention away from stock-specific news. We do this by analyzing the effect of corona-news readership on market reactions following an earnings announcement in the Norwegian stock market.

The findings in Chapter 4 indicate that people prioritize news about corona over other news. Using daily readership data provided by NRK on the number of pageviews and time spent reading an article, we create a measure for attention. By dividing each variable by the number of articles written that day we can rule out the possibility that the number of articles is what causes the effect. When clicks and seconds spent reading each corona articles increases the amount of readership for other articles decreases. This shows that corona is a suitable proxy for distraction, which is a necessity for our other hypotheses.

In Chapter 5, we test whether the effect documented also translates into investors' reactions to earnings news. We use earnings announcements as a scheduled news event that contains crucial new information about a company's performance. Since we cannot measure attention to earnings news directly, we indirectly measure it by different stock market movements surrounding its release. The three key metrics used in the analysis are abnormal -trading volume, -volatility and -returns. If corona-news has a distracting effect, we expect the short-term reaction to be negatively affected.

We find that corona-news readership has a significant negative effect on abnormal trading volume. A one standard deviation increase in the amount of corona-readership is associated with a 23% (0.23) decrease in abnormal volume following an earnings announcement. We find no significant relationship between corona-news readership and abnormal volatility or returns. Several control variables are used to control for other possible explanations for market reactions. These include earnings surprise, market capitalization, book-to-market, institutional ownership, number of analysts who have posted an analysis of the company and month. Our findings are still robust after the introduction of these variables. To further test the robustness of our findings we also run placebo regressions to test whether the effect is still there when ignoring the effect of earnings announcements. The effect of corona-news readership disappears in the placebo tests, meaning our findings is indeed caused by corona-news having a distracting effect on investors.

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A.Appendix

A.1 Variable Description

Table A.1: Variable Definitions

Variable	Definition	Unit	Source
PUB_DATE	Date article j was published.	Date	NRK
SUBJECT	The subject of article j	Subject	NRK
$N_{i,t}$	Number of articles published in category i, on day t.		NRK
$Pageviews_{i.t}$	The total number of pageviews on articles published in category i on day t.	Pageviews	NRK
$\widetilde{Pageviews}_{i,t}$	The total number of pageviews (in 1,000's) on articles in category i, on day t, divided by $N_{i,t}$	1,000 Pageviews	
$CNEWS_t$	The total number of pageviews (in 1,000's) on corona articles, on day t, divided by the number of corona articles published on day t.	1,000 Pageviews	
$Readtime_{i,t}$	The total readtime in seconds on articles published in category i on day t.	Seconds	NRK
$\widetilde{Readtime}_{i,t}$	The log-transformed total readtime in seconds on articles in category i, on day t, divided by $N_{i,t}$		
EA_DATE	Earnings announcements date for company i.	Date	Oslo Børs NewsWeb
$Close_{c,t}$	The closing price of the stock for company c on day t.	NOK	Bloomberg
$PNormal_c$	The closing price for company c, on January 31st 2020.	NOK	Bloomberg
$NumTrades_{c,t}$	The number of trades of company c on day t.	Buy or sell	Bloomberg
$NOKVolume_{c,t}$	Volume measured in NOK of company c on day t. Calculated by taking $V_{c,t}$ multiplied by $Close_{c,t}$.	NOK	
$R_{c,t}$	Close-to-close returns for company c on day t.	%	

$MCap_{c,i,t}$	The market capitalization for company c in industry i on day t.	BNOK	Bloomberg
$MR_{c,i,t}$	Market return for all companies in industry i, except c on day t.	%	
$EPS_{c,t}$	Earnings per share for company c for earnings announcement date t.	NOK	Bloomberg
$\widehat{EPS_{c,t}}$	Estimated earnings per share for company c for earnings announcement date t.	NOK	
$ES_{c,t}$	The earnings surprise for company c, for earnings announcement date t.		
ES TOP_t	Dummy variable for earnings surprise quintile. 1 for the top earnings surprise quintile and 0 for the bottom quintile.	0/1	
$AbsES_{c,t}$	The absolute earnings surprise for company c, for earnings announcement date t.		
$AV_{c,i,t}$	Abnormal volume for company c in industry i on day t.		
$AVOLA_{c,i,t}$	Abnormal volatility for company c in industry i on day t.		
$CAR_{c,i,t}$	Cumulative abnormal returns for company c in industry i on day t.		
Nr. of $Analysts_{c,t}$	The total number of analysts who have posted a financial analysis on company c the month of day t.		Bloomberg
Inst. $Ownership_{c,t}$	Total shares of company c on day t owned by non-private institutions divided by total outstanding shares.	%	Bloomberg
$Book\text{-}to\text{-}Market_{c,t}$	The total value of a company's assets (book value) divided by market capitalization for company c, on day t.	%	Bloomberg
Share $Turnover_{ct}$	The average number of company c shares traded over the last 30 days from day t divided by the average outstanding shares the last 30 days from day t.	%	
Outstanding $shares_{c,t}$	The total number of outstanding shares for company c on day t.		Bloomberg

A.2 Additional Figures

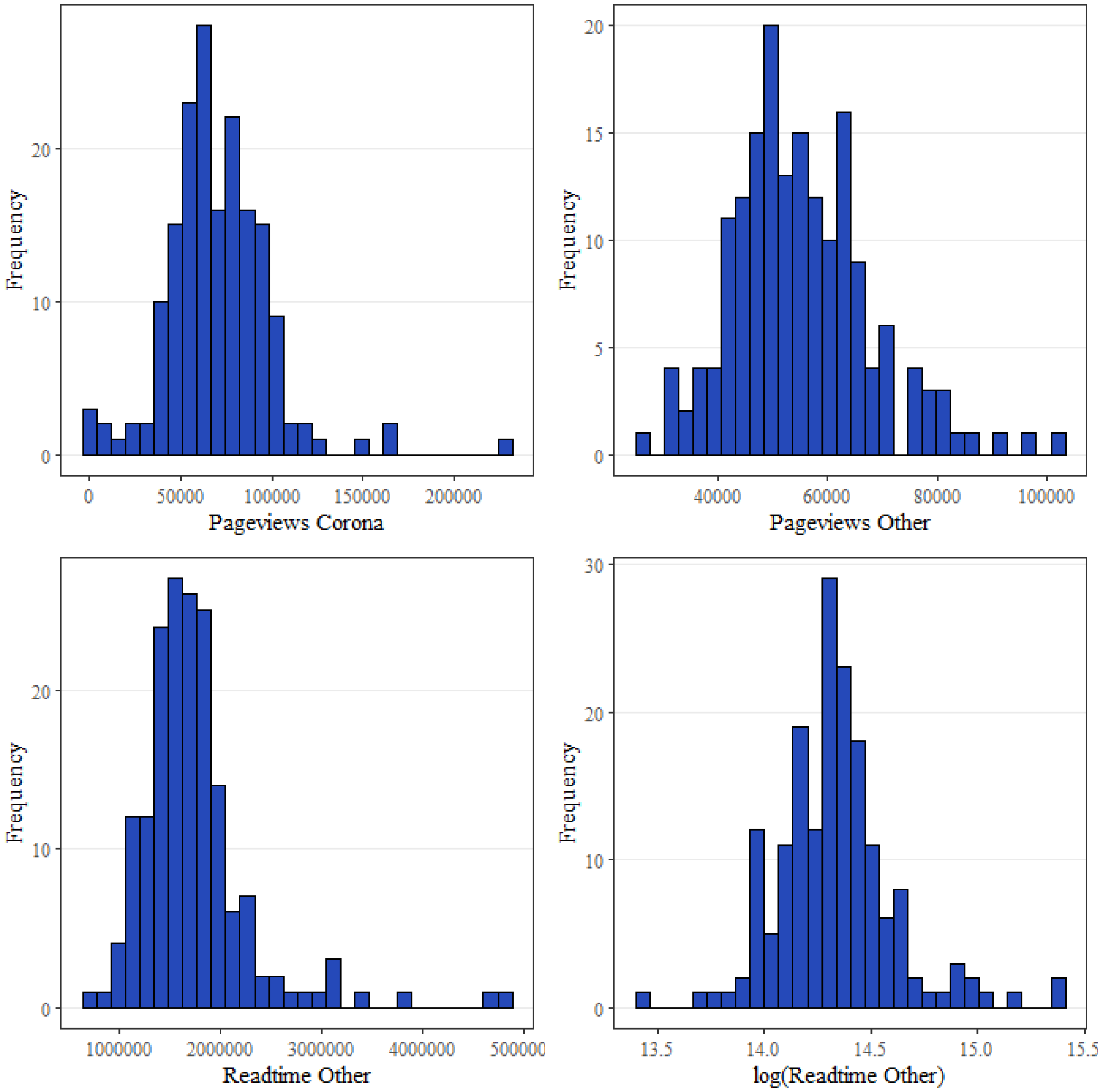

Figure A.1: *Distribution of readership statistics. From the top left, we show the distributions of (1) pageviews on corona articles, (2) pageviews on other articles, (3) readtime on other articles, and (4) the log-transformed values of readtime on other articles.*

A.3 Additional Tables

Table A.2:
Linear Regression Models of Corona-News Readership Effects on Abnormal Volatility

Table A.2 shows same regression as Table 5.3 with all control variable coefficients. Table A.2 shows the results of the multivariate regression on how the number of clicks on corona articles published by NRK affects the abnormal volatility of stocks around earnings announcements. Abnormal volatility for each stock is the average abnormal volatility of day 0 and 1. Since volatility is expected to react to both positive and negative earnings surprises, the absolute earnings surprise is used and divided into five quantiles. An indicator variable for each earnings quantile is included. Control variables include indicators for each month, log(market capitalization), market-to-book ratio, institutional ownership share, log(1 + number of analysts) and share turnover the last 30 days. Coefficients are reported in basis points for readability. Standard errors are adjusted for heteroskedasticity, and robust t-values are reported in the parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent variable:	
	AVOLA[0,1]	
	(1)	(2)
CNEWS	-0.011	-0.054
	(-0.077)	(-0.339)
Market cap (BNOK)		-3.014
		(-0.603)
Book-to-Market (%)		0.477
		(0.981)
Nr. of Analysts		0.106
		(0.375)
Inst. Ownership (%)		-6.021
		(-0.744)
Share Turnover (%)		37.403
		(1.037)
Abs ES Q2		9.392
		(1.003)
Abs ES Q3		2.525
		(0.282)
Abs ES Q4		5.692
		(0.316)
Abs ES Q5		10.121
		(0.619)
March		-92.438**

		(-2.314)
April		-20.345
		(-0.802)
May		-26.796**
		(-2.496)
June		-137.274
		(-1.254)
July		0.175
		(0.014)
August		-5.871
		(-0.289)
September		-246.493
		(-1.236)
Observations	595	595
$\overline{R}^2$	-0.002	0.013

Table A.3:
Placebo Linear Regression Models of Corona-News Effects on Abnormal Volatility

Table A.3 shows the results of the multivariate placebo regression on how the number of pageviews on corona articles published by NRK effects abnormal volatility of stocks around earnings announcements. Coefficients are reported in basis points. Abnormal volatility for each stock is the average abnormal volatility of day 0 and 1. AVOLA[0,1] of the firms with earnings announcements are swapped for the corresponding value on the same day as their closest competitor in terms of market Capitalization. Since volatility is expected to react to both positive and negative earnings surprise the absolute earnings surprise is used and divided into five quantiles. Control variables include indicators for each month, market capitalization deciles, market-to-book ratio deciles, the share of institutional ownership, log(1+number of analysts) and share turnover the last 30 days. Standard errors are adjusted for heteroskedasticity and robust t-values are reported in the parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent variable:	
	AVOLA[0,1]	
	(1)	(2)
CNEWS	0.358	0.214
	(1.045)	(0.800)
Company controls		X
Abs ES indicators		X
Month indicators		X
Observations	585	585
$\overline{R}^2$	0.001	0.151

Table A.4:
Linear Regression Models of Corona-News Readership Effects on Abnormal Returns

Table A.4 shows same regression as Table 5.4 with all control variable coefficients. Table A.4 shows the results of the multivariate regression on how the amount of pageviews on corona articles (1,000) published by NRK (CNEWS) affects cumulative abnormal returns of stocks around earnings announcements (CAR[0,1]). Abnormal returns are the returns for each company adjusted for the market return for the industry they are within. Earnings surprises are divided into five quantiles, where the first quintile is the most negative surprise (ES=1) and the fifth quintile the most positive (ES=5). Control variables include indicators for each month, log(market capitalization), market-to-book ratio, institutional ownership share, log(1 + umber of analysts), and share turnover the last 30 days. All control variables are interacted with the earning surprise quantiles rank. All coefficients are reported in basis points for better readability. Regression (3) only includes observations in the most negative and positive earnings surprise quantiles. In regression (3), ES TOP is an indicator variable for the most positive earnings surprises. Coefficients are reported in basis points. Standard errors are adjusted for heteroskedasticity, and robust t-values are reported in the parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent variable:		
	CAR[0,1]		
	(1)	(2)	(3)
CNEWS	2.860	3.128	5.747
	(1.178)	(1.276)	(1.422)
ES	86.529*	178.307	
	(1.842)	(1.445)	
ES × CNEWS	-0.763	-0.755	
	(-1.051)	(-1.048)	
TOP ES			160.686
			(1.102)
TOP ES × CNEWS			-1.242
			(-1.288)
Market cap (BNOK)		55.898	14.689
		(1.327)	(0.277)
Book-to-Market (%)		-2.759	-7.890
		(-0.379)	(-0.644)
Nr. of Analysts		1.003	1.154
		(0.457)	(0.438)
Inst. Ownership (%)		-33.655	-16.918
		(-0.443)	(-0.203)
Share Turnover (%)		-599.406	-5,509.043

	(-0.042)	(-0.306)
March	725.413	35.663
	(1.389)	(0.059)
April	52.086	325.380
	(0.219)	(1.063)
May	401.697**	649.822**
	(2.293)	(2.548)
June	-996.972	-1,077.499
	(-1.563)	(-1.090)
July	74.924	-152.495
	(0.286)	(-0.490)
August	158.218	178.939
	(0.896)	(0.695)
September	-153.527	210.496
	(-0.261)	(0.341)
ES × Market cap (BNOK)	-5.856	
	(-0.406)	
ES × Book-to-Market (%)	4.563	
	(0.735)	
ES × Nr. of Analysts	0.036	
	(0.053)	
ES × Inst. Ownership (%)	12.518	
	(0.545)	
ES × Share Turnover	-503.944	
	(-0.129)	
ES × March	-203.886	
	(-1.384)	
ES × April	27.097	
	(0.337)	
ES × May	-122.765**	
	(-2.247)	
ES × June	252.571	
	(1.559)	
ES × July	-57.993	
	(-0.815)	
ES × August	-49.006	
	(-0.987)	
ES × September	-30.929	
	(-0.228)	
ES TOP × Market cap (BNOK)		11.068

			(0.623)
ES TOP × Book-to-Market (%)			11.743
			(1.071)
ES TOP × Nr. of Analysts			-0.368
			(-0.472)
ES TOP × Inst. Ownership (%)			13.395
			(0.523)
ES TOP × Share Turnover			1,138.801
			(0.261)
ES TOP × March			-74.401
			(-0.493)
ES TOP × April			83.747
			(0.815)
ES TOP × May			-154.801**
			(-2.295)
ES TOP × June			254.775
			(1.162)
ES TOP × July			-49.741
			(-0.653)
ES TOP × August			-36.536
			(-0.588)
ES TOP × September			-34.841
			(-0.262)
Observations	595	595	238
$\overline{R}^2$	0.006	0.023	0.046

Table A.5:
Placebo Linear Regression Models of Corona-News Effects on Abnormal Returns

Table A.5 shows the results of the multivariate placebo regression on how the number of pageviews on corona articles published by NRK affects abnormal returns of stocks around earnings announcements. Coefficients are reported in basis points for readability. Abnormal returns are the returns for each company adjusted for the market return for the industry they are within. CAR[0,1] of the firms with earnings announcements are swapped for the corresponding value on the same day as their closest competitor in terms of market capitalization. Earnings surprises are divided into five quantiles, where the first quintile is the most negative surprise, and the fifth quintile the most positive. Control variables include indicators for each month, log(market capitalization), market-to-book ratio, the share of institutional ownership, log(1 + number of analysts), and share turnover the last 30 days. All control variables are interacted with the earning surprise quintile rank. Regression (3) only includes observations in the most negative and positive earnings surprise quintiles. In regression (3), ES TOP is an indicator variable for the most positive earnings surprises. Standard errors are adjusted for heteroskedasticity and t-values are reported in the parentheses. *, **, and *** represent significance at the 10%, 5% and 1% level, respectively.

	Dependent variable:		
		CAR[0,1]	
	(1)	(2)	(3)
CNEWS	0.287	0.560	1.294
	(0.174)	(0.338)	(0.501)
ES	18.236	109.979	
	(0.558)	(1.153)	
ES * CNEWS	-0.206	-0.297	
	(-0.420)	(-0.622)	
TOP ES			101.886
			(0.754)
TOP ES * CNEWS			-0.429
			(-0.687)
Company controls		X	X
Abs ES indicators		X	X
Month indicators		X	X
Observations	595	595	239
$\overline{R}^2$	-0.004	0.052	0.093