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**Bachelor Thesis International Bachelor’s in Economics and Business Economics**

***The impact of two emergency use requests for vaccines anti-Covid-19 on stock market returns in the United States***

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**Preface**

**I would like to thank my supervisor Yashvir Gangaram-Panday for all his assistance in writing my bachelor’s thesis. I would also like to thank my family for their advice and support. With them in mind, I was able to write a better thesis. Finally, I want to thank Erasmus School of Economics for giving me the opportunity to finish my bachelor’s degree here.**

**Abstract**

**After the World Health Organisation (WHO) declared Covid-19 a pandemic, the stock market became extremely volatile. The question is what the magnitude of the effects of this pandemic on stock market returns was. Particularly, the analysis centers on the abnormal returns around November 20, and November 30, the dates BionTech and Pfizer, and Moderna applied for Emergency Use Authorisation for their vaccines against Covid-19. The empirical analysis proves that around these two dates, there were significant abnormal returns, and large in magnitude, for almost all sectors. The size of companies also impacted the magnitude of the abnormal returns. These results are substantial and prove that the effects of pandemics are not yet understood and deserve more attention in future studies.**

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**1. Introduction**

It is difficult to gauge the effects of a pandemic on stock market returns. The reason for that is that many developments and news around the novel virus happen at the same time. This is also the case for the Covid-19 virus, also known as the novel coronavirus, or SARS-CoV-2, recognized by the World Health Organisation (WHO) on December 31st, 2019. However, the world got aroused by the news of a virus which could be spread among people for the first time on January 20, 2020. As such, a plethora of studies appeared investigating the effect of mass news about the novel virus on January 20/21st on stock market returns. Such papers include the one written by Liu, Manzoor, Wang, Zhang and Manzoor (2020), who find that around January 20, Covid-19 had a significant negative effect on stock markets from all the affected countries (e.g. Hong Kong, Malaysia, Japan, Thailand). Al-Awadhi, Alsaifi, Al-Awadhi, Alhammadi (2020) also report a negative interaction of the disease with stock market returns in Shanghai and Hong Kong. Similarly, He, Sun, Zhang, Li (2020) find that the transportation, mining, electric and heating, and environmental industries in China were heavily affected around January 23rd.

Most studies investigate the impact of Covid-19 in the Asian markets. As such, this paper aims to examine how the stock market in the United States reacted to the news of emergency use authorization requests for two Covid-19 vaccines on November 20 and November 30. And why might there be abnormal returns around these news? The answer lies in the fact that the vaccines were supposedly developed less than a year after the emergence of this virus. It is important to study this topic because, according to multiple sources, the normal development time for a vaccine is 10-15 years according to Medical News Today (2020) and History of Vaccines (2021), or “10+ years”, according to the World Economic Forum (2020).

The news to be researched are selected from the American Journal of Managed Care (AJMC). The AJMC (2020) provides a timeline of all important Covid-19 announcements. The news are as follows:

1. *On November 20, Pfizer and BioNTech apply for emergency use authorization (EUA) for their vaccine with the Food and Drug Administration (FDA);*
2. *On November 30, Moderna applies for EUA for their vaccine with the FDA.*

The effects these two announcements had on the stock market will therefore be analysed. Thus, the following research question is put forward:

***What is the effect of the news of applications for Emergency Use Authorisation for vaccines against Covid-19 on stock market returns within the S&P 500?***

Several papers have been written on how news affect stock prices. Since the outbreak of Covid-19, Liu et al. (2020) have investigated the effect of the outbreak on stock prices on the days of the first known cases, i.e. January 20. Similarly, He et al. (2020) look at the impact of the outbreak on stock prices across different sectors, around January 23. Finally, Mazur, Dang and Vega (2021) analyse the march 2020 stock market crash by looking at companies within the S&P 1500. However, literature on how the stock market reacted to requests for emergency use authorization for vaccines is definitely lacking. In this sense, the research question is scientifically relevant, because it adds to existing literature. On another note, according to Statista (2021), 55% of the United States adults had shares in the stock market in 2019 and 2020. Therefore, the research question is socially relevant, because it helps the individual investor understand how different news have different impacts on stock prices.

The Global Industry Classification Standard groups companies in the S&P 500 in 11 sectors: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, Utilities, Real Estate (MSCI, 2021). Of these, the energy, real estate, financials, utilities, consumer staples, industrials, and healthcare sectors have underperformed in 2020 when compared to the average returns of these industries between 2010-2019. (Statista, 2021). Previous studies also suggest that specific sectors may be affected in different ways during a pandemic, such as hotels, pharmaceutical, and biotech sectors (Al-Awadhi, Alsaifi, Al-Awadhi, Alhammadi, 2020). As a result, this paper will also look at which sectors were affected the most around the two selected announcements.

At last, the report is organized as follows. Section 2 constructs the theoretical foundation of this research. Relevant literature is reviewed and discussed to formulate sub-questions and the hypotheses. Section 3 discusses the different data sources that were used, as well as how the data was prepared and cleaned to be later used for analysis. Section 4 presents the variables and the models that were used to derive the results. Section 5 presents and discusses the results of the technical analysis. This section also reports various tables and figures. Section 6 concludes the paper. It includes a review of the paper, a discussion of the work done, limitations of the research done here, as well as recommendations for future research. Finally, other facts and figures that support the claims of this report can be found in the Appendix.

2. Literature review

2.1. The impact of Covid-19 related announcements on market returns

As of today, 22nd of September 2021, Statista (2021) registers 43,242,302 coronavirus cases in the United States of America and a death toll of 675,051 people. Amidst worldwide panic, between the 12th of February 2020 and 18th of March 2020, the stock market plunged roughly 27.39% (Statista, 2021). The US stock market was not the only one affected by Covid-19 developments in 2020. Rahman, Amin and Al Mamun (2021) use an event study methodology and analyse four announcements related to Covid-19. In particular, they identify two negative events, namely: January 30, 2020, when WHO declares Covid-19 as a public health emergency, and 11th of March 2020, when WHO declares Covid-19 a pandemic. Further, Rahman et al. (2021) find significantly negative CARs given event windows of [-5,5] and [-7,7] days for the negative events. On the other hand, they identify two positive events, a 66.4 billion Australian dollar (AUD) stimulus package on the 22nd of March 2020, and the AUD130 billion JobKeeper package. Surprisingly, they find a negative and statistically significant cumulative abnormal return for the first positive event. This result may arise because the AUD66.4 billion package does not reduce uncertainty with regards to the pandemic, and it does not increase investor confidence (Rahman et al., 2021).

Another interesting result of Rahman et al. (2021) is that their cumulative average abnormal return is generally higher in the longer event windows, compared to the shorter, (-3,3) event window. This finding is in contrast with the efficient market hypothesis, which theoretically states that the cumulative abnormal return should not change significantly after an event date, because of the quick incorporation of information into stock prices. However, in practice, “apparent underreaction to information is about as common as overreaction, and postevent continuation of abnormal returns is as frequent as postevent reversals”, according to Malkiel (2003). The results found by Rahman et al. (2021) are also economically meaningful. For example, given that the average market cap of the firms in their sample was AUD8.011 million, then the average cost associated with the negative event on March 11th over the (-5,5) event window was approximately AUD352 million. Therefore, given the economic importance of understanding events such as the pandemic, and the literature on abnormal returns associated with different events of the Covid-19 pandemic, the following hypothesis is formulated:

*H1: Companies within the S&P 500 exhibited abnormal returns around the dates November 20, and November 30.*

2.2. The impact of different company characteristics on abnormal returns

Wu, Hou, Zhang (2020) look at how other fundamentals and characteristics of a company and industry may have affected the returns using an event study methodology. The amount of cash held did not have a significant effect on the CARs they calculated. According to them, the industry, size, return on assets, the amount of leverage and fixed assets had a significant impact on stock returns. Chan, Hamao and Lakonishok (1991) look at the effect of the earnings yield, size, book to market ratio and cash yield on stock returns in the Japanese stock market. Of these, the book-to-market variable is the most positively impactful when predicting returns. The cash flow yield also had a significant positive impact on expected returns (Chan, Hamao and Lakonishok, 1991).

Therefore, given the existing literature on how company fundamentals affect the abnormal return, the following sub-question is formulated: “*What is the effect of company fundamentals on stock price reaction around the time of news?*” For the scope of this paper, however, this sub-question is too broad. Therefore, a better sub-question would be “*Do larger firms exhibit larger abnormal returns?”,* and its underlying hypothesis is:

*H2: The level of total assets of a company had a positive effect on the cumulative abnormal return.*

2.3. The relation between sector and the abnormal returns

He et al. (2020) start their paper stating that 2020 will be recorded in history because of an extraordinary turn of events. They study the impact of covid-19 on stock prices through an event-study methodology. The event day of the Covid-19 outbreak is January 23rd, 2020. Their regression shows that the Shanghai and Shenzhen A-shares showed no significant cumulative abnormal returns on the day of the outbreak. However, starting with the 15th day after the outbreak, both stock exchanges’ shares significantly dropped. They find that the CARs were negative for the Shanghai stock exchange (SE) and positive for the Shenzhen SE. This discrepancy is explained by differences in industry characteristics of the companies listed on each exchange. In particular, the Shanghai SE listed companies are mostly based in the transportation, mining, electricity and heating and environment industries whereas the Shenzhen SE includes companies which are highly technological.

He et al. (2020) further break the impact of covid-19 on each industry with different event windows. 30 days after the event day, the sectors which showed the largest negative CARs are agriculture (CAR ~ -1.12%), electric&heating (CAR~ -0.59%), transportation (CAR ~ -0.33%), environment (CAR~-0.73%) and information technology (CAR~ -0.65%). These are significant at the 1% confidence level. Lastly, He et al. (2020) investigate how covid-19 impacted companies with different equity properties, and argue they have different capabilities to deal with external shocks. They find that the non-technological companies showed significant negative CARs on all event windows chosen. In contrast, most technological companies showed significant positive CARs on all event windows.

In another paper, Xiong, Wu, Hou and Zhang (2020) investigate the investors’ responses to the Covid-19 pandemic using the event study method. They find that institutional investors have a significantly negative impact on market reaction of the companies. They also show that firms in the industries that are more affected by the emergence of the virus show significantly lower CARs. They take over which industries are vulnerable to a pandemic from previous research by Kong and Su (2019) and Shen et al. (2020). They also use an event study methodology and various regressions to explain their findings. Cheng, Jang and Kim (2020) examine the effect of the SARS outbreak on Taiwanese hotel stock movements. Hotel stocks had significant declines in earnings and stock prices, as the industry faced higher than average risk during the SARS-outbreak period.

Given the academic literature on the relation between the industry type of a company, and the cumulative abnormal return, the following sub-question is formulated: *Was market reaction to the news of Emergency Use Authorisation requests different across different industries?* The underlying hypothesis is:

*H3: The industry type had an effect on the cumulative abnormal return.*

3. Data

3.1 Description of data sources

To examine whether there are abnormal returns around the vaccine approval announcements, I use data on the S&P 500 index and the companies it includes from various sources. Specifically, the S&P 500 constituents were retrieved from *Slickcharts*, a website containing up-to-date information on the stock tickers, prices, and their weights in the S&P 500. This paper uses constituents that date from July 26, 2021.

The data on S&P 500 index daily returns comes from Wharton Research Data Services, over January 2, 1998, until December 31, 2020. The database is provided by Wharton School of the University of Pennsylvania. Furthermore, WRDS mostly includes data on business and finance as well as major data sets used in academic research (WRDS, 2021). Their data is used by global institutions and provides insights into the latest discoveries in academic research.

The data on the risk-free rate, which is the one-month Treasury bill rate, comes from the Kenneth R. French data library (French, 2021). The initial data is selected over July 1, 1926, until May 28, 2021. This data source is owned by Professor Kenneth R. French and is posted on Dartmouth University’s website. Finally, the Kenneth R. French library includes data sets on the Fama-French factors and portfolio returns.

The data on daily stock prices is obtained from CRSP/Compustat Merged Database (CCM), retrieved from the WRDS database, between November 1, 2019, and December 31, 2020. This is also the estimation period, discussed in sub-section 5.1.3. The Center for Research in Security Prices (CRSP) provides historical stock market data. Compustat database includes financial, statistical and market information on companies all over the world. Lastly, the CRSP/Compustat Merged Database adds Compustat data items to CRSP data. In the merged CRSP/Compustat database, the Compustat variables can be accessed using CRSP's PERMNO/PERMCO identifiers and Compustat's GVKEY identifiers (WRDS, 2021).

3.2 Data cleaning

For the purpose of this paper, the analysis requires additional (quarterly) data on the industry type, total assets, and market value of companies. This dataset was downloaded from Compustat, and it initially included additional variables, namely the currency type, population source, data format, level of consolidation, industry format, data format, and the active/inactive status marker. They were redundant, and immediately dropped, in the data cleaning process. Later, this dataset was merged with the data on daily stock prices of the companies within the S&P 500, obtained from the CCM database on the basis of GVKEY identifiers. The latter dataset included redundant variables, namely the cash equivalent distributions, the daily total return factor, and the issue id – dividends variables. These variables were also dropped.

The next step in preparing the data for analysis involves merging the S&P 500 returns data obtained from WRDS with the merged datafile between Compustat and CCM. After this step, the return of each individual company is computed and added as a variable in the dataset. Finally, the risk-free rate data set, obtained from the Kenneth R. French library is also added to obtain a ready-for-analysis dataset. The variables this dataset contains, and others will be explained through descriptive statistics and thoroughly discussed in the Methodology section (Section 4).

3.3 The selection of the sample

The research population of this study comprises of all indexes which are made up of companies with the largest capitalizations in their country. These are usually the most popular stock indexes in their countries, too. For example, it includes the FTSE 100 in the UK, the S&P 500, the Nikkei 225 in Japan, and the S&P/TSX Composite Index in Canada. These indexes make up a large share of the equity markets in their respective countries: the FTSE 100 makes up 42.5% of all value on the London stock exchange; Nikkei 225 covers 64% of the Tokyo Stock Exchange 1st Section (Nikkei, 2014); the S&P/TSX Composite index makes up 95% of all value on the Canadian stock exchange (TSX Inc., 2021).

This paper focuses on companies within the S&P 500. This index and its incorporating companies were chosen for analysis, because the first two vaccines against Covid-19 were approved within the US borders. The S&P 500 includes 505 large cap companies that make up about 80% of the equity market in the US (S&P Dow Jones Indices, 2021). This aspect is important, as, due to its size, this index is quite representative of the equity market behaviour in the US. Furthermore, due to their popularity, data on the S&P 500, as well as data on the other most major indexes of developed countries is widely available on several platforms, ensuring the study’s replicability.

4. Methodology

4.1 Event study specification

The method employed in this paper for studying the existence of abnormal returns around an event date is an event study, and follows the framework described by MacKinlay (1997). The theory states that if a market is efficient, i.e. the efficient market hypothesis holds, the impact of an occurence will be reflected by the stock price change. Therefore, event studies are widely used in finance to quantify the impact of specific events (Liu et al., 2020). However, there are a few limitations to an event study. One special case is when the event days are close to one another, as is the case in this paper. Henderson (1990) briefly mentions this problem in his report, and his solutions are presented in sub-section 6.1 (Discussion). All in all, this method is preferred because, given that a market is rational, the security prices will immediately incorporate any effects of new events. Therefore, the economic impact of an event can be constructed using actual stock prices over a relatively short time period, i.e. using an event study(MacKinlay, 1997). Thus, the following paragraphs are dedicated to explaining the event study methodology used in the technical analysis for this paper. I use the same notations thorughout.

*4.1.1 Pre-AR calculations*

The preliminary dataset obtained after data cleaning (Section 4.2) includes the stock and market (i.e. S&P500) prices only. Therefore, I compute the stock and market returns with the following formulas:

Where:

* is the price of stock *i* within the S&P 500 at time *t;*
* is the return of stock *i* within the S&P 500 at time *t;*
* is the price of the S&P 500 at time *t*;
* is the return of the S&P 500 at time *t*.

The next step is to calculate the actual excess market returns, as well as the actual excess returns for each stock, using the following formulas:

Where:

* is the actual return of stock *i* within the S&P 500 in excess of the risk-free rate at time *t;*
* is the actual return of the S&P 500 in excess of the risk-free rate at time *t*, also known as the market premium*;*
* is the return provided by the risk-free rate at time *t.*

*4.1.2 Model specification*

Before calculating the abnormal returns, I first need to generate the predicted or expected stock returns for each company. He et al. (2020) use the market model in their event study to generate expected returns. Rahman et al. (2021) also use the market model to predict stock returns. Furthermore, according to Brenner (1979), market models are the most widely used and display good predictive power. Therefore, the first choice for generating expected returns in this paper is the market model. However, for the period analysed in this study, namely between November 2019 and December 2020, the risk-free rate takes extremely low values, between 0 and 0.00007, with a mean value of 0.0000223. Therefore, I add this variable to form the excess returns model (also known as the empirical capital asset pricing model):

Where:

* is the expected (or predicted) stock return for company *i* at time *t;*
* measures the sensitivity of on the market premium;
* is the error term, with an expected value of 0. This term is assumed to be uncorrelated with the S&P 500 excess return, and uncorrelated with another individual stock excess return , where *j≠i;*

Abnormal returns are calculated by subtracting the predicted or expected return from the actual (excess) return:

Where:

* is the abnormal return of company *i* at time *t*.

Finally, I calculate the cumulative abnormal return (CAR) over several event windows. The CAR is obtained by summing all abnormal returns of all companies during the time frame of the event window:

Where:

* is the cumulative abnormal return for event window *k,* where k takes values from 1 to 5, denoting each of the 5 event windows selected in the next sub-section.

*4.1.3 Event windows*

The event dates are November 20, 2020 and November, 2020. These are the dates Pfizer and Biontech, and Moderna applied for EUA for the first two vaccines against SARS-CoV-2 inside the US borders. The forecast period is roughly 260 trading days before each event for both events. This ensures that for each company there is a year of data prior to the two events examined in this paper. It also improves forecast accuracy (He et al., 2020). Next, the event windows are selected. Since the Covid-19 pandemic was a volatile period for the stock market, according to Morgan Stanley (2020), I limit the estimation to a maximum of 7 trading days before and after each event date. This reduces the confounding effect of other events related to Covid-19 (Rahman et al, 2021). In other words, this limitation of the event windows improves the results, in the sense that the two events, although close to each other, do not interfere with one another as much as they would with larger event windows. As a result, I select 5 event windows for each event date: (0,0), (-1,1), (-3,3), (-5,5) and (-7,7).

4.2 Level-log regression

As per Sections 2.2 and 2.3 in the literature review, I need to test the market reaction of the cumulative abnormal returns on size and industry. I use the level-log model below:

Where:

* is the natural logarithm of total assets, i.e. the size of a firm;
* is a categorical variable, which consists of the industry classification of the firms within the S&P 500, according to the Fama-French classification of 12 industries classification. This classification is used, because it is more compact than the Global Industry Classifications Standard, provided by MSCI (2021);
* the betas are the regression coefficients;
* is the error term specific the cumulative abnormal return for a particular event window, .

As a mention to why the level-log model is preferred, the level of total assets of companies inside the S&P 500 is skewed to the right, and appears to follow a log normal distribution, as per Figure 8.1 in the Appendix. Therefore, to reach normality, I apply the natural logarithm to total assets which results in a normal, bell-shapped distribution, as per figure 8.2 in the Appendix. Descriptive statistics are also shown in Table 8.3 in the Appendix.

5. Results

After cleaning the data, as explained in the Data cleaning section (Section 3.2), I am left with 467 companies within the S&P 500. Data on the other companies was dropped for two reasons: first, the fiscal year of some companies ended midway in 2020, and second, more recent data did not exist on these companies; whereas the analysis centers on the month of November 2020. Furthermore, as specified in sub-section 4.1.3 (Event windows), I calculate CARs over several event windows. This is to try and capture the entire reaction of the market around the event dates of November 20, 2020, and November 30, 2020. Lastly, this section presents the results in response to the hypotheses formulated in Section 2 (Literature Review).

5.1 Abnormal returns around the event dates

The first hypothesis that was formulated is:

*H1: Companies within the S&P 500 exhibited abnormal returns around the dates November 20, and November 30.*

To test this hypothesis, I run one-sample t-tests on each of the CARs. As per Table 5.1.1, the mean of the estimated CARs is positive for each event window around November 20. This is consistent with the initial claim that the application for EUA by Pfizer and Biontech is a positive event for the economy. Furthermore, they are all significant at the 5% level, except for CAR(-7,7) for the first event date, November 20. Given Figure 5.1.1, the reason for this is that on trading days November 11 and 12, the abnormal returns are large in magnitude and negative, they switch sign between November 13 and November 22, only to be again negative, but smaller in magnitude between November 23 and November 27. I can find two possible reasons for this. First, another (negative unexpected) event took place at least 6 trading days before November 20, producing large negative CARs, and thus leaving large costs in the economy. Second, there was an over reaction between November 13 November 15, possibly due to leaked insider information, leading to large and positive abnormal returns, followed by a small correction between November 23 and November 27. Therefore, the first hypothesis is not rejected for November 20.

Table 5.1.1

*One sample t-tests for cumulative abnormal returns given event windows of (0,0), (-1,1), (-3,3), (-5,5) and (-7,7) around the event date November 20, 2020*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Obs. | Mean | St. Err. | t-value | p-value |
| CAR(0,0) | 467 | .003 | 0.001 | 3.878 | 0 |
| CAR(-1,1) | 467 | .011 | 0.002 | 7.088 | 0 |
| CAR(-3,3) | 467 | .015 | 0.003 | 5.035 | 0 |
| CAR(-5,5) | 467 | .023 | 0.004 | 6.448 | 0 |
| CAR(-7,7) | 467 | .005 | 0.004 | 1.258 | .209 |

Figure 5.1.1

*Mean abnormal stock returns 7 trading days before and after November 20, 2020 for companies within the S&P500*

Table 5.1.2 presents one sample t-tests for the cumulative abnormal returns, given the second event window, November 30. Firstly, the mean of abnormal returns is small and negative, up to 3 days before and after the event date. Then, the mean becomes positive for the other event windows. Second, all the computed CARs are significant at the 5% level. Moreover, Figure 5.1.2 can be used to explain the discrepancies of the means. As such, 7 to 3 days before the event date, abnormal returns were positive, possibly due to insider information, as was the case around November 20 too. Later, 2 days before and after the event date, the abnormal returns were negative and small, probably because the stock prices were inflated due to the overreaction in the previous days. Finally, 3 to 7 days after the event date, the abnormal returns are once again positive. The overall effect signaled around the event is positive, as reflected by positive abnormal returns. As a result, the first hypothesis is not rejected for November 30.

Table 5.1.2

*One sample t-tests for cumulative abnormal returns given event windows of (0,0), (-1,1), (-3,3), (-5,5) and (-7,7) around the event date November 30, 2020*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Obs. | Mean | St. Err. | T-value | p-value |
| CAR(0,0) | 467 | -.005 | 0.001 | -5.314 | 0 |
| CAR(-1,1) | 467 | -.012 | 0.002 | -5.573 | 0 |
| CAR(-3,3) | 467 | -.007 | 0.003 | -2.321 | .021 |
| CAR(-5,5) | 467 | .009 | 0.004 | 2.408 | .017 |
| CAR(-7,7) | 467 | .015 | 0.004 | 3.819 | 0 |

Figure 5.1.2

*Mean abnormal stock returns 7 trading days before and after November 30, 2020 for companies within the S&P500*

5.2 The impact of firm size and industry type on cumulative abnormal returns

This section presents the results for the following two hypotheses:

*H2: The level of total assets of a company had a positive effect on the cumulative abnormal return.*

*H3: The industry type had an effect on the cumulative abnormal return.*

To test these two hypotheses, I generate the results using the level-log regression model in the Methodology section (sub-section 4.2, Level-log regression). The results for the first event date, November 20, are found in Table 5.2.1. The size of a firm, proxied by the Natural Logarithm of Total Assets in Table 5.2.1, is significant at the 5% level for the (-3,3) and (-7,7) event windows. If firm size increases by 1 billion USD, then the cumulative abnormal return CAR(-3,3) increases by 12.43 percentage points. Similarly, if firm size increases by 1 billion USD, the cumulative abnormal return CAR(-7,7) increases by 16.58 percentage points. The 1 billion USD increments are valid, as the average firm size is 88.432 billion USD, as per Table 8.1 in the Appendix. These results are economically meaningful and result in a lot of created value around the first event date. Therefore, the second hypothesis, H2, is not rejected.

On the other hand, Table 5.2.1 also displays the effect different industries had on the cumulative abnormal returns. The results in this table show that for event window, there were several industries which affected the CAR, significant at the 10%, 5% and 1% levels. Looking at CAR (0,0), all the industry types which are significant are negative in magnitude; for example, firms exhibited 1.2 percentage points lower cumulative abnormal returns, significant at the 5% level, if their assigned industry was Wholesale, Retail, and Some Services. Furthermore, the Oil, Gas, and Coal Extraction and Products industry exhibited has the largest positive impact of all industries on the CARs. It is significant at the 1% level for event windows (-1,1), (-3,3), (-5,5) and (-7,7). For the (-7,7) event window, if a company is assigned to the Oil, Gas, and Coal Extraction and Products, the cumulative abnormal return increases by 15.5 percentage points. Likewise, CAR(-7,7) increases by 9.7 percentage points, significant at the 1% level, if the industry type is Telephone and Television Transmission. In contrast, given the Utilities industry, CAR(-3,3) decreases by 4 percentage points, significant at the 5% level, and CAR(-5,5) decreases by 7.2 percentage points, significant at the 1% level. When working with large caps, as is the case with companies within the S&P 500, these abnormal returns, which are large in magnitude and overall positive result in hundreds of billions of value, created as a result of the news announcement on November 20. Thus, given the significance of the results, H3 is not rejected, meaning that the industry type had an effect on abnormal returns.

Table 5.2.1

*Results of level-log regression of total assets and industry type on cumulative abnormal returns calculated over event windows (0,0), (-1,1), (-3,3), (-5,5) and (-7,7) for event date November 20, 2020*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) |
|  | CAR(0,0) | CAR(-1,1) | CAR(-3,3) | CAR(-5,5) | CAR(-7,7) |
| Natural Logarithm of Total Assets | -0.001 | -0.000 | 0.006\*\* | 0.005 | 0.008\*\* |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
|  |  |  |  |  |  |
| Consumer Durables -- Cars, TV's, Furniture, Household Appliances | -0.008  (0.01) | 0.008  (0.01) | 0.045\*  (0.02) | 0.035  (0.03) | 0.042  (0.03) |
|  |  |  |  |  |  |
| Manufacturing -- Machinery, Trucks, Planes, Off Furn, Paper, Com Printing | -0.009\*  (0.00) | -0.002  (0.01) | -0.005  (0.01) | -0.011  (0.02) | 0.011  (0.02) |
|  |  |  |  |  |  |
| Oil, Gas, and Coal Extraction and Products | -0.003 | 0.097\*\*\* | 0.124\*\*\* | 0.129\*\*\* | 0.155\*\*\* |
|  | (0.00) | (0.01) | (0.02) | (0.02) | (0.02) |
|  |  |  |  |  |  |
| Chemicals and Allied Products | -0.003 | 0.003 | 0.011 | 0.007 | 0.020 |
|  | (0.00) | (0.01) | (0.02) | (0.02) | (0.02) |
|  |  |  |  |  |  |
| Business Equipment -- Computers, Software, and Electronic Equipment | -0.009\*\*  (0.00) | -0.001  (0.01) | -0.009  (0.01) | -0.011  (0.02) | 0.040\*  (0.02) |
|  |  |  |  |  |  |
| Telephone and Television Transmission | 0.004 | 0.018 | 0.039\* | 0.050\* | 0.097\*\*\* |
|  | (0.00) | (0.01) | (0.02) | (0.02) | (0.03) |
|  |  |  |  |  |  |
| Utilities | -0.002 | -0.010 | -0.040\*\* | -0.072\*\*\* | -0.041 |
|  | (0.00) | (0.01) | (0.01) | (0.02) | (0.02) |
|  |  |  |  |  |  |
| Wholesale, Retail, and Some Services (Laundries, Repair Shops) | -0.012\*\*  (0.00) | -0.019\*  (0.01) | -0.035\*  (0.02) | -0.043\*  (0.02) | -0.016  (0.02) |
|  |  |  |  |  |  |
| Healthcare, Medical Equipment, and Drugs | -0.005 | -0.013 | -0.043\*\* | -0.039\* | 0.002 |
|  | (0.00) | (0.01) | (0.01) | (0.02) | (0.02) |
|  |  |  |  |  |  |
| Finance | -0.008\*\* | -0.004 | -0.007 | -0.023 | 0.010 |
|  | (0.00) | (0.01) | (0.01) | (0.02) | (0.02) |
|  |  |  |  |  |  |
| Other -- Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment | -0.014\*\*\*  (0.00) | -0.004  (0.01) | 0.007  (0.01) | 0.008  (0.02) | 0.029  (0.02) |
|  |  |  |  |  |  |
| Constant | 0.019\*\* | 0.012 | -0.047\* | -0.014 | -0.099\*\* |
|  | (0.01) | (0.01) | (0.02) | (0.03) | (0.03) |
| Observations | 467 | 467 | 467 | 467 | 467 |

Standard errors in parentheses

\* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001

Similarly, for the November 30 event date, H2 and H3 are tested using the level-log regression model in the Methodology section (sub-section 4.2, Level-log regression). The results are found in Table 5.2.2. On the day of the event, firm size had a negative impact on the cumulative abnormal return on that day. Once again, the proxy for firm size is the natural logarithm of total assets. Therefore, if firm size increased by 1 billion USD, then CAR(0,0) decreased by 6.22 percentage points, significant at the 1% level. In contrast, 3 days before and after the event, firm size had a significant positive impact on the cumulative abnormal return. If firm size increased by 1 billion USD, then CAR(-3,3) increased by 14.51 percentage points, significant at the 1% level. A similar interpretation can be offered for the (-5,5) and (-7,7) event windows, which after an increase in firm size by 1 billion USD, give even larger percentage point increases in the cumulative abnormal return for each event window, significant at the 5% level. Therefore, H2 is not rejected for November 30.

The industry a company activated in also seems to have heavily affected the cumulative abnormal return on November 30, even more so than on November 20. The results in Table 5.2.2 show several industries moving the abnormal return up or down by a large margin, significant at either the 10%, 5% or 1% levels. For the event window of one day before and after the event, almost every industry shifted the abnormal return by a couple percentage points. Most notably, if a company was in the Business Equipment -- Computers, Software, and Electronic Equipment industry, CAR(-1,1) increased by 5.3 percentage points, significant at the 1% level. In the same event window, there were similar results for other industries. If a company was in the Telephone and Television Transmission industry, CAR(-1,1) increased by 4.9 percentage points, significant at the 1% level. If a company was in the Healthcare, Medical Equipment, and Drugs, CAR(-1,1) increased by 5.7 percentage points, also significant at the 1% level. Other industries that give coefficients significant at the 1% level for the (-1,1) event window are found in Table 5.2.2.

Finally, as was the case on November 20, the Oil, Gas, and Coal Extraction and Products produced the results which were the largest in magnitude, and the most highly significant. Particularly, given the (-7,7) event window, if a company activated in the Oil, Gas, and Coal Extraction and Products industry, CAR(-7,7) increased by 19.4 percentage points, significant at the 1% level. A possible explanation for such a large increase in the abnormal return is as follows. Expectations were adjusted with regards to the normal functioning of the economy, once a second company (Moderna) requested emergency use authorization for their vaccine. Thus, given viable vaccines against Covid-19, demand for fuel produced in the Oil, Gas, and Coal Extraction and Products industry would increase in the near future, thus leading to the large abnormal returns. Given the high statistical significance of the results, H3 is not rejected for the November 30 event date.

Table 5.2.2

*Results of level-log regression of total assets and industry type on cumulative abnormal returns calculated over event windows (0,0), (-1,1), (-3,3), (-5,5) and (-7,7) for event date November 30, 2020*

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | (1) | | (2) | | (3) | | (4) | (5) |
|  | | CAR(0,0) | | CAR(-1,1) | | CAR(-3,3) | | CAR(-5,5) | CAR(-7,7) |
| Natural Logarithm of Total Assets | | -0.003\*\*\* | | -0.002 | | 0.007\*\*\* | | 0.008\*\* | 0.010\*\* |
|  | | (0.00) | | (0.00) | | (0.00) | | (0.00) | (0.00) |
|  |  |  |  | |  | |
| Consumer Durables -- Cars, TV's, Furniture, Household Appliances | | -0.011  (0.01) | | 0.025  (0.02) | | 0.021  (0.02) | | 0.037  (0.03) | 0.053  (0.03) |
|  | |  | |  | |  | |  |  |
| Manufacturing -- Machinery, Trucks, Planes, Off Furn, Paper, Com Printing | | -0.010\*  (0.00) | | 0.024\*  (0.01) | | 0.011  (0.01) | | 0.015  (0.02) | 0.024  (0.02) |
|  | |  | |  | |  | |  |  |
| Oil, Gas, and Coal Extraction and Products | | -0.050\*\*\*  (0.01) | | -0.035\*\*  (0.01) | | 0.028  (0.02) | | 0.155\*\*\*  (0.02) | 0.194\*\*\*  (0.02) |
|  | |  | |  | |  | |  |  |
| Chemicals and Allied Products | | -0.005 | | 0.033\*\* | | 0.016 | | 0.031 | 0.038 |
|  | | (0.01) | | (0.01) | | (0.02) | | (0.02) | (0.02) |
|  | |  | |  | |  | |  |  |
| Business Equipment -- Computers, Software, and Electronic Equipment | | 0.007  (0.00) | | 0.053\*\*\*  (0.01) | | 0.046\*\*\*  (0.01) | | 0.050\*\*  (0.02) | 0.042\*  (0.02) |
|  | |  | |  | |  | |  |  |
| Telephone and Television Transmission | | 0.005 | | 0.049\*\*\* | | 0.054\*\* | | 0.065\*\* | 0.064\* |
|  | | (0.01) | | (0.01) | | (0.02) | | (0.02) | (0.03) |
|  | |  | |  | |  | |  |  |
| Utilities | | -0.007 | | 0.019 | | 0.010 | | 0.008 | -0.024 |
|  | | (0.00) | | (0.01) | | (0.02) | | (0.02) | (0.02) |
|  | |  | |  | |  | |  |  |
| Wholesale, Retail, and Some Services (Laundries, Repair Shops) | | 0.003  (0.00) | | 0.046\*\*\*  (0.01) | | 0.038\*  (0.02) | | 0.028  (0.02) | 0.022  (0.02) |
|  | |  | |  | |  | |  |  |
| Healthcare, Medical Equipment, and Drugs | | 0.009  (0.00) | | 0.057\*\*\*  (0.01) | | 0.042\*\*  (0.01) | | 0.033  (0.02) | 0.022  (0.02) |
|  | |  | |  | |  | |  |  |
| Finance | | -0.008\* | | 0.032\*\*\* | | 0.032\* | | 0.032\* | 0.022 |
|  | | (0.00) | | (0.01) | | (0.01) | | (0.02) | (0.02) |
|  | |  | |  | |  | |  |  |
| Other -- Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment | | -0.006  (0.00) | | 0.026\*\*  (0.01) | | 0.047\*\*\*  (0.01) | | 0.048\*\*  (0.02) | 0.048\*  (0.02) |
|  | |  | |  | |  | |  |  |
| Constant | | 0.025\*\*\* | | -0.023 | | -0.115\*\*\* | | -0.114\*\*\* | -0.120\*\*\* |
|  | | (0.01) | | (0.02) | | (0.02) | | (0.03) | (0.03) |
| Observations | | 467 | | 467 | | 467 | | 467 | 467 |

Standard errors in parentheses

\* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001

6. Discussion and conclusion

6.1 Discussion

The results presented in the previous section are consistent with one another and similar for both event dates. Cumulative abnormal returns were found on November 20 and November 30, and as a result the first hypothesis was not rejected. What is more, firm size affected the cumulative abnormal return for almost all event windows, for both event days. This means that the second hypothesis is not rejected either. Finally, the industry a company activated in positively or negatively affected the cumulative abnormal return, depending on the type of industry for both event dates. As a result, the third hypothesis was not rejected either. However, the results also present limitations. First off, the two event dates, on November 20 and on November 30 are in close proximity to each other. This problem is known as event clustering. Henderson (1990) proposes that joint generalized least squares (GLS) are used to incorporate contemporaneous covariance in the models, to solve this problem. Alternatively, a multivariate regression model could be used to solve the event clustering problem. However, neither approach was taken in this report. However, as a precaution, the event windows limited to up to 7 days before and after each event date, to not include the effects of one or the other event.

Second of all, the basis of the estimation of expected returns in this paper is the CAPM model. Perhaps a more extensive approach could be conducted, one which also checks for industry clustering. Industry clustering happens when two or more events are concentrated in the same industry. As per Tables 5.2.1 and 5.2.2, there were very large effects of the Oil, Gas, and Coal Extraction and Products industry on the cumulative abnormal return for both event dates. Henderson (1990) suggests a more complex portfolio model is used to solve the event clustering issue. On another note, due to the unavailability of data at the time of this report, the study was conducted on 467 companies, out of 501 in the S&P 500. For future studies, it is of critical importance that complete data on all companies that make up the index is available at the time of the report. All in all, the limitations come down to the availability of more advanced econometric techniques, checks and test statistics, which can be applied to reduce potential bias and increase the accuracy of the results.

6.2 Conclusion

This paper analysed the impact of two news announcements on the S&P 500. The news were that Pfizer with Biontech and Moderna applied for emergency use authorization for their anti-Covid 19 vaccines on November 20, and November 30, respectively. The research question was “*What is the effect of the news of applications for Emergency Use Authorisation for vaccines against Covid-19 on stock market returns within the S&P 500?”.* To answer this question, three hypotheses were formulated after reviewing relevant literature in the literature review of this report. The hypotheses were tested, and the results showed that the news in question did in fact have an effect on stock market returns. This was shown through the existence of abnormal returns around the days the news took place. The size of a company was shown to positively affect the abnormal return. What is more, the industry a company activated in also impacted the abnormal return. Therefore, the research question was answered, and the effects of the news were determined and quantified.

Since this study was done on large cap companies within the S&P500, which capture a large portion of the American stock market, it can be replicated to include the S&P middle cap and small cap companies for more extensive results. Therefore, this is a recommendation for future research. In addition, this study can be replicated on other big indexes, like the Nikkei 225. To build up on the discussion, it would also be interesting to apply more advanced econometric techniques, to reduce bias, for example, in a more extensive study of the same type. On another note, there is a wide variety of responses of governments to the Covid-19 pandemic, which had not yet been analysed. Therefore, another recommendation for future research could be to quantify the long-term impact of different policies adopted during the pandemic on stock market returns. In conclusion, this report finds large inefficiencies in the stock market, as shown by the existence of abnormal returns. Future research should be conducted, using more advanced econometric techniques, to shed more light on the underlying causes for such inefficiencies. This is important, because of the large number of stakeholders involved in the stock market.

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8. Appendix

Table 8.1 Descriptive statistics for total assets and for the natural logarithm of total assets of companies within the S&P 500

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Obs | Mean | Std. Dev. | Min | Max |
| Total Assets | 468 | 88432.639 | 274782.95 | 1200.102 | 3386071 |
| Natural Logarithm of Total Assets | 468 | 10.209 | 1.362 | 7.09 | 15.035 |
| *Note.* The Mean, Std. Dev., Min, Max of Total Assets are expressed in USD millions*.* | | | | | |
|  | | | | | |

Figure 8.1

Chart, histogram

Description automatically generated*Histogram of total assets of companies within the S&P 500*

*Note.* Total Assets is expressed in USD thousands.

Figure 8.2

*Histogram of the natural logarithm of total assets of companies within the S&P 500*

Chart, histogram

Description automatically generated