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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, 2020, and November 30, 2020, 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. The abnormal returns increased substantially with company size, and with the industry type. Therefore, because abnormal stock market returns are caused by different announcements during the Covid-19 pandemic, this indicates that the effects of this pandemic need to be studied more in the future.

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1. Introduction

The world got aroused by the news of a deadly new virus outbreak for the first time on January 20, 2020. It spread panic among people, and governments tried to control it with policies, with a debatable effect. This virus also affected the volatility of the stock market and raised uncertainty about the future of many listed companies. As such, a plethora of studies appeared investigating the effect of mass news about the novel virus on stock market returns. How the novel virus, i.e., Covid-19 affected the stock markets is clear. Papers written by Liu, Manzoor, Wang, Zhang, and Manzoor (2020) find that 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. Finally, He, Sun, Zhang, and Li (2020) find that emergence of the virus affected the transportation, mining, electric and heating, and environmental industries in China.

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 (EUA) requests for two Covid-19 vaccines. Namely, Pfizer and BioNTech applied for EUA for a vaccine they developed in collaboration on November 20, 2020. Ten days later, Moderna applied for EUA for their vaccine, on November 30, 2020. The reason why the stock market reaction to these news is worth investigating is due to the extremely short development time of the Covid-19 vaccines. The Covid-19 vaccines were developed less than a year after the emergence of the Covid-19 virus. However, 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, 2020, Pfizer and BioNTech apply for emergency use authorization (EUA) for their vaccine with the Food and Drug Administration (FDA);*
2) *On November 30, 2020, Moderna applies for EUA for their vaccine with the FDA.*

It is difficult to gauge the effects of a pandemic on stock market returns. The reason is that many developments and news around it happen at the same time. The difference as to why I expect to find abnormal returns around the above-lying two dates lies in the fact that they were the first news of positive news of this kind during the pandemic. 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. Similarly, He et al. (2020) look at the impact of the outbreak on stock prices across different sectors. 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, as well as descriptive statistics. 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 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 announcements, namely: the date WHO declared Covid-19 as a public health emergency, and the date WHO declared Covid-19 a pandemic. Further, Rahman et al. (2021) find significantly negative CARs for the negative events.

On the other hand, they identify two positive events, the announcement of a 66.4 billion Australian dollar (AUD) stimulus package and the announcement of 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). However, the abnormal returns are positive during the JobKeeper package announcement, as expected. 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 benefit associated with the positive JobKeeper package announcement was approximately AUD411 million.

The two announcements studied in this paper, on November 20, 2020, and November 30, 2020, are, of nature, viewed as positive events. This is because they are related to the re-opening of the economy, hence an increase in economic activity. Thus, they are expected to lead to benefits in the economy, if I am to follow the model offered by Rahman et al. (2021). Therefore, given the economic importance of understanding catastrophies 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 positive abnormal returns around the dates November 20, 2020, and November 30, 2020.

2.2. The impact of firm size on abnormal returns

According to Han, He, Rapach and Zhou (2018), as many as 94 firm characteristics affect stock returns over time, and 30 firm characteristics affect stock returns at each point in time. In their study, they measure the sensitivity of the average stock return to firm characteristics. In particular, Han et al. (2018) find that the decline in the average return is mainly due to an increase in the magnitude of the size characteristic. Xiong, Wu, Hou, Zhang (2020) look at how firm fundamentals affected the returns of Chinese-listed companies given unexpected announcements related to the Covid-19 pandemic. They use an event study methodology. They prove that for two different announcements, firm size had a significant impact on the cumulative abnormal return. Namely, firm size positively affected the abnormal return during pandemic announcements.

Haw and Kim (1991) look at how firm size affects stock returns in the case of unexpected changes in dividends. In contrast to Xiong et al. (2020), they find a negative relationship between size and the extent of abnormal returns, i.e., higher size leads to lower abnormal returns. Similar results are found by Chan, Hamao and Lakonishok (1991). They look at the effect of the earnings yield, size, book to market ratio and cash yield on stock returns in the Japanese stock market. They show that “a reliably negative relationship exists between firm size and future returns” (Chan et al., 1991). Furthermore, the findings of Chan et al. (1991) strengthen the existence of the “size effect”, i.e., small firms’ tendency to outperform larger firms in terms of stock returns.

Therefore, the existing literature mostly shows a negative effect between firm size and the return of a company, apart from Xiong et al. (2020). As this paper looks at the abnormal returns of companies, it will evaluate the impact of firm size on the abnormal return. Therefore, the following sub-question is formulated “*Do larger firms exhibit smaller abnormal returns around the two EUA application announcements?”,* and its underlying hypothesis is:

H2: The size of a company had a negative effect on the cumulative abnormal return.

2.3. The relation between sector and the abnormal returns

He, Sun, Zhang and Li (2020) study the impact of the Covid-19 outbreak on abnormal returns. Their findings are that the sectors which showed the largest negative cumulative abnormal returns are agriculture, mining, electric, heating, transportation, environment and information technology. In other words, companies from non-technological industries are expected to exhibit negative cumulative abnormal returns. On the other hand, He et al. (2020) find that companies from technological industries exhibited significant positive cumulative abnormal returns.

In another paper, Xiong, Wu, Hou and Zhang (2020) investigate the investors' responses to the Covid-19 pandemic using the event study method. They also show that firms in the industries that are more affected by the emergence of the virus show significantly lower CARs. Those industries are transportation, food and beverage retail, hotel and tourism, postal warehouse, real estate, video entertainment, and construction. Their finding is aligned with He et al. (2020), as these industries with show lower CARs are non-technological. Previous research done by Kong and Su (2019) and Shen et al. (2021) shows a similar pattern.

In the context of the research done here, it is difficult to hypothesize exactly how each industry affected the market reaction, as measured by abnormal returns, around the two announcements related to EUA applications. Therefore, this paper will analyse whether there was a relation between the type of industry and the abnormal return. Thus, 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 EUA applications 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 ensures a year of available data prior to each of the two events. 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 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 based on 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. Descriptive statistics for the variables used for analysis are provided in Section 4.3 (Descriptive Statistics).

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 501 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 behavior 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. There were only two stock splits in the period analysed in this paper, as shown by the data. Those two stock splits are the ones by Apple and Tesla on August 28th, 2020. Therefore, I compute the stock and market returns with the following formulas:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}$$

$$R_{m,t} = \frac{P_{m,t} - P_{m,t-1}}{P_{m,t-1}}$$

Where:

- $P_{i,t}$ is the price of stock *i* within the S&P 500 at time t and it is adjusted such that stock splits are accounted for*;*
- $R_{i,t}$ is the return of stock *i* within the S&P 500 at time *t;*
- $P_{m,t}$ is the price of the S&P 500 at time t;
- $R_{m,t}$ 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:

$$ExcessR_{i,t} = R_{i,t} - r_{f,t}$$

$$ExcessR_{m,t} = R_{m,t} - r_{f,t}$$

Where:

- $ExcessR_{i,t}$ is the actual return of stock *i* within the S&P 500 in excess of the risk-free rate at time *t;*
- $ExcessR_{m,t}$ 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*;*
- $r_{f,t}$ is the return provided by the risk-free rate at time *t.*

4.1.2 Model specification

Before calculating the abnormal returns, I first regress the excess market return on the actual excess stock return, and both were calculated in the above section. Then, I use the the generated intercept (α_i) and slope (β_i) coefficients to generate the predicted returns:

$$Pred\_R_{i,t} = \alpha_i + \beta_i ExcessR_{m,t} + \varepsilon_{i,t}$$

Where:

- $Pred\_R_{i,t}$ is the expected (or predicted) stock return for company *i* at time *t;*
- β_i measures the sensitivity of $Pred\_R_{i,t}$ on the market premium;
- $\varepsilon_{i,t}$ 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 $ER_{j,t}$, where *j≠i;*

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

$$AR_{i,t} = ExcessR_{i,t} - Pred\_R_{i,t}$$

Where:

- $AR_{i,t}$ 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:

$$CAR_k = \sum AR_{i,k}$$

Where:

- CAR_k 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 30, 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 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. The long forecast period 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. Days before the event date are selected is to measure large abnormal reactions in stock prices to the announcements before they were released to the public. As a result, the event windows were selected to include days before and after the event, namely (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:

$$CAR_k = \beta_0 + \beta_1 \ln(AT) + \sum_{i=1}^{11} \beta_i Industry\_type^1 + \varepsilon_k$$

Where:

- $\ln(AT)$ is the natural logarithm of total assets, i.e. the size of a firm;
- $Industry\_type$ 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 (βs) are the regression coefficients;
- ε_k is the error term specific the cumulative abnormal return for a particular event window, $k = \overline{1{,}5}$.

The regression is based on ordinary least-squares (OLS), using robust standard errors. However, the required assumptions of the OLS are also tested, to ensure the quality of the analysis. The results of the tests specific to each assumption are in Table 4.2.1. The first assumption tested is that of no multicollinearity, i.e. the independent variables should not be highly correlated. This means that the variance inflation factor (VIF) should not be greater than 5, which is the case. The test for normality of Shapiro-Wilk test is employed as a safety check. The p-value is 0.0001, smaller than a significance level of 0.05, which means that the hypothesis that the data are normally distributed is violated, i.e. the distribution of the natural logarithm of total assets is not normal. Finally, the hettest for heteroskedasticity is also employed. Its corresponding p-value is 0.001, which means that the null hypothesis that there is heteroskedasticity is rejected.

[1] Industry fixed effects are added to make the results more robust. They show that the results are not driven by a few industries only. However, that is not the case in this paper. The Industry Classification is used here check if market reaction was different across different industries.

Table 4.2.1

Specification tests for the OLS assumptions

Specification tests	VIF	Shapiro-Wilk W test p-value	hettest p-value
ln_at	1.24	0.0001	0.001

4.3 Descriptive statistics

Descriptive statistics are shown in Table 4.3.1. They are used in Section 5 to explain the results. On another note, the variables of interest are Market Value and Total Assets. The kurtosis is greater than 3 for both of them, which implies the data is leptokurtic. Further, the skewness is greater than 0 for both variables too, which means the data is rightly skewed.

Table 4.3.1

Descriptive statistics for market value by industry, total assets and market value for companies within the S&P 500

	Mean	Std. Dev.	Variance	Skewness	Kurtosis
Consumer Durables -- Cars, TV's, Furniture, Household Appliances	88.012	208.000	43264	2.634	8.007
Manufacturing -- Machinery, Trucks, Planes, Off Furn, Paper, Com Printing	33.570	30.874	953.204	1.583	4.458
Oil, Gas, and Coal Extraction and Products	35.197	49.670	2467.109	2.278	6.589
Chemicals and Allied Products	53.180	65.564	4298.638	2.775	10.73
Business Equipment -- Computers, Software, and Electronic Equipment	129.000	326.000	106276	4.094	19.68
Telephone and Television Transmission	90.344	97.737	9552.521	.608	1.557
Utilities	31.163	27.704	767.512	2.943	12.931

Wholesale, Retail, and Some Services (Laundries, Repair Shops)	106.000	329.000	108241	4.468	21.321
Healthcare, Medical Equipment, and Drugs	72.425	81.110	6578.832	2.317	9.316
Finance	53.730	80.914	6547.075	3.208	13.165
Other -- Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment	54.184	102.000	10404	3.863	18.216
Consumer NonDurables – Food, Tobacco, Textiles, Apparel, Leather, Toys	43.169	59.664	3559.793	2.226	7.011
Market Value	69.135	175.000	30625	7.226	63.941
Total Assets	88.433	275.000	75625	8.05	80.018
Note. Values for mean and standard deviation are expressed in USD billions.					

5. Results

5.1 Abnormal returns around the event dates

The first hypothesis that was formulated is:

H1: Companies within the S&P 500 exhibited positive abnormal returns around the dates November 20, 2020, and November 30, 2020.

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, the CARs 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. The reason is that a large amount of news regarding the US Presidential elections, which took place on November 3rd, negatively interfered with the abnormal returns on the larger (-7,7) event window. Finally, the results are economically meaningful. Take for example the (-5,5) event window which shows a cumulative average abnormal return of 2.3%. Given the average market capitalization of USD69.135 billion of the firms in the sample, as per Table 4.3.1, it implies an average benefit to the economy of 0.023 x 69.135 = USD1.590 billion. Therefore, the first hypothesis is not rejected for November 20, 2020.

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	0.3%	0.001	3.878	0
CAR(-1,1)	467	1.1%	0.002	7.088	0
CAR(-3,3)	467	1.5%	0.003	5.035	0
CAR(-5,5)	467	2.3%	0.004	6.448	0
CAR(-7,7)	467	0.5%	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, adjusted for outliers

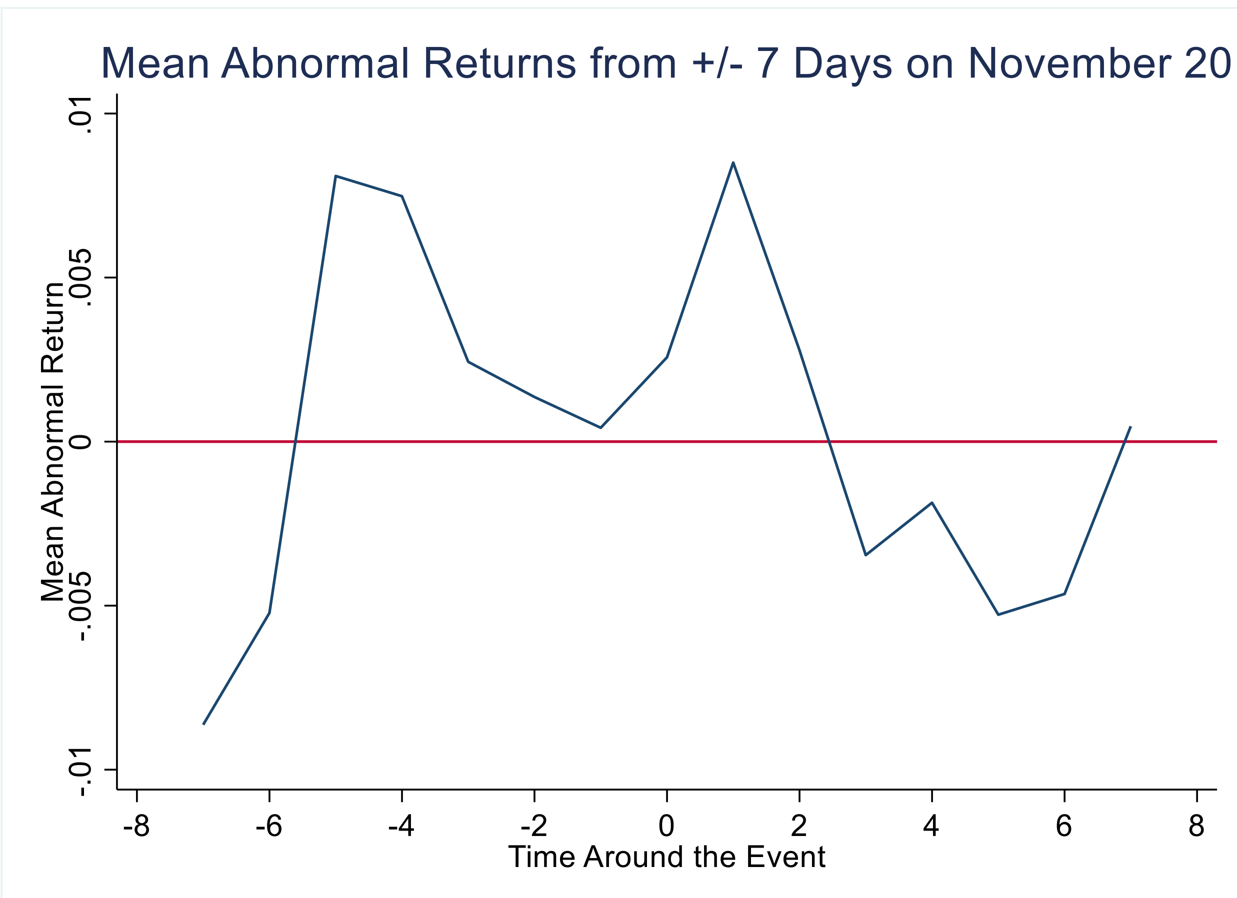


Table 5.1.2 presents one sample t-tests for the cumulative abnormal returns, given the second event window, November 30. Firstly, the mean of abnormal returns is small and negative, up to 3 days before and after the event date. Then, the mean becomes positive for the other event windows. Second, all 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 The reason for this is that, 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). 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 and large abnormal returns. In the (-7,7) event window, the cumulative average abnormal return is 1.5%. Given the average market capitalization of USD69.135 billion of the firms in the sample as per Table 4.3.1, the average benefit to the economy is 0.015 x 69.135 = USD1.037 billion. As a result, the first hypothesis is not rejected for November 30, 2020.

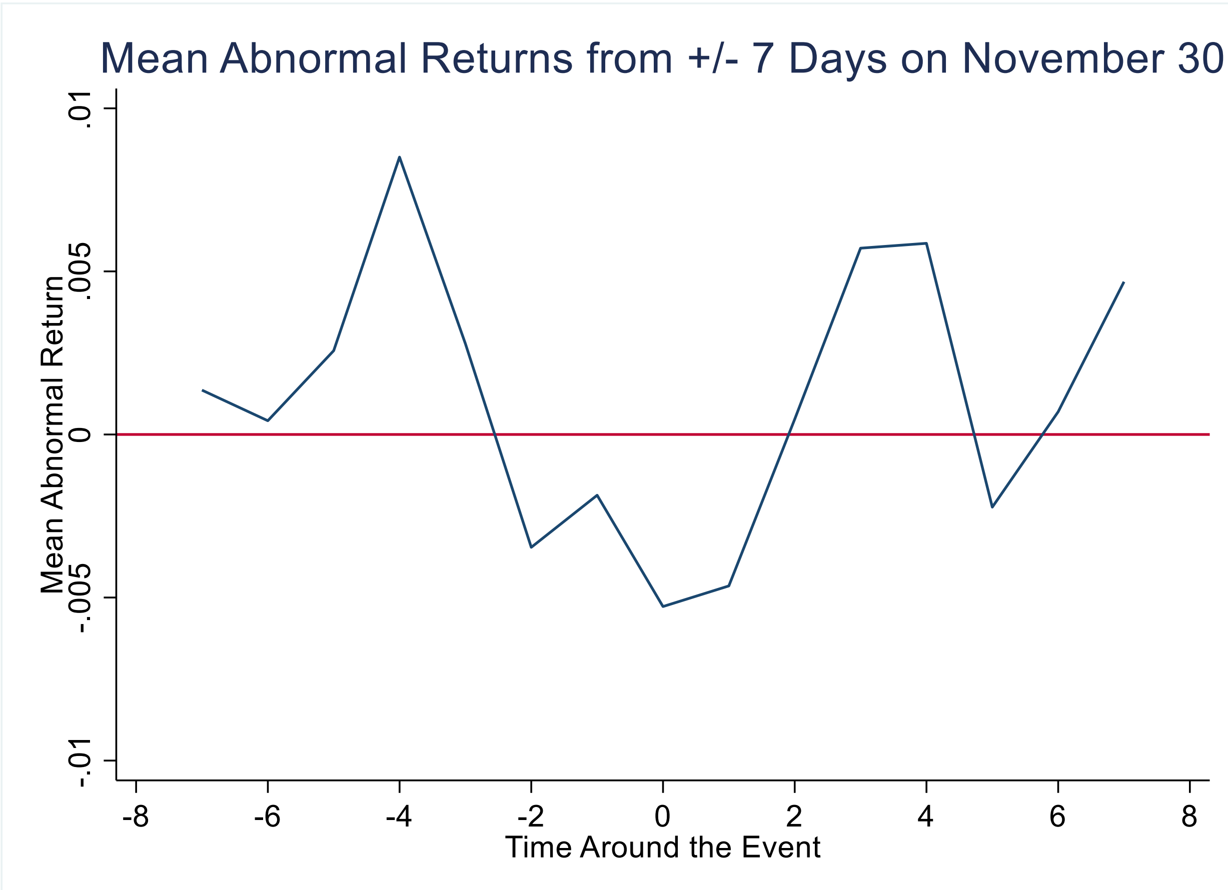
Table 5.1.2

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	-0.5%	0.001	-5.314	0
CAR(-1,1)	467	-1.2%	0.002	-5.573	0
CAR(-3,3)	467	-0.7%	0.003	-2.321	.021
CAR(-5,5)	467	0.9%	0.004	2.408	.017
CAR(-7,7)	467	1.5%	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, adjusted for outliers



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 size of a company had a negative 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, 2020 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. The interpretation of the level-log regression is as follows: If the level of total assets of a company increases by 1%, then I expect the CAR(-3,3) to increase by increases 0.006/100 = 0.00006 percentage points. Although significant, this increase is way too small. What is more, the effect on the cumulative abnormal return is positive, not negative as hypothesised, for the (-3,3) and (-7,7) event windows. Thus, the second hypothesis, H2, is 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. As per Table 4.3.1, the average size of a company in this industry is USD35.197 billion. Economically, this means that the value created for a company in the Oil, Gas, and Coal Extraction and Products around the (-7,7) event window was 0.155 x 35.197 = USD5.456 billion. 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. 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) CAR(0,0)	(2) CAR(-1,1)	(3) CAR(-3,3)	(4) CAR(-5,5)	(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	0.008	0.045*	0.035	0.042
	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)
Manufacturing -- Machinery, Trucks, Planes, Off Furn, Paper, Com Printing	-0.009*	-0.002	-0.005	-0.011	0.011
	(0.00)	(0.01)	(0.01)	(0.02)	(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**	-0.001	-0.009	-0.011	0.040*
	(0.00)	(0.01)	(0.01)	(0.02)	(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**	-0.019*	-0.035*	-0.043*	-0.016
	(0.00)	(0.01)	(0.02)	(0.02)	(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***	-0.004	0.007	0.008	0.029
	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)
Consumer NonDurables – Food, Tobacco, Textiles, Apparel, Leather, Toys	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, 2020 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, the interpretation of the level-log regression is as follows: if the level of total assets of a company increases by 1%, then CAR(0,0) decreases by 0.003/100 = 0.00003 percentage points, significant at the 1% level. Although the effect is small, this means that H2 is not rejected on the day of the event. In contrast, interpreting the level-log regression for the (-5,5) and (-7,7) event windows, after increasing the level of total assets by 1%, CAR(-5,5) and CAR(-7,7) increase by 0.00008 and 0.0001 percentage points respectively, significant at the 5% level. Overall, the effect of total assets is positive and significant on the CAR, albeit small, therefore, H2 is rejected for the November 30, 2020 announcement.

The industry a company activated in also seems to have heavily affected the cumulative abnormal return on November 30, 2020, even more so than on November 20, 2020. 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, 2020, 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. This means that, given an average market cap of 35.197 USD billion for a company in the Oil, Gas, and Coal Extraction and Products sector, the value created on average was 0.194 x 35.197 = 6.828 USD billion. 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 soon, thus leading to large abnormal returns. Given the high statistical significance of the results, H3 is not rejected for the November 30, 2020 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) CAR(0,0)	(2) CAR(-1,1)	(3) CAR(-3,3)	(4) CAR(-5,5)	(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	0.025	0.021	0.037	0.053
	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)
Manufacturing -- Machinery, Trucks, Planes, Off Furn, Paper, Com Printing	-0.010*	0.024*	0.011	0.015	0.024
	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)
Oil, Gas, and Coal Extraction and Products	-0.050***	-0.035**	0.028	0.155***	0.194***
	(0.01)	(0.01)	(0.02)	(0.02)	(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	0.053***	0.046***	0.050**	0.042*
	(0.00)	(0.01)	(0.01)	(0.02)	(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	0.046***	0.038*	0.028	0.022
	(0.00)	(0.01)	(0.02)	(0.02)	(0.02)
Healthcare, Medical Equipment, and Drugs	0.009	0.057***	0.042**	0.033	0.022
	(0.00)	(0.01)	(0.01)	(0.02)	(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	0.026**	0.047***	0.048**	0.048*
	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)
Consumer NonDurables – Food, Tobacco, Textiles, Apparel, Leather, Toys	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. The first hypothesis stated that positive abnormal returns are exhibited around the event dates. Cumulative abnormal returns were found on November 20, 2020, and November 30, 2020, and as a result the first hypothesis was not rejected, i.e., abnormal returns were present around the event dates and were positive. What is more, the second hypothesis investigated a negative relation between firm size and the cumulative abnormal return. It was therefore rejected, as the results showed that firm size positively affected the abnormal return. Finally, the third hypothesis investigated the effect of the industry type on the cumulative abnormal return. The industry a company activated in was shown to affect the cumulative abnormal return positively or negatively, depending on the type of industry for both event dates. As a result, the third hypothesis was not rejected.

The results also present limitations. First off, the two event dates, on November 20 and on November 30 are near 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. Neither approach was taken in this report. On the other hand, as a precaution, the event windows limited to up to 7 days before and after each event date, to exclude the confounding effects of the two events on each other.

Second, 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 models, 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 announcements 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. The results make sense when looking at the magnitude of the effects by industry, for the following reason. The more a specific industry impacted the cumulative abnormal return positively around the two positive announcements, the more that industry was previously negatively affected by the pandemic. In contrast, the negative effect of an industry on the cumulative abnormal return meant that specific industry benefitted from the pandemic. 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. In that case, it is expected that the results would be similar, but the larger sample would give way to a more accurate representation of the stock market in the US. 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 another 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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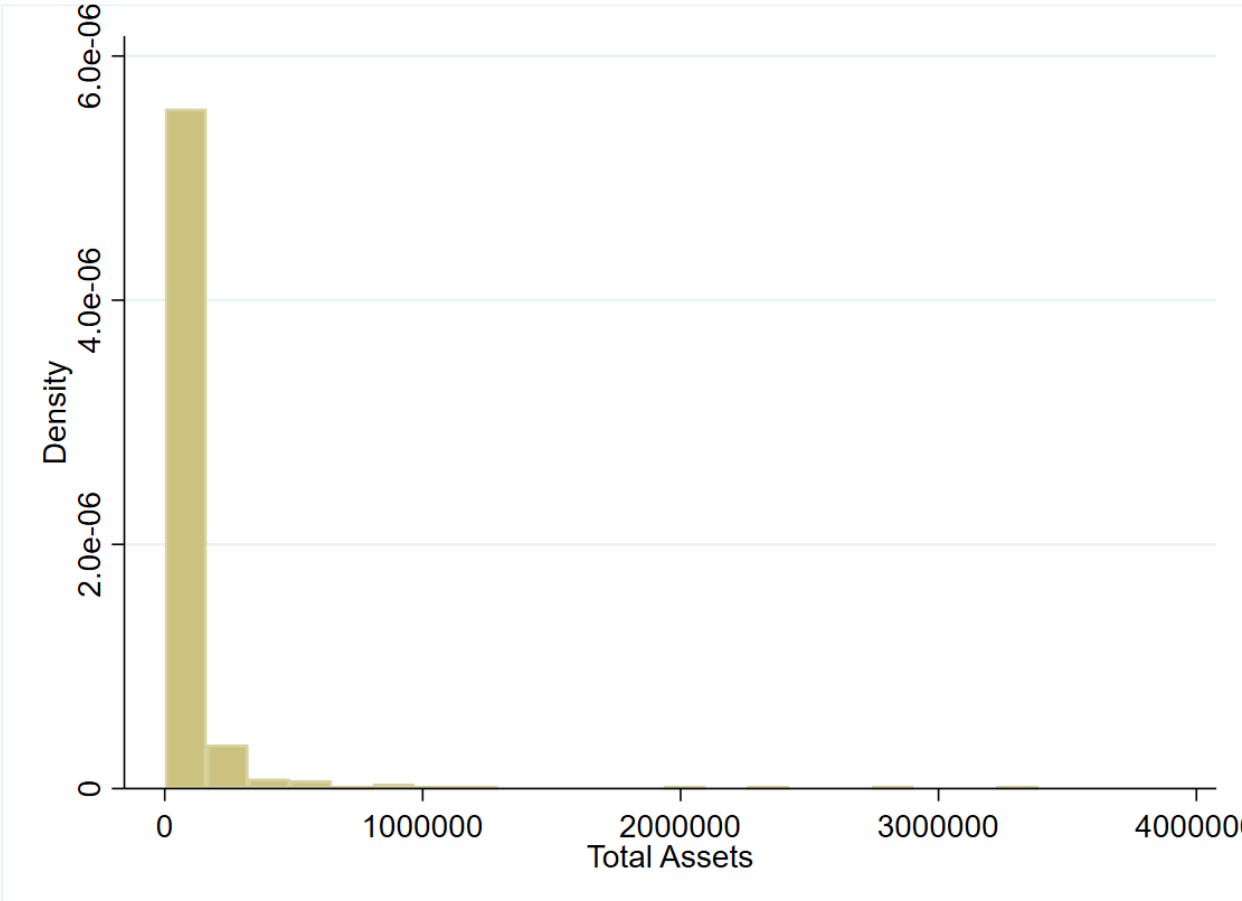
8. Appendix

Figure 8.1

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

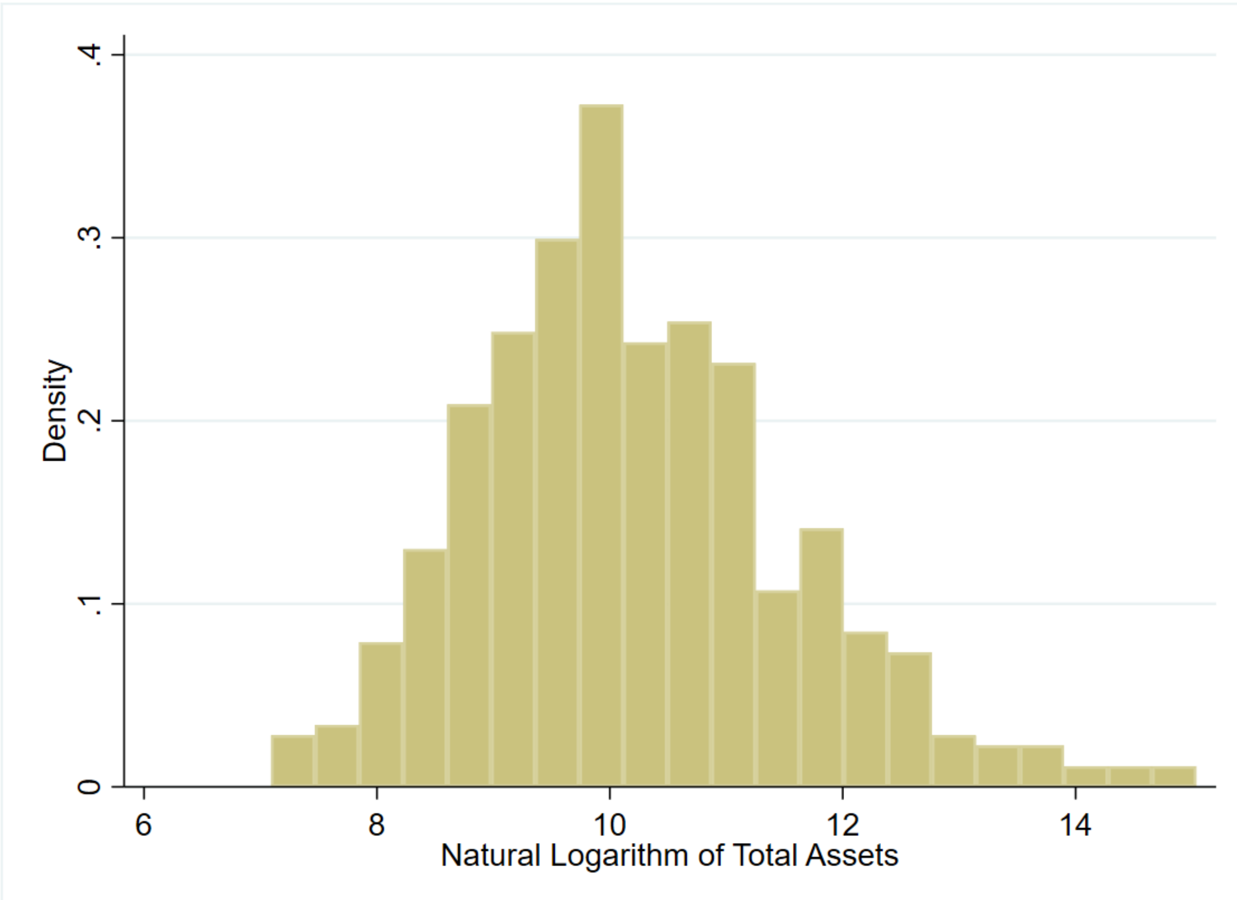


Figure 8.3

Mean Abnormal Returns Around the Event Dates