The impact of COVID-19 on the Dutch stock market

Author: Milan Nijhuis

University of Twente

P.O. Box 217, 7500AE Enschede

The Netherlands

ABSTRACT,

This paper studies the impact of the COVID-19 pandemic on the Dutch stock market. By calculating abnormal returns, based on both the CAPM and FF models, the study compares the performance of the three Dutch stock indices to those of the global market index, after three COVID-19 related events. The findings based on the CAPM model show that the Dutch stock market was negatively impacted by the pandemic, and this impact was most significant closely after the events. However, the findings based on the FF model show no significant negative impact of COVID-19 on the Dutch stock market.

Graduation Committee members:

X. Huang

L. Spierdijk

Keywords

COVID-19, stock returns, AMX, AScX, AEX, Dutch stock market

1. INTRODUCTION

We are all now tragically familiar with the enormous costs in lives of the COVID-19 pandemic (Goodell, 2020). Despite extensive research related to COVID-19, our understanding of COVID-19 and its effects on market quality are still relatively limited (Chatjuthamard et al., 2021). This paper studies the impact of the pandemic on the stock returns of the Dutch stock market. Previous research has examined stock markets in different countries. However, no research has previously been done on the effects of the COVID-19 pandemic on the Dutch stock market and its returns.

While no research has been conducted on the impact of COVID-19 on the Dutch stock market, there are several reasons why such a study is relevant.

First of all, Chatjuthamard et al. (2021), who studied the effect of the pandemic on the global market, concluded that “although the COVID-19 shock has been global, not all countries have been impacted in the same way, and they have not reacted in the same way.” This difference in reactions means that the Dutch stock market could have been impacted completely different than stock markets in other countries.

Secondly, Dwyer Jr & Hafer (1988) show that “there is no reliable relationship between the levels of prices in various stock markets, even though changes in the different market measures may be related.” Because there is no reliable relationship between the different stock markets, no reliable assumptions can be made for the impact of COVID-19 on the Dutch market based on the impact on other markets. These previous research papers provide good reasons to examine the Dutch stock market and find out if this market had a different reaction to the pandemic than the other stock markets, which have been previously researched.

Another reason why investigating the Dutch market is relevant is because of their economy. Any estimate of stock-market effects must rest on an evaluation of the importance of wealth in consumer behaviour (Bosworth et al., 1975). So, the economy of a country can be an important factor in stock returns. The Netherlands have a prosperous, small, open economy with a large financial sector, large international capital flows and a trade balance surplus (Muysken et al., 2017). This is very different from countries that have already been researched. Countries like Australia, the US, India, and Vietnam are way larger and also have completely different economies. Therefore, it is interesting to research whether the Netherlands have reacted differently to the pandemic than these other countries.

This paper also contributes to the existing literature by expanding the knowledge of the impact of big events on the Dutch stock market. It is important for all stakeholders associated with the stock market, i.e. individual investors, fund and portfolio managers, firms, policymakers and regulators, to learn about the nature of the challenge they are facing when a big event impacts the stock market (Apergis & Apergis, 2022). Therefore, this study is relevant to these stakeholders, as it will improve their knowledge of the impact of COVID-19 on the stock market, which gives them a better understanding into the impact of possible similar events in the future.

The research question which this paper will answer is: What are the effects of the COVID-19 pandemic on the returns of stocks in the Dutch stock market?

Existing research regarding the impact of COVID-19 on different stock markets is analyzed, as well as research on other big events that impacted the stock market. Based on this research, the hypothesis of this paper is that stock returns will be lower after the outbreak of the COVID-19 pandemic, especially around the dates of impactful events.

To answer the research question, an event study is used. The study will compare the actual returns of the Amsterdam Exchange Index (AEX), the Amsterdam Midkap Index (AMX), and the Amsterdam Small Cap Index (AScX) to their respective expected returns during the COVID-19 pandemic. To examine the impact of the pandemic, this study looks at the abnormal returns of the indices. Both the

Capital Asses Pricing Model (CAPM), and the Fama-French (FF) model are used for calculating abnormal returns. An estimation window of 90 trading days before the event day is used to create the models. After the event, five windows consisting of 6 trading days each are used: (0, 6), (7, 13), (14, 20), (21, 27), (28, 34). The information on the historical stock prices of the indices that are used are extracted from Refinitiv Eikon[1]. The returns of the stocks are calculated based on their historical daily prices.

The results of the study show different outcomes when using the CAPM model, compared to those when using the FF model. Based on the CAPM model, the results indicate that COVID-19 had a significant negative impact on the Dutch stock market, and this impact was more severe closely after the event occurred. Based on the FF model, no significant impact of COVID-19 on the Dutch stock market was found.

2. THEORETICAL FRAMEWORK

2.1 Efficient market theory and behavioural finance

The efficient market hypothesis explains a market in which firms can make production-investment decisions, and investors can choose among the securities that represent ownership of firms' activities under the assumption that security prices at any time "fully reflect" all available information. A market in which prices always "fully reflect" available information is called "efficient" (Fama, 1970). The efficient market hypothesis is associated with the idea of a “random walk.” The logic of the random walk idea is that if the flow of information is unimpeded and information is immediately reflected in stock prices, then tomorrow’s price change will reflect only tomorrow’s news and will be independent of the price changes today. And because news is by definition unpredictable, resulting price changes must be unpredictable and random. So, neither technical analysis nor fundamental analysis would enable an investor to achieve returns greater than those that could be obtained by holding a randomly selected portfolio of individual stocks, at least not with comparable risk (Malkiel, 2003). The efficient market theory is later classified into three distinct categories: weak efficiency, semi-strong efficiency, and strong efficiency (Brealey et al., 2020). In weak efficient markets, share prices are based only on past prices. In semi-strong efficient markets, share prices reflect all publicly available information, including information from the media and press. In strong efficient markets, share prices reflect all information, both public and private. However, the market cannot be perfectly efficient, as this would mean that informed traders could not earn a return on their information (Grossman and Stiglitz, 1980).

Big events, for instance natural disasters, financial crises, or in this case a pandemic, usually have an impact on stock markets. A reason behind this impact is the behaviour of investors. Undoubtedly, investment decisions depend on the object and its financial status in the future, but often short-term price changes are driven by market participants that are not always based on logic, but sometimes are inspired by mood or instantly "received news" (Bikas et al., 2013). Feelings of investors provide the value weights assigned to possible outcomes to motivate their decisions and actions (Hirshleifer, 2015). Affective reactions can also cause making fast use of urgent information about the environment (Slovic et al. 2002). This can be a good thing, because a risky investment opportunity may trigger fear and, with that, useful hesitation. However, feelings often short-circuit useful analysis, as with exiting the stock market in sudden panic or buying a hot stock on the basis of enthusiasm rather than critical evaluation (Hirshleifer, 2015). As big (negative) events usually cause fear and uncertainty among investors, resulting in them panic selling their stocks, these events have a negative impact on stock markets and their returns. Therefore, behavioural finance can be a very important factor in stock returns.

[1] https://eikon.refinitiv.com/

2.2 Big events and their impact on the stock market

The existing research literature on the relationship between emergencies and stock prices mainly focuses on different crises: terrorist attacks, natural disasters, political behavior, and financial crises (He et al., 2020). A crisis is commonly described as an unanticipated, surprising and ambiguous event posing a significant threat and leaving only a short decision time (Kornberger et al., 2019).

Nikkinen et al. (2008) investigated the impact of the 9/11 attacks on the global stock market. Their findings indicate that "the impact of the attacks resulted in significant increases in volatility across regions and over the study period. However, stock returns experienced significant negative returns in the short-run but recovered quickly afterwards."

Yousaf et al. (2022) recently researched the impact of the Russia–Ukraine conflict on the global stock market. They looked at the abnormal returns of stock indexes from multiple countries in their event study. Their "aggregate stock market analysis indicates a significant and negative impact of the Russia–Ukraine conflict on the event day and post event days."

Righi and Ceretta (2011) found that the volatility of the German, French, and British stock markets were increased because of the European debt crisis. This increase of volatility and decrease of correlations were most significant near the dates of important events during the crisis.

So, these events all had a negative impact on stock returns across several stock markets. However, these negative impact are mostly significant for a short period of time, following the event. After a while, the stock returns and volatilities seem to return to their 'normal' level.

2.3 COVID-19 impact in different countries

With the COVID-19 outbreak, more researchers started to focus on the effect of the pandemic on stock markets as well. Baker et al. (2020) concluded that COVID-19 has had an unprecedented effect on stock markets' returns and volatility, while previous pandemic diseases such as bird flu, SARS, swine flu, Ebola, and MERS did not have an effect on the stock market anywhere near that of the COVID-19 pandemic. This makes the impact of COVID-19 on stock returns a very relevant and interesting topic for more research.

There have been previous studies into the impact of COVID-19 on the stock markets in various countries. Apergis & Apergis (2022) did research into the effect of COVID-19 on the Chinese stock market. They use a GARCHX model to analyze this effect. A GARCH (generalized autoregressive conditional heteroskedasticity) model is used to model risk and its forecasting in a time series. The GARCHX model allows to include information on certain additional important controls that are allowed to impact the mean of stock returns. The authors added the daily total confirmed cases in China and the total daily deaths in China from COVID-19 into the model as additional controls. The findings of this paper documented that COVID-19 cases and deaths both had a significant negative impact on stock returns. They also indicate that COVID-19 had a positive and statistically significant effect on the volatility of stock returns. So, in this study in China, the stock returns decreased and the volatility increased as the COVID-19 cases and deaths increased.

Mugiarni & Wulandari (2021) researched the effect of the virus on the stock market in Indonesia. They use a panel-data regression approach to examine the impact of the COVID-19 pandemic on stock returns. They use a sample of 89 public firms listed on the Indonesia Stock Exchange. Their research looked into the impact of two independent variables, the daily percentage of total confirmed cases and the daily percentage of total death cases, into the dependent variable, the stock return of public firms listed on the Indonesia Stock Exchange. The market capitalization and market-to-book ratio were used as control variables in this research. Based on their sample, the researchers concluded that the daily development of the total confirmed cases of COVID-19 negatively affects stock returns. As a reason for this negative relationship, the writers believe that "the growth of confirmed cases may have caused the government to limit economic activities that can affect a company's performance.” The results also show that the stock market has responded negatively to the daily growth of the total COVID-19 deaths. The researchers believe that the death cases may have caused panic among people. “The symptoms of panic caused a decrease in purchasing power, demand, production, income, and an increasingly heavy burden of production costs which could impact the company's performance.”

Narayan et al. (2022) used a sample of 478 firms listed on the Australian Securities Exchange. They specifically focus on the effect of coronavirus fear on Australian investors. The researchers use a quantile regression framework to examine the effect of coronavirus on the performance of Australian listed firms at the market level, sector level, and firm size categories. They use February 24, 2020 as their event date, because this date illustrates a sharp decline in the All Ordinaries index price, which corresponds to an increase in the number of confirmed coronavirus cases. The writers conclude that “investors in Australia underreacted to coronavirus fear, and this underreaction was prevalent across a range of sectors and firm size categories.”

Alam et al. (2020) researched the impact of COVID-19 on the Indian market. They used a time window of 35 days (20 days pre-lockdown and 15 days present lockdown period) and the data of 31 companies listed on the Bombay Stock Exchange (the largest stock exchange in India). The researchers computed the abnormal returns (AR) for each of the stocks, the average abnormal returns (AAR) of the sample of 31 companies and the cumulative average abnormal returns (CAAR) to determine the impact of a lockdown on the stock exchange. The results of their study indicate that the market reacted positively with significantly positive AAR during the present lockdown period, whereas in the pre-lockdown period there was a negative AAR. These results indicate that investors on the Indian stock market panicked when a lockdown was announced, resulting in a negative AAR, but they were prepared for the lockdown once it arrived, resulting in a positive AAR.

Dang Ngoc et al. (2021) conducted research on the stock market in Vietnam and their response to the COVID-19 outbreak. They used a sample of 364 companies listed on Ho Chi Minh Stock Exchange (HOSE, the Vietnamese stock exchange). The researchers looked at the AR, AAR, and CAAR from these Vietnamese stocks during event windows after multiple events related to the COVID-19 pandemic. They found an “enormous impacts of the Covid- 19 pandemic on the business performance.” They also concluded that this impact varies among different sectors across the market. On top of that, the findings revealed that the level of influence varied from each stage of Covid-19 prevention measure in Vietnam. The paper concluded that the Covid-19 pandemic information can be used to predict stocks’ prices.

Lee et al. (2023) studied the impact of the COVID-19 pandemic on the Chinese and US stock markets. They analyse two US indices, the NASDAQ Composite Index and the NYSE Composite Index, as well as two Chinese indices, the Shenzhen Stock Exchange Composite Index and the Shanghai Stock Exchange Composite Index. The researchers use the abnormal return method to examine the impact of the pandemic on the stock indices. They use three event days: 31 December 2019, when the World Health Organization (WHO) was first officially informed of the first COVID19 cluster, 23 January 2020, the day of the announcement and implementation of the Wuhan lockdown, and 11 March 2020, the day when the WHO announced COVID-19 as a global pandemic. The results of the research show that there were no cumulative abnormal return after the first event. With the second event, however, the results show that market volatility increased by two times in the US and four times in China. The third event had the biggest impact on both markets. Negative cumulative abnormal returns appeared right from the beginning until the end of the event window period in all the composite indices. They also found a significant connection between the US and Chinese stock markets that appeared only during this event.

2.4 COVID-19 impact on the global stock market

There has also been some research conducted on the impact of COVID-19 on global stock markets. A few of these research papers are discussed below.

Basuony et al. (2022) use an asymmetric exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model to research the impact of COVID-19 on stock returns, conditional volatility, conditional skewness, and bad state probability. They created a sample of stocks from 9 countries (United States, Italy, Spain, United Kingdom, Germany, China, Brazil, Russia, and India) and examined their returns during a time period from January 1, 2013 to December 31, 2020, with the year 2020 being the COVID-19 period and the years before the pre-COVID-19 period. The findings of this research indicate that the COVID-19 pandemic caused an "unprecedented rise in conditional volatilities and bad state probabilities across all the markets."

Vidya & Prabheesh (2020) conducted a study to analyze the impact of the COVID-19 pandemic on the world trade network. They apply Trade Network Analysis on the top 15 global trading countries for the pre- and post- COVID-19 outbreak period. These countries are: Canada, the US, the UK, Germany, France, Italy, Japan, South Korea, China, Hong Kong, India, Indonesia, Russia, Netherlands, and Singapore. The research looks at the first quarter of 2020, as this is when the pandemic really started. After their analysis, the authors conclude that "there has been drastic reduction in trade interconnectedness, connectivity, and density among countries in the first quarter of 2020 as compared to 2018." So, the world trade network has been negatively impacted by the COVID-19 outbreak. This negative impact on the world trade network can also negatively impact the stock market, as a lot of companies are very dependent on international trade.

Chowdhury et al. (2022) also conducted an event study on the impact of COVID-19 on the global market. They collected daily panel data of 12 countries covering four continents within a time period of January to April 2020, using the prime stock index of each country. The results of this study show a decrease of mean returns after the COVID-19 outbreak, resulting in an increase in the volatility of all the countries except for the United States and United Kingdom.

Based on all of the existing research regarding the COVID-19 pandemic and its effect on the stock market, a few expectations can be set. First of all, it is expected that the stock returns decrease during the pandemic. There are also multiple papers that have found that the impact of big events on the stock market is more (or even only) significant very closely after the event (Teitler-Regev & Tavor, 2019; Brounen & Derwall, 2010; Antoniuk, & Leirvik, 2024) Therefore, it is also expected that these changes are most significant around dates that were important regarding the outbreak of the pandemic and the implementation of restrictions by the government. These effects were observed in all the countries that were previously studied, and will therefore also likely be present in the Dutch stock market. However, based on the differences between these counties and the Netherlands, it can also be expected that there will be differences in the magnitude of the impact. The Netherlands are very dependent on (international) trade. However, Chowdhury et al. (2022) stated that "in this era of globalization, the world has ironically witnessed the separation of countries through the withdrawal of international events, movements, and trades. Freights by air, sea, and land has come to a standstill." Because of this decrease in international trades, the impact of COVID-19 is expected to have had a big impact on the Dutch stock market, possibly a bigger impact than on other markets.

A summary of the research, regarding the impact of COVID-19 on the stock markets, mentioned above can be found in the table below.

Authors (year)	Method	Countries	Results
Apergis & Apergis (2022)	GARCHX model	China	Stock returns decreased and volatility increased as COVID-19 cases and deaths increased
Mugiarni & Wulandari (2021)	Panel-data regression approach	Indonesia	Daily development of the total confirmed cases and deaths of COVID-19 negatively affects stock returns
Narayan et al. (2022)	Quantile regression framework	Australia	Investors in Australia underreacted to coronavirus fear
Alam et al. (2020)	Abnormal returns	India	Panic before lockdown, but no negative abnormal returns after the lockdown
Dang Ngoc et al. (2021)	Abnormal returns	Vietnam	Pandemic had a huge impact on the stock market, but impact differs between sectors and prevention methods for COVID.
Lee et al. (2023)	Abnormal returns	US and China	Negative cumulative abnormal returns from the beginning until the end of the event window. Correlation between US and Chinese market only during the event
Basuony et al. (2022)	EGARCH model	United States, Italy, Spain, United Kingdom, Germany, China, Brazil, Russia, and India	COVID-19 pandemic caused an unprecedented rise in conditional volatilities and bad state probabilities across all the markets
Vidya & Prabheesh (2020)	Trade Network Analysis	Top 15 global trading countries	The world trade network has been negatively impacted by the COVID-19 outbreak
Chowdhury et al. (2022)	Panel vector autoregressive model	12 countries across the globe	Decrease of mean returns and increase of volatility in all the countries except for the United States and United Kingdom

Table 1: Overview of literature regarding the impact of COVID-19 on stock markets

2.5 Hypotheses

This above presented researched showed that COVID-19 has had a negative impact on stock returns in multiple countries around the world. To test whether this impact was also present in the Netherlands, and how big this possible impact was, this paper will test two hypotheses.

The first hypothesis states that the three indices show negative abnormal returns after the three events:

H1: *"In the 35 trading days after the three COVID-19 related events, the three Dutch stock indices will show significant negative abnormal returns."*

H2: *"The event windows shortly after the events (0-6) and (7-13) will have more significant negative abnormal returns than the later event windows (14-20), (21-27) and (28-34)."*

The next chapter will explain how these hypotheses are tested.

3. METHODS

3.1 The event study

An event study is used to determine the impact of the COVID-19 pandemic on the Dutch stock market. The objective of an event study is to assess the extent to which investors earn abnormal stock returns from an event that carries new informational content, where an abnormal return is the difference between the observed return and the return expected in the absence of the event, predicted by an appropriate benchmark asset pricing model (Sorescu et al., 2017). The benchmark model that is used is the Capital Asset Pricing Model (CAPM). The Fama-French model is also used to calculate expected returns. Fama and French (1992, 1996, and 2004) argued that CAPM's beta was not completely capable of explaining cross-sectional market returns, and they introduced the three factor model, which also included size and value factors. Later on, both models were tested in a lot of research. Most papers found that the Fama-French model performed better (Bahl, 2006; Davis, 2006; Sattar, 2017; Bello, 2008), but there are also papers which conclude that CAPM performs well (Levy, 2010; Liu et al., 2023). Therefore, both models are used to calculate expected returns.

The event study will examine the abnormal returns (ARs) and cumulative abnormal returns (CARs) to determine the impact of the pandemic on the stock returns (MacKinlay, 1997). Abnormal returns fluctuations are one of the issues that investors and managers should consider and refer to in order to perform a preliminary screening or preliminary assessment of market movements when an event that could trigger contagious risk occurs (Dang Ngoc et al., 2021).

To assess the impact on the Dutch market, this study focusses on the three Dutch indices: the AEX index, the AMX index, and the AScX index. The AEX, or Amsterdam Exchange Index, consists of the 25 largest stocks traded on the Euronext Amsterdam (formerly known as the Amsterdam Stock Exchange). The AMX, or Amsterdam Midkap Index, is composed of the stocks that rank 26-50 in size on the Euronext Amsterdam. The AScX, or Amsterdam Small Cap Index, are the firms ranked 51-75 in size on the Euronext Amsterdam. Firm size is commonly used in numerous empirical asset pricing models as a determinant of expected stock returns (Astakhov et al., 2019). Therefore, this study uses all three Dutch indices, to examine whether the COVID-19 pandemic had a different impact on different sized firms.

On top of that, the research considers multiple event days during the pandemic. The first event day which is used in this study is February 27, 2020, when the first case of COVID-19 in the Netherlands was reported (Alderweireld et al., 2020). The second day is March 11, 2020, as this is the date when the World Health Organization (WHO) has declared the COVID-19 outbreak a global pandemic (Cucinotta & Vanelli, 2020). The third event day is January 23, 2021, which is the day when the Dutch government introduced the 'avondklok' (de Jong, 2021). This measure prevented people from going outside between certain times. These three events all caused shock and uncertainty among investors. Therefore, they could all have impacted the stock returns of the Dutch indices. This study will examine that possible impact.

The estimation window provides the information needed to calculate the expected returns during the event window. An estimation window of 90 trading days before the event day is used (Wang et al., 2013, Jeng, 2015). As there is a lot of uncertainty in the stock market, too long a window may not be accurate (Liu et al., 2020). To study the influence in different periods, multiple event windows consisting of 35 trading days after the event day are used: (0, 6), (7, 13), (14, 20), (21, 27), (28, 34) (Liu et al., 2020).

3.2 Formulas for calculating returns

The actual stock returns in this study were calculated as the difference between a day's closing price and the previous day's closing price divided by the previous day's closing price (Bodie et al., 2014). The data on stock returns are extracted from Refinitiv Eikon.

$$Ri,t = \frac{(Pi,t - Pi,\text{t-1})}{Pi,\text{t-1}}$$

Formula for calculating return, where Ri, t is the return of index i on trading day t, with t=0 on the event day. Pi,t is the closing price of stock i on day t, and Pi,t-1 is the closing price of stock i on the previous day.

To examine the impact of COVID-19 on the stock returns, the expected return is used for comparison. The expected return is calculated according to the CAPM model:

$$E\ (Ri,t) = \ Rf + \beta i * (Rm,t - Rf)$$

Formula for calculating expected return with CAPM, where E (Ri, t) is the expected return of index i trading day t, with t=0 on the event day. Rf is the risk-free rate, βi is the Beta of index i and Rm, t is the market return on trading day t. The FR Global Price Return Index, an international index reflecting the overall performance of stock markets across the world, is selected as the benchmark index to calculate the market return (Liu et al., 2020).

The beta of the indices are calculated as follows:

$$\beta i = \frac{Cov(Ri,Rm)}{Var\ (Rm)}$$

Formula to calculate the beta for index i, where Cov (Ri, Rm) is the covariance of index i and market index m and Var (Rm) is the variance of the market index.

Besides the CAPM model, the Fama-French (FF) model is also used to calculate the expected return of the indices. The expected return according to the FF model is calculated with the formula:

$$E\ (Ri,t) = Rf,t + \beta i1(Rm,t - Rf,t) + \beta i2\ (SMB,t) + \beta i3\ (HML,t)$$

Formula for calculating expected return with FF model. Bi1 is the factor sensitivity of index i of excess return on market portfolio factor, βi2 is that of index i of the size factor, and βi3 of index i of the value factor. Rm – Rf is the market risk premium, or market factor, SMB is the size factor, and HML the value factor (Bahl, 2006).

SMB, Small Minus Big, measures the additional return investors have historically received by investing in stocks of companies with relatively small market capitalization. This additional return is often referred to as the "size premium". HML, High Minus Low, has been constructed to measure the "value premium" provided to investors for investing in companies with high book-to-market values (Mehta & Chander, 2010). The Ordinary Least Squares method of estimation is used to calculate the values for β1, β2, and β3 (Bahl, 2006). The data for the historical factor scores are retracted from the Kenneth R. French data library[2].

The abnormal return (AR) is calculated by subtracting the expected return from the actual return:

$$ARi,t = Ri,t - E(Ri,t)$$

Formula for calculating AR of index i on trading day t, with t=0 on the event day.

The average abnormal return (AAR) is calculated for each event window. The formula to calculate the AAR is:

$$AARi,t = \frac{1}{N}\sum_{i=1}^{N} ARi,t$$

Formula to calculate AAR of index i on trading day t, where t = (0,1,2 . . . 32,33,34), and N is the total number of observations.

The cumulative abnormal return (CAR) of index i over a time period from t0 to t1 is calculated as follows:

$$CAR\ (t0,t1) = \sum_{t=t0}^{t1} ARi,t$$

Formula for calculating CAR of index i over the time period t0 to t1. t0 is the event day, t1 is 1 trading day after the event.

[2] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

3.3 Statistical tests

To examine the provided hypotheses, statistical tests are used. Paired sample t-tests are conducted to evaluate whether a statistically significant difference exist between the returns and expected returns (Gakhar et al., 2015). After all three events, the difference between the returns of the Dutch indices are compared to their respective expected returns. This is then done for all of the 5 event windows, following each event, as well as for the entire window consisting of all 35 trading days after the event.

First of all, the data is tested for normality. The Shapiro-Wilk test (Shapiro & Wilk, 1965) is used to test normality, as this is the most powerful normality test (Razali & Wah, 2011; Hernandez, 2021; Khatun, 2021; Yap & Sim, 2011). This test will show a significant p-value (<0,1) when the data is not normally distributed. When the data is significantly not normally distributed, the Wilcoxon signed-rank test (Wilcoxon, 1945), or z-test, is used to test the significance of abnormal returns (Pandey & Kumari, 2021; Maneenop & Kotcharin, 2020). When there is no significant result for the Shapiro-Wilk test, the Student's t-test (Brown & Warner, 1985) is used to compare the means between the two groups (Mishra et al., 2019).

The t-test and/or z-test are used to test for significant AR in all of the event windows. To test hypothesis 1, the results of all 35 trading days after each event are examined. The t-test/z-test will test the following hypotheses:

H_0: ARi,t ≥ 0

H_A: ARi,t < 0

Where ARi,t is the abnormal return of index i on trading day t, with t=0 on the event day. So, a p-value below 0,1 will result in rejecting H_0 and therefore assuming that the return of index i is significantly lower than its expected return, meaning that it has a significant negative AR. This means that significant results of these tests will result in accepting hypothesis 1, while non-significant results will result in rejecting the hypothesis.

Under the null hypothesis, H_0, that the event has no impact on the behaviour of returns (mean or variance), the distribution of the sample abnormal return of a given observation in the event window is (MacKinlay, 1997):

$$ARi,t \sim N\ (0, \sigma^2(ARi,t))$$

Where ARi,t is the abnormal return of index i on trading day t, with t=0 on the event day. To test hypothesis 2, all of the event windows of 7 trading days after the events are used. Once again, The Shapiro-Wilk test (Shapiro & Wilk, 1965) is used to test normality. When the data is significantly not normally distributed, the Wilcoxon signed-rank test, or z-test, is used to test the significance of abnormal returns (Pandey & Kumari, 2021; Maneenop & Kotcharin, 2020). When there is no significant result for the Shapiro-Wilk test, the Student's t-test (Brown & Warner, 1985) is used to compare the means between the two groups. The t-test/z-test will test the following hypotheses, comparing the AR of the first two event windows to the AR of the later windows:

H_0: ARi (0-13) $\geq$ ARi (14-34)

H_A: ARi (0-13) $<$ ARi (14-34)

Where ARi is the abnormal return of index i during the event window between brackets. If the windows close to the events (0-6) and (7-13) show significantly lower AR than the later event windows, hypothesis 2 can be accepted. If this is not the case, hypothesis 2 is rejected (Mishra et al., 2019).

4. RESULTS

The data that was used for the returns from all indices is included in the appendix.

4.1 Beta values

For the CAPM model, the beta values are calculated for all three indices over all three time periods, based on the 90 trading days prior to the event day. The results are shown in table 2.

	AEX	**AMX**	**AScX**
February 27, 2020	0.930***	0.954***	0.728***
March 11, 2020	0.914***	0.953***	0.740***
January 23, 2021	0.491***	0.594***	0.530***

*Table 2: Beta values of the Dutch indices compared to the global index, based on 90 trading days before each event. *** indicates that the beta value is significant at the 1% level.*

The beta values in table 2 show that all beta values are significantly different from 0 at the 1% confidence level. The data also shows that the AEX and the AMX move very similar to the global index before the first two event days, while the AScX already has smaller beta values. This is not in line with previous research, which states that "beta is negatively related to a firm's size" (Banz, 1981) (Binder, 1992). This would mean that bigger firms have smaller beta values than smaller firms, but the opposite is true here. Besides that, it is clear that the beta values for the third event day are very low for all three indices, compared to the previous values. This indicates that the Dutch market was not moving very similar to the global market at the end of 2020 and beginning of 2021. A reason for this could be the impact of the Dutch government. As Wallenburg et al. (2022) state: "The Dutch government gradually lost control over time. This happened when the acute crisis turned into a more enduring one, and 'cracks and gaps' emerged in the policed policy strategy, fostered by the intervention of more conservative experts that got a voice through the media that was on top of all details of the Covid-crisis. Several new measures were introduced by the Dutch government. These measures have become increasingly debated on all policy levels as well as among experts, and conflicts are widely covered in the Dutch media. On top of that, a new government was about to be elected in 2021. With these elections ahead, this meant an additional test of the resilience of the Dutch socio-political system and the Dutch health care system." All of this combined meant that the Dutch government seemed to succeed in their policies at first, but they did not seem very successful in the long run. This impacted the Dutch stock market, but not the international market. That could be why the beta values of the Dutch indices are lower in 2021 than they were in 2020.

For the Fama-French model, multiple beta values are calculated as well. For all three indices, beta values are calculated for the three factors of the FF model, for all three events. The results are shown in table 3.

	AEX	AMX	AScX
February 27, 2020			
Mkt-RF	0.493***	0.550***	0.429***
SMB	0.380*	0.332	0.230
HML	-0.027	-0.163	0.043
March 11, 2020			
Mkt-RF	0.602***	0.634***	0.465***
SMB	0.884***	1.049***	0.641***
HML	0.205	0.245	0.312**
January 23, 2021			
Mkt-RF	0.230**	0.164	0.165
SMB	-0.188	-0.025	-0.037
HML	0.109	0.102	0.133

*Table 3: Fama-French factor beta values for the Dutch indices based on the 90 trading days prior to the event. *, **, and *** indicate significance at respectively the 10%, 5%, and 1% level.*

The results in table 3 show that the market factor is significantly positive for all indices before the first two events. In the estimation window of the third event, the market factor is only significant for the AEX index. The size factor is significantly positive for all indices before the second event, and for the AEX index after the first event. It does not have a significant effect in the other estimation windows. The value factor only has a significant, positive effect on the AScX index before the second event, and no other significant effect on the indices in all estimation windows.

The average risk-free rate in the Netherlands in 2020 was 1.6%, while it was 0.9% in 2021 (Statista)[3]. With the beta values, the risk-free rates and the global index returns, the expected returns for the indices were calculated, using both the CAPM and the FF model. With the data from the actual returns of the indices, the abnormal returns were then calculated as well, for all three event days. The results are shows below.

[3] https://www.statista.com/statistics/1030955/average-risk-free-rate-the-netherlands/#:~:text=The%20average%20risk%20free%20rate,an%20investment%20with%20zero%20risk.

4.2 Abnormal returns after the first event

Index	**AAR (0-6)**	**z-Value**	**p-Value**
AEX	-0.730%	-1.014	0.188
AMX	-1.150%	-1.183	0.148
AScX	-1.083%	-1.183	0.148
Index	**AAR (7-13)**	**t-Test**	**p-Value**
AEX	-0.668%	-0.535	0.306
AMX	-1.406%*	-1.543	0.087
AScX	-3.302%***	-4.819	0.001
Index	**AAR (14-20)**	**t-Test**	**p-Value**
AEX	1.046%	1.197	0.862
AMX	0.639%	0.748	0.759
AScX	-0.385%	-0.394	0.354
Index	**AAR (21-27)**	**t-Test**	**p-Value**
AEX	0.092%	0.184	0.570
AMX	-0.182%	-0.215	0.418
AScX	-0.328%	-0.415	0.346
Index	**AAR (28-34)**	**t-Test**	**p-Value**
AEX	-0.215%	-0.260	0.402
AMX	-0.245%	-0.225	0.415
AScX	-0.364%	-0.340	0.373
Index	**AAR (0-34)**	**t-Test / z-Value**	**p-Value**
AEX	-0.095%	-0.252	0.401
AMX	-0.469%**	-1.703	0.045
AScX	-1.093%***	-2.661	0.006

*Table 4: AAR for all the event windows after January 27th 2020, based on the CAPM model. *, **, and *** indicate significance at respectively the 10%, 5%, and 1% level. The Wilcoxon signed-rank test is used for all three indices during the window (0-6), and for the AMX during the window (0-34), because these results were not normally distributed.*

Table 4 shows the statistical test results for the AAR of the Dutch indices, based on the CAPM model. The results indicate a significant negative AAR for the AScX and AMX index over the 35 days after the event, but no significant effect on the AEX index. The results for the AScX and AMX are in line with hypothesis 1, while the results for the AEX do not confirm this hypothesis.

There are barely any significant AAR during the 7 day windows, as only the AMX and AScX show significant negative AAR during the (7-13) window, which indicates that hypothesis 2 cannot be confirmed based on these results.

Index	AAR (0-6)	z-Value	p-Value
AEX	-0.928%	-1.183	0.148
AMX	-1.484%	-1.183	0.148
AScX	-0.816%	-1.183	0.148
Index	**AAR (7-13)**	**t-Test**	**p-Value**
AEX	-1.697%	-1.425	0.102
AMX	-2.542%**	-2.194	0.035
AScX	-3.692%***	-4.324	0.002
Index	**AAR (14-20)**	**t-Test**	**p-Value**
AEX	1.453%*	1.467	0.904
AMX	0.943%	0.713	0.749
AScX	0.287%	0.232	0.588
Index	**AAR (21-27)**	**z-Value**	**p-Value**
AEX	0.240%	0.845	0.813
AMX	-0.210%	-1.183	0.148
AScX	0.159%	0.169	0.594
Index	**AAR (28-34)**	**t-Test**	**p-Value**
AEX	0.118%	0.120	0.546
AMX	-0.075%	-0.062	0.476
AScX	0.243%	0.204	0.578
Index	**AAR (0-34)**	**t-Test**	**p-Value**
AEX	-0.163%	-0.383	0.352
AMX	-0.674%*	-1.329	0.096
AScX	-0.764%*	-1.558	0.064

*Table 5: AAR for all the event windows after January 27th 2020, based on the FF model. *, **, and *** indicate significance at respectively the 10%, 5%, and 1% level. The Wilcoxon signed-rank test is used for all three indices during the windows (0-6) and (21-27), because these results were not normally distributed.*

The results in table 5 show very similar results to those in table 4. Using the FF model to calculate expected returns, the AMX and AScX show significant negative AAR over the window of 35 trading days after the event, while the AEX does not show significant AAR. So, just like with the CAPM model, the results for the AScX and AMX are in line with hypothesis 1, while the results for the AEX do not confirm this hypothesis.

Only the AMX and AScX show significant negative AAR during the (7-13) window, just like with the CAPM model. The AEX actually shows a significant positive AAR during the (14-20) window. These results are not in line with hypothesis 2.

4.3 Abnormal returns after the second event

Index	**AAR (0-6)**	**t-Test**	**p-Value**
AEX	0.544%	0.422	0.656
AMX	-0.658%	-0.765	0.237
AScX	-3.056%***	-3.891	0.004
Index	**AAR (7-13)**	**t-Test**	**p-Value**
AEX	0.262%	0.339	0.627
AMX	0.102%	0.105	0.540
AScX	-0.707%	-0.688	0.259
Index	**AAR (14-20)**	**t-Test**	**p-Value**
AEX	0.092%	0.190	0.572
AMX	0.283%	0.370	0.638
AScX	0.734%	1.038	0.830
Index	**AAR (21-27)**	**t-Test**	**p-Value**
AEX	-0.750%	-0.645	0.271
AMX	-0.959%	-0.740	0.244
AScX	-1.485%	-1.357	0.112
Index	**AAR (28-34)**	**t-Test**	**p-Value**
AEX	0.262%	0.257	0.597
AMX	1.214%	1.374	0.891
AScX	0.737%	0.799	0.773
Index	**AAR (0-34)**	**t-Test**	**p-Value**
AEX	0.082%	0.195	0.577
AMX	-0.004%	-0.009	0.497
AScX	-0.755%*	-1.650	0.054

*Table 6: AAR for all the event windows after March 11 2020, based on the CAPM model. *, **, and *** indicate significance at respectively the 10%, 5%, and 1% level.*

Table 6 shows the statistical test results for the AAR of the Dutch indices after the second event, based on the CAPM model. When looking at all 35 trading days after the event, only the AScX shows a significant negative AAR. This result is in line with hypothesis 1. However, the AEX and AMX do not show any significant AAR, with the AEX even showing a slightly positive AAR (although not significant). So, the AAR of the AEX and AMX after the second event, do not provide evidence for accepting the first hypothesis.

Although the first event window shows a significant negative AAR for the AScX, all of the other windows show no significant AAR for any of the indices. These results do not provide any evidence for accepting hypothesis 2.

Index	AAR (0-6)	t-Test	p-Value
AEX	-0.131%	-0.098	0.462
AMX	-1.368%	-0.949	0.190
AScX	-3.278%***	-3.220	0.009
Index	**AAR (7-13)**	**t-Test**	**p-Value**
AEX	1.166%	1.185	0.860
AMX	0.998%	0.801	0.773
AScX	0.381%	0.320	0.620
Index	**AAR (14-20)**	**t-Test**	**p-Value**
AEX	0.475%	0.764	0.763
AMX	0.630%	0.839	0.783
AScX	1.341%*	1.766	0.936
Index	**AAR (21-27)**	**t-Test**	**p-Value**
AEX	-0.351%	-0.306	0.385
AMX	-0.604%	-0.435	0.339
AScX	-0.710%	-0.640	0.273
Index	**AAR (28-34)**	**t-Test**	**p-Value**
AEX	-0.886%	-0.736	0.245
AMX	-0.195%	-0.209	0.421
AScX	0.060%	0.054	0.521
Index	**AAR (0-34)**	**t-Test**	**p-Value**
AEX	0.055%	0.116	0.546
AMX	-0.108%	-0.208	0.418
AScX	-0.441%	-0.857	0.199

*Table 7: AAR for all the event windows after January 27th 2020, based on the FF model. *, **, and *** indicate significance at respectively the 10%, 5%, and 1% level.*

The results in table 7, where the FF model is used, are, just like with the first event, pretty similar to the AAR results of the CAPM model in table 6. However, opposed to the results of the CAPM model, there is no significant AAR for any of the three indices in the 35 trading days after the event. This means that hypothesis 1 cannot be supported based on these results.

Just like with the CAPM model, the AAR of the FF model show a significant negative AAR during the first event window for the AScX. The (14-20) event window shows a significant positive AAR, also for the AScX. All other event windows do not show significant AAR, meaning that these results do not provide evidence to confirm hypothesis 2.

4.4 Abnormal returns after the third event

Index	**AAR (0-6)**	**t-Test**	**p-Value**
AEX	-0.572%**	-2.478	0.024
AMX	-0.279%	-0.901	0.201
AScX	-0.405%	-0.821	0.222
Index	**AAR (7-13)**	**t-Test**	**p-Value**
AEX	-0.414%**	-2.328	0.029
AMX	-0.317%*	-1.478	0.095
AScX	-0.737%***	-4.223	0.003
Index	**AAR (14-20)**	**t-Test**	**p-Value**
AEX	-0.245%	-0.637	0.274
AMX	-0.453%*	-1.444	0.099
AScX	-0.140%	-0.344	0.371
Index	**AAR (21-27)**	**t-Test**	**p-Value**
AEX	-0.530%*	1.624	0.078
AMX	-0.281%	0.999	0.178
AScX	-0.052%	0.117	0.455
Index	**AAR (28-34)**	**t-Test**	**p-Value**
AEX	-0.296%	0.832	0.216
AMX	-0.363%	0.999	0.175
AScX	-0.044%	0.095	0.464
Index	**AAR (0-34)**	**t-Test**	**p-Value**
AEX	-0.411%***	-3.093	0.002
AMX	-0.339%***	-2.662	0.006
AScX	-0.276%*	-1.635	0.056

*Table 8: AAR for all the event windows after January 23 2021, based on the CAPM model. *, **, and *** indicate significance at respectively the 10%, 5%, and 1% level.*

Table 8 shows the statistical test results for the AAR of the Dutch indices after the third event, based on the CAPM model. In the (0-34) window, all three indices show a significant negative AAR. These results are in line with hypothesis 1.

The event window (7-13) also show significant negative AAR for all three indices, while the (0-6) window shows significant negative AAR for the AEX. The AMX shows a significant negative AAR during the (14-20), and the AEX during the (21-27) window. All other event windows do not show significant AAR. These results do not provide evidence for rejecting hypothesis 2.

Index	AAR (0-6)	t-Test	p-Value
AEX	-0.123%	-0.340	0.373
AMX	0.061%	0.151	0.557
AScX	0.007%	0.013	0.505
Index	**AAR (7-13)**	**t-Test**	**p-Value**
AEX	0.240%	1.352	0.887
AMX	0.225%	0.891	0.796
AScX	-0.162%	-0.757	0.239
Index	**AAR (14-20)**	**t-Test**	**p-Value**
AEX	0.028%	0.064	0.524
AMX	-0.229%	-0.640	0.273
AScX	0.111%	0.259	0.598
Index	**AAR (21-27)**	**t-Test**	**p-Value**
AEX	-0.195%	-0.373	0.361
AMX	-0.067%	-0.148	0.444
AScX	0.199%	0.328	0.623
Index	**AAR (28-34)**	**t-Test**	**p-Value**
AEX	0.220%	0.473	0.673
AMX	0.041%	0.091	0.535
AScX	0.402%	0.810	0.776
Index	**AAR (0-34)**	**t-Test**	**p-Value**
AEX	0.034%	0.194	0.576
AMX	0.006%	0.038	0.515
AScX	0.112%	0.541	0.704

*Table 9: AAR for all the event windows after January 23 2021, based on the FF model. *, **, and *** indicate significance at respectively the 10%, 5%, and 1% level.*

Table 9, where the AAR after the third event are calculated based on the FF model, shows quite remarkable results. Not a single event window, for any of the three indices, show significant AAR. While the results based on the CAPM model show significant negative AAR for all indices in the 35 trading days after the event, the AAR based on the FF model are slightly positive (although not significant). These results provide evidence for rejecting both of the hypotheses.

5 DISCUSSION AND CONCLUSION

5.1 Key findings

This study investigates the impact of the COVID-19 pandemic on the Dutch stock market. It uses the expected and actual returns of the three Dutch indices after three COVD-19 related events to compute abnormal returns. Then, the average abnormal returns (AAR) are used to conduct statistical tests to test the hypotheses of the study.

This paper uses both the CAPM and the Fama-French (FF) model for calculating the expected returns of the Dutch indices after the events. This caused a difference in AAR and therefore also in the findings of this paper.

When using the CAPM model for calculating the expected returns, the AMX and AScX show significant negative AAR after the first event. After the second event, only the AScX index shows a significant negative AAR. All three indices show significant negative AAR after the third event. These findings do not provide enough evidence to reject the first hypothesis: "*In the 35 trading days after the three COVID-19 related events, the three Dutch stock indices will show significant negative abnormal returns.*" So, it can be concluded that the Dutch stock indices show significant negative abnormal returns after the three COVID-19 related events, when using the CAPM model to calculate expected returns. These findings are in line with previous research, which has concluded that the COVID-19 outbreak had a negative (short-term) impact on the stock markets of developed countries (He et al., 2020).

These negative returns could be attributed to the behaviour of investors, as investors' sentiments tend to grow more negative when the market is heading downward, and they will often hold off investing in the market until a recovery starts (Burns et al., 2011, pp. 659-661; Baker & Wurgler, 2006, p. 1677). This could cause a big decrease in stock return after a negative event. Another possible reason behind the negative abnormal returns could be the restrictions implemented by the government. Baker et al. (2020) concluded: "government restrictions on commercial activity and voluntary social distancing are the main reasons the stock market reacted so much more forcefully to COVID-19 than to previous pandemics."

Regarding the 7-day event windows, a total of 9 out of 45 windows (5 windows per index per event) show significant negative AAR. Out of these 9, 7 are either in the (0-6) or (7-13) windows. These results do not provide enough evidence to reject the second hypothesis: *"The event windows shortly after the events (0-6) and (7-13) will have more significant negative abnormal returns than the later event windows (14-20), (21-27) and (28-34)."* So, based on these results it is assumed that the impact of the COVID-19 related events was larger closely after the event, and decreased over time. These findings are in line with previous research, which have shown that the impact of major events is most significant closely after the event (Teitler-Regev & Tavor, 2019; Antoniuk & Leirvik, 2024).

When using the FF model to calculate the expected returns, the outcomes are different however. After the first event, the AMX and AScX show significant negative abnormal returns while the AEX doesn't, just like with the CAPM model. However, contrary to the results based on the CAPM model, none of the indices show significant AAR after the second or third event when using the FF model. These findings mean that, based on the FF model, the first hypothesis is assumed not to be true, and the COVID-19 related events did not have a significant negative effect on the Dutch stock market. These results are in line with some previous research, as Pandey & Kumari (2021) concluded that "in the shorter window period, the impacts on the developed markets are not significant." The research of Chowdhury et al. (2022) also found that "abnormal returns were insignificant for most of the countries in the initial period."

When looking at the 7-day event windows, 3 out of 45 windows show a significant negative average abnormal return, while 2 windows actually show a significant positive AAR. Although all three windows that have a significant negative AAR are either (0-6) or (7-13) windows, there is not enough evidence to accept the second hypothesis. Therefore, based on the FF model, it is not assumed that the COVID-19 related events had a bigger negative impact on the Dutch stock market closely after the event, compared to later on.

So the results of this paper show that there are different outcomes based on which model is used to calculate expected returns. When using the CAPM model, the results show that the COVID-19 related events had a negative impact on the Dutch stock market, and this impact is most significant in the first 14 trading days after the event. When using the Fama-French model, the results show that there is no significant negative impact of the COVID-19 events on the Dutch stock market.

Although the results based on the CAPM model show that the Dutch stock indices were negatively impacted after the COVID-19 related events, it cannot be said with absolute certainty that these events caused the decrease in stock returns. There are other factors that could have influenced the returns, creating negative AAR which would not be due to the COVID-19 event.

5.2 Limitations

There are also several limitations regarding this study. First of all, this study only focusses on the Dutch stock market. Although this provides insights that are useful for investors in the Dutch stock market, it does limit the generalizability of the findings. So, the conclusions drawn from the results of this paper, might not be useable for investors outside of the Dutch stock market.

Another limitation of this research is the use of indices instead of singular stocks. When using singular stocks to research the abnormal return, one may find a difference in abnormal returns after the events between stocks, or between industries. These differences are not found when using indices, as all of the different stocks and industries are combined into ‘only’ three indices.

The event windows that were used can also be considered as a limitation. The choice of event window could impact the outcome of the study. For instance, using 10-day windows instead of 7-day windows, might result into more significant AAR in that window.

The choice of events can also change the results of the study. Three COVID-19 related events were picked to test the AAR after these events. However, choosing other events can lead to other findings, and therefore also different conclusions.

5.3 Future research

The limitation mentioned above can be used for future research. For example, the same study could be conducted, but by using all singular stocks that are included in the indices. This study could give more insights into the different reaction of various industries on the COVID-19 related events. Because it might be possible that one industry did show significant negative AAR, while another industry showed positive AAR. These results would not be visible when using indices, but they would be when using singular stocks. These differences could provide useful information for investors, and therefore this could be a useful future study.

It could also be interesting for future researchers to use different event windows in their study. This could provide useful insights into the difference in results when using various event windows in the study. The same can be done for choosing different COVID-19 related events, and see how the stock market reacted after these particular events.

Undoubtedly, there will be more big events in the future, which will impact stock markets all over the world. Future research should investigate the impact of these events on all kinds of different stock markets and industries, so investors and researchers can improve their knowledge of the stock market and its reactions to different kinds of events.

6 REFERENCES

Alam, M. N., Alam, M. S., & Chavali, K. (2020). Stock market response during COVID-19 lockdown period in India: An event study. *The Journal of Asian Finance, Economics and Business (JAFEB)*, *7*(7), 131-137.

Alderweireld, C. E., Buiting, A. G., Murk, J. A. N., Verweij, J. J., Berrevoets, M. A., & van Kasteren, M. E. (2020). COVID-19: patient zero in the Netherlands. *Nederlands tijdschrift voor geneeskunde*, *164*.

Antoniuk, Y., & Leirvik, T. (2024). Climate change events and stock market returns. *Journal of Sustainable Finance & Investment*, *14*(1), 42-67.

Apergis, N., & Apergis, E. (2022). The role of Covid-19 for Chinese stock returns: evidence from a GARCHX model. *Asia-Pacific Journal of Accounting & Economics*, *29*(5), 1175-1183.

Astakhov, A., Havranek, T., & Novak, J. (2019). Firm size and stock returns: A quantitative survey. *Journal of Economic Surveys*, *33*(5), 1463-1492.

Bahl, B. (2006). Testing the Fama and French three-factor model and its variants for the Indian stock returns. *Available at SSRN 950899*.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The journal of Finance*, *61*(4), 1645-1680.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *The review of asset pricing studies*, *10*(4), 742-758.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of financial economics*, *9*(1), 3-18.

Basuony, M. A., Bouaddi, M., Ali, H., & EmadEldeen, R. (2022). The effect of COVID-19 pandemic on global stock markets: Return, volatility, and bad state probability dynamics. *Journal of Public Affairs*, *22*, e2761.

Bello, Z. Y. (2008). A statistical comparison of the CAPM to the Fama-French Three Factor Model and the Carhart's Model. *Global Journal of Finance and Banking Issues*, *2*(2).

Bikas, E., Jurevičienė, D., Dubinskas, P., & Novickytė, L. (2013). Behavioural finance: The emergence and development trends. *Procedia-social and behavioral sciences*, *82*, 870-876.

Binder, J. J. (1992). Beta, firm size, and concentration. *Economic Inquiry*, *30*(3), 556-563.

Bodie, Z., Kane, A., & Marcus, A.J. (2014). Investment, Asia global edition (9th ed.). McGraw-Hill Education.

Bosworth, B., Hymans, S., & Modigliani, F. (1975). The stock market and the economy. *Brookings Papers on Economic Activity*, *1975*(2), 257-300.

Brealey, R. A., Myers, S. C., & Allen, F. (2014). *Principles of corporate finance*. McGraw-hill.

Brounen, D., & Derwall, J. (2010). The impact of terrorist attacks on international stock markets. *European Financial Management*, *16*(4), 585-598.

Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of financial economics*, *14*(1), 3-31.

Burns, W. J., Peters, E., & Slovic, P. (2012). Risk perception and the economic crisis: A longitudinal study of the trajectory of perceived risk. *Risk Analysis: An International Journal*, *32*(4), 659-677.

Chatjuthamard, P., Jindahra, P., Sarajoti, P., & Treepongkaruna, S. (2021). The effect of COVID-19 on the global stock market. *Accounting & Finance*, *61*(3), 4923-4953.

Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance*, *34*(8), 1911-1921.

Chowdhury, E. K., Khan, I. I., & Dhar, B. K. (2022). Catastrophic impact of Covid-19 on the global stock markets and economic activities. *Business and Society Review*, *127*(2), 437-460.

Cucinotta, D., & Vanelli, M. (2020). WHO declares COVID-19 a pandemic. *Acta bio medica: Atenei parmensis*, *91*(1), 157.

Dang Ngoc, H., Vu Thi Thuy, V., & Le Van, C. (2021). Covid 19 pandemic and Abnormal Stock Returns of listed companies in Vietnam. *Cogent Business & Management*, *8*(1), 1941587.

Davis, J. (2006). Reviewing the CAPM. *Canadian Investment Review*, R21.

De Jong, M. A. D. W. (2021). Tijd voor een Wet maatregelen virusuitbraak? Over grondslagen voor afdwingbare gedragsvoorschriften.

Dwyer Jr, G. P., & Hafer, R. W. (1988). Are national stock markets linked?. *Review*, *70*.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*(2), 383-417.

Fama, E. F., & French, K. R. (2004). The capital asset pricing model: Theory and evidence. *Journal of economic perspectives*, *18*(3), 25-46.

Fama, E. F., & French, K. R. (1996). The CAPM is wanted, dead or alive. *The Journal of Finance*, *51*(5), 1947-1958.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance*, *47*(2), 427-465.

Gakhar, D. V., Kushwaha, N., & Ashok, V. (2015). Impact Of Union Budget On Indian Stock Market. *Scholedge International Journal of Management & Development*, *2*(11).

Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. *Finance research letters*, *35*, 101512.

Grossman, S., & Stiglitz, J. (1982). On the impossibility of informationally efficient markets: Reply. *American Economic Review*, *72*(4), 875-875.

He, Q., Liu, J., Wang, S., & Yu, J. (2020). The impact of COVID-19 on stock markets. *Economic and Political Studies*, *8*(3), 275-288.

He, P., Sun, Y., Zhang, Y., & Li, T. (2020). COVID–19's impact on stock prices across different sectors—An event study based on the Chinese stock market. *Emerging Markets Finance and Trade*, *56*(10), 2198-2212.

Hernandez, H. (2021). Testing for normality: What is the best method. *ForsChem Research Reports*, *6*, 2021-05.

Hirshleifer, D. (2015). Behavioral finance. *Annual Review of Financial Economics*, *7*, 133-159.

Jeng, J. L. (2015). *Analyzing Event statistics in corporate finance: methodologies, evidences, and critiques*. Springer.

Khatun, N. (2021). Applications of normality test in statistical analysis. *Open Journal of Statistics*, *11*(01), 113.

Kornberger, M., Leixnering, S., & Meyer, R. E. (2019). The logic of tact: How decisions happen in situations of crisis. *Organization Studies*, *40*(2), 239-266.

Lee, H. A., Liew, V. K. S., Ghazali, M. F., & Riaz, S. (2023). Reaction of US and Chinese Stock Markets to COVID-19 News. *International Journal of Financial Studies*, *11*(2), 59.

Levy, H. (2010). The CAPM is alive and well: A review and synthesis. *European Financial Management*, *16*(1), 43-71.

Liu, H., Manzoor, A., Wang, C., Zhang, L., & Manzoor, Z. (2020). The COVID-19 outbreak and affected countries stock markets response. *International Journal of Environmental Research and Public Health*, *17*(8), 2800.

Liu, W., Kolari, J., & Pynnonen, S. (2023). The CAPM is Not Dead: It Works Better for Average Daily Returns.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of economic literature*, *35*(1), 13-39.

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of economic perspectives*, *17*(1), 59-82.

Maneenop, S., & Kotcharin, S. (2020). The impacts of COVID-19 on the global airline industry: An event study approach. *Journal of air transport management*, *89*, 101920.

Mehta, K., & Chander, R. (2010). Application of fama and french three factor model and stock return behavior in indian capital market. *Asia Pacific Business Review*, *6*(4), 38-56.

Mishra, P., Singh, U., Pandey, C. M., Mishra, P., & Pandey, G. (2019). Application of student's t-test, analysis of variance, and covariance. *Annals of cardiac anaesthesia*, *22*(4), 407.

Mugiarni, A., & Wulandari, P. (2021). The Effect of Covid-19 Pandemic on Stock Returns: An Evidence of Indonesia Stock Exchange. In *Journal of International Conference Proceedings* (Vol. 4, No. 1, pp. 28-37).

Muysken, J., Bonekamp, B., & Meijers, H. (2017). *Stock-flow consistent data for the Dutch economy, 1995-2015* (No. 2017-045). United Nations University-Maastricht Economic and Social Research Institute on Innovation and Technology (MERIT).

Narayan, P. K., Gong, Q., & Ahmed, H. J. A. (2022). Is there a pattern in how COVID-19 has affected Australia's stock returns? *Applied Economics Letters*, *29*(3), 179-182.

Nikkinen, J., Omran, M. M., Sahlström, P., & Äijö, J. (2008). Stock returns and volatility following the September 11 attacks: Evidence from 53 equity markets. *International Review of Financial Analysis*, *17*(1), 27-46.

Nofsinger, J. R., & Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. *The Journal of finance*, *54*(6), 2263-2295.

Pandey, D. K., & Kumari, V. (2021). Event study on the reaction of the developed and emerging stock markets to the 2019-nCoV outbreak. *International Review of Economics & Finance*, *71*, 467-483.

Razali, N. M., & Wah, Y. B. (2011). Power comparisons of shapiro-wilk, kolmogorov-smirnov, lilliefors and anderson-darling tests. *Journal of statistical modeling and analytics*, *2*(1), 21-33.

Righi, M. B., & Ceretta, P. S. (2011). Analyzing the structural behavior of volatility in the major European markets during the Greek crisis. *Economics Bulletin*, *31*(4), 3016-3029.

Sattar, M. (2017). CAPM Vs Fama-French three-factor model: an evaluation of effectiveness in explaining excess return in Dhaka stock exchange. *International journal of Business and Management*, *12*(5), 119.

Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika*, *52*(3/4), 591-611.

Slovic, P., Finucane, M., Peters, E., MacGregor, D.G. (2002). The affect heuristic. *Heuristics and Biases: The Psychology of Intuitive Judgment*.

Sorescu, A., Warren, N. L., & Ertekin, L. (2017). Event study methodology in the marketing literature: an overview. *Journal of the Academy of Marketing Science*, *45*, 186-207.

Teitler-Regev, S., & Tavor, T. (2019). The impact of disasters and terrorism on the stock market. *Jàmbá: Journal of Disaster Risk Studies*, *11*(1), 1-8.

Vidya, C. T., & Prabheesh, K. P. (2020). Implications of COVID-19 pandemic on the global trade networks. *Emerging Markets Finance and Trade*, *56*(10), 2408-2421.

Wallenburg, I., Helderman, J. K., Jeurissen, P., & Bal, R. (2022). Unmasking a health care system: The Dutch policy response to the Covid-19 crisis. *Health Economics, Policy and Law*, *17*(1), 27-36.

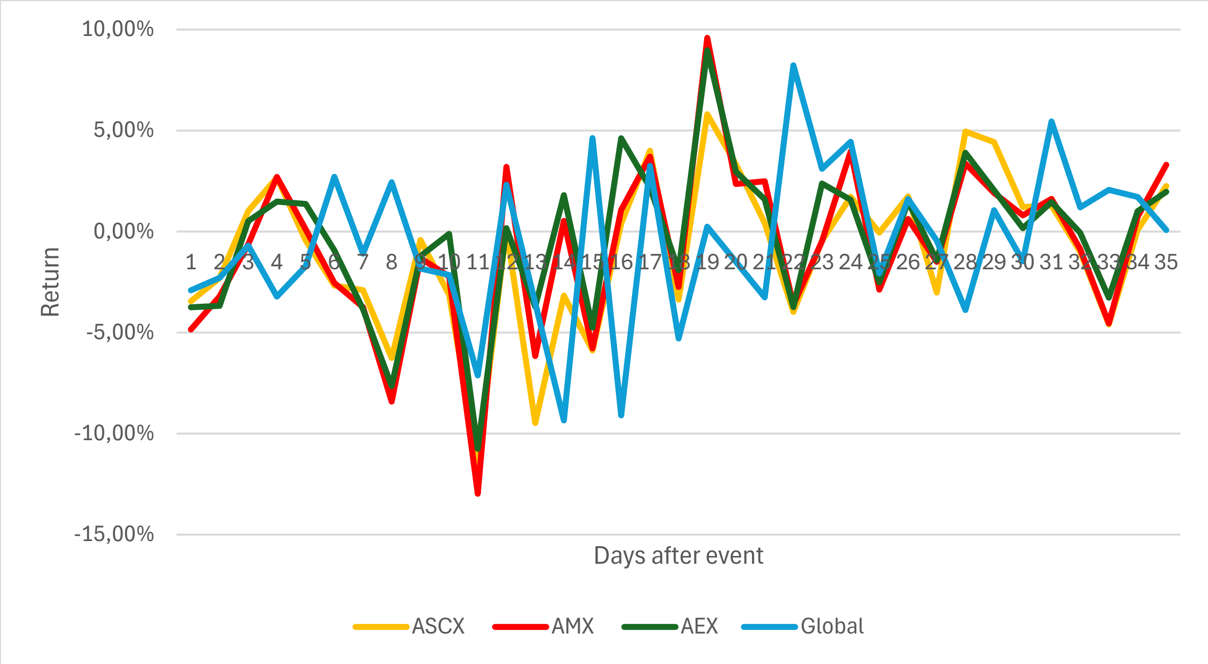
Wang, Y. H., Yang, F. J., & Chen, L. J. (2013). An investor's perspective on infectious diseases and their influence on market behavior. *Journal of Business Economics and Management*, *14*(sup1), S112-S127.

Wilcoxon, F. (1945). Individual comparison by ranking methods. Biometrics 1, 80–83.

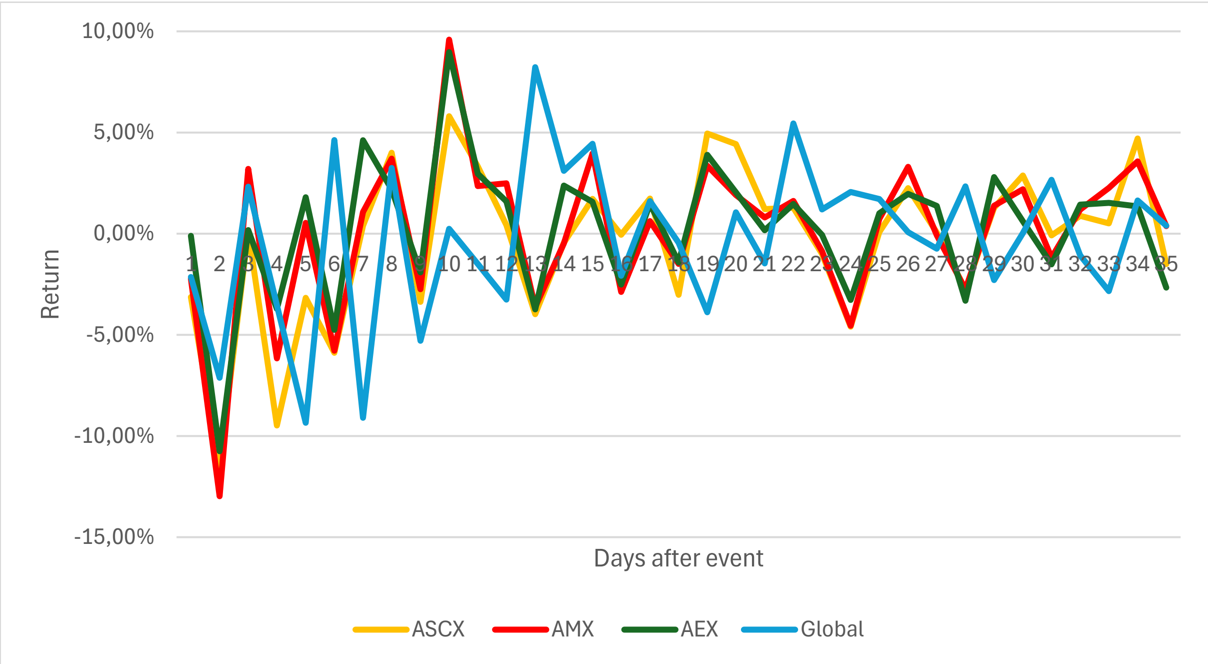
Yap, B. W., & Sim, C. H. (2011). Comparisons of various types of normality tests. *Journal of Statistical Computation and Simulation*, *81*(12), 2141-2155.

Yousaf, I., Patel, R., & Yarovaya, L. (2022). The reaction of G20+ stock markets to the Russia–Ukraine conflict “black-swan” event: Evidence from event study approach. *Journal of Behavioral and Experimental Finance*, *35*, 100723.

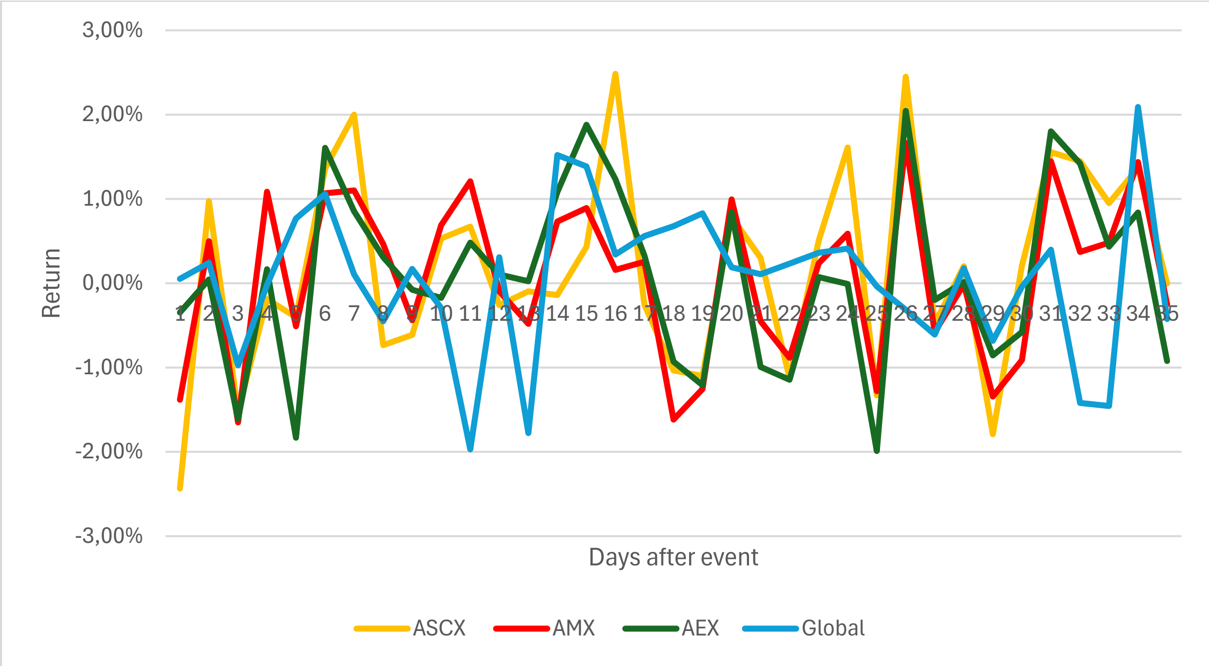
APPENDIX



Appendix 1: Return data of all 4 indices after the first event



Appendix 2: Return data of all 4 indices after the second event



Appendix 3: Return data of all 4 indices after the third event