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Analysis of the Impact of Shocks on Worldwide Stock Market Fluctuations: The Russia-Ukraine war and US presidential election 2020

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ABSTRACT

In this article, I analyze the impact of the shocks on worldwide stock market fluctuations. The Russia-Ukraine war is an example of a negative shock, and the US presidential election 2020 is an example of a positive shock. I focus on the impact of these two events on the stock. My four main findings are: (1) The Russia-Ukraine war impacted the whole stock market more than the US presidential election 2020. The greater the magnitude of the event, the greater the impact; (2) The impact of the Russia-Ukraine war is delayed by one day, while the effects of the US presidential election 2020 are immediate; (3) The impact of the Russia-Ukraine war recovers within a day, but the impact of the US presidential election 2020 lasts for some time; (4) News sentiments are important in both shocks, but the emotional intensity of the Russia-Ukraine war is higher and more significant for the stock market. This study lays the groundwork for future research on the impact of positive and negative events on global stock markets.

THEORY

The stock market is an important part of the global financial market. As Financial Technology (Fintech) becomes increasingly popular, more researchers are trying to find more advanced approaches to predict the trend of stock prices. So far, the forecasting approaches for stock price predictions have two different directions, technical analysis and peripheral analysis [1]. Most researchers focus on technical analysis like the historical data but ignore the impact of outside-market factors. For example, significant shocks around the world are a major cause of stock volatility. When shocks occur, investors make choices based on the market situation and decide whether to buy or sell stocks. Global events can always affect the financial conditions of the entire market. It is necessary to study the impact of shocks on stocks, which can avoid many losses for investors.

News is one major source to reflect these outside-market factors. They imply many reasons why trade markets are volatile in response to events [2]. In Big Data Era, the number of online textual resources is tremendously increasing. Text mining can retrieve information from the textual resource and represent text numerically which is easier to analyze by machine. There are some approaches to text representation. Positive and negative frequencies can count the frequency of positive and negative words separately; the bag-of-words approach examines the relationship between the number of occurrences and the stock price movements [3]; Term Frequency - Inverse Document Frequency (TF-IDF) measures how important a term is within a document relative to a collection of documents......With the help of this large volume of news and the development of natural language processing (NLP), a higher possibility of accurate prediction of stock prices can be realized.

Nowadays, most researchers focus on individual stocks rather than the market as a whole [4]. However, shocks often have an impact on the entire market. Studying the stock situation of the whole stock market is also significant. Economists can forecast the overall economic environment, and governments can better specify policies. Many indices reflect the aggregate condition of the stock market. FTSE 100 is an index of the 100 largest companies in the stock market of the United Kingdom; S&P 500 is an index of the 500 largest publicly traded companies in the United States; the Shanghai Composite Index is an index of all the A-shares and B-shares listed on the Shanghai Stock Exchange in China. Analyzing indexes like these can reflect the impact of shocks on different stock markets.

Sentiment analysis is an opinion-oriented natural language processing [5]. It is dedicated to extracting sentiment from text information and analyzing this sentiment information. Through the interpretation of the existing studies and the generalization of the findings, few researchers consider that news sentiments can affect the fluctuations of stock prices. Besides news, social media is another important source of natural language processing. The emotions and opinions of the individual investors can be retrieved from public users' comments. Although investor sentiment is richer in social media, there is also a lot of emotion in the news. Many positive and negative words are still used in news writing. Many researchers have been devoted to analyzing sentiments in social media, but have yet to pay attention to the emotional terms used in the news. Analyzing the sentiments in the news to study the volatility of the entire stock market is meaningful for studying the movement of stock prices.

LITERATURE REVIEW

Stock price predictions have always been the focus of research. It not only helps investors to manage risk and make more informed decisions, but also helps economists to assess the overall economic environment. However, the stock market is highly volatile and non-stationary. Economic conditions, company performance, investor sentiment and global events will all affect stock fluctuation [6]. Despite that, many researchers and investors still make efforts to predict the stock to get as much profit as possible.

So far, the prediction approaches for stock price prediction have two different directions, technical analysis-based and peripheral analysis-based [1]. The technical analysis analyzes the information of the market, like historical data. As early as 1900, French mathematician Louis

Bachelier presented a mathematical model for predicting stock prices based on Brownian motion [7]. Recently, much progress has come from the technical point of view. Tayor [8] built a time-series data model by employing stochastic volatility; Zarandi [9] proposed a new hybrid clustering algorithm by using simulated annealing (SA) to optimize parameters. Furthermore, Wei [10] analyzed more of the non-trend drawback of model evaluation results, solving the classic prediction error problems that cannot guide actual securities trading. Even though mathematical modelling has progressed sufficiently, it's very difficult to improve the accuracy of predictions with mathematical modelling alone after years of development. Combining new technology with traditional mathematical methods may yield more comprehensive and accurate predictions.

However, the accuracy of the analyses about the technology still has some limitations because of ignoring some outside-market factors. Some significant events can always make a sudden change in the stock price. Fewer researchers have considered the importance of social impact. In Big Data Era, the number of online textual resources is tremendously increasing. With the development of text mining and natural language processing (NLP), peripheral analyses of real-time news events about the financial market play a huge role in stock trend predictions. Text mining is the study of how to extract information from text. For example, Mei and Nahm [11] proposed a general text mining framework employing an information extraction (IE) model to transform textual documents into structured data. They discovered prediction rules from the extracted data. Loughran and McDonald [12] tried to find specific words in financial markets and list them to returns, trading volume or other metrics to construct a better dictionary. These studies have fueled textual information related to research stock price predictions.

Many researchers studied two main sources, financial news and social media. More attention got to financial news because news is more authoritative, and disinformation will be less intrusive. Significant events are generally responded to on time through the news. Many new policies will also be announced on some news websites for the first time. News information can predict the trend of stocks in advance. Li's team [13] applied a sentence-level summarization model to handle daily full-length articles on stock price forecasting. Experiments have shown that the prediction on the summarization of news can outperform the forecasting based on full-length essays. Hagenau et al. [14] enhanced the text mining approach by employing more expressive features to encode text to numerical representations, and used market feedback as one selection standard. This try improved the accuracy of classification algorithms. NLP does incorporate outside-market factors that can never be considered in historical data analysis into the forecasting metrics, making stock price prediction more comprehensive and complete.

Besides predicting based on news, sentiment analysis prediction is also widely researched. Sentiment analysis is a process of retrieving emotions from a piece of text. Emotions are always contagious, causing more investors to make investment decisions that are influenced by their emotions, or even no longer sensible. Asgarian [15] et.al proposed three Generative Adversarial Network (GAN) models to collect sentiment features from social media and optimized price features, improving the performance of predictive stock models. Vu et.al explored the correlation between public. The sentiment is generally considered to affect only short-term fluctuations in stocks, Reeves [16] used a neural network algorithm to prove sentiment does hold an effect over long-term growth. Most studies like to gather information from social media, but ignore the fact that news contains emotions as well.

Meanwhile, most researchers focus on the movement of a company's stock or a region's stock, but rarely consider the global stock market as a whole [7][8][9][10][11][12][13][14][15][16]. Fischer et.al [17] selected many Corona-related events in Germany and US to analyze the impact of the Corona Crisis on the worldwide stock market, they found only the March 2020 event significantly impacted the returns and volatility. In this research, I combine a technical analysis approach and a peripheral analysis approach to investigate the relationship between shocks and the worldwide stock market. Sentiment analysis also makes this research more comprehensive.

METHODOLOGY

In this section, I describe the details of my methodology to analyze how the emotions from the shock news led to the stock markets fluctuating. I first describe the process of collecting the data, including the textual news of shocks during the events happening and stock information of different financial markets; then, I introduce the approach to retrieving the sentiment from the news and quantifying the sentiment. Last, I describe the econometric analysis methods for researching the impact of emotions on stock movements.

Data

(1) Stock trading data: The stock market has several indicators that measure the situation of stocks in the whole markets, in addition to the stocks of companies. To consider more financial markets and cover as much of the world as possible, I choose 30 different market indices, like FTSE 100 (an index of the 100 largest companies in the stock market of the United Kingdom) and S&P 500 (an index of the 500 largest publicly traded companies in the United States). The selected time is around the shocks that happened.

When analyzing stock price volatility, I need the stocks' adjusted closing prices and volumes. The data is collected from Yahoo Finance (https://finance.yahoo.com/), which offers a wide range of stock quotes. A method named 'get_data_yahoo' belongs to the 'pandas_datareader' model. It can help retrieve all the stock information in Yahoo Finance without needing to download and save the data locally.

(2) Shocks news data: The choice of events is symbolic. I needed to choose the events which impact the whole world. These events should ideally occur within a short period of time and not occur at the same time as other events. I've picked two main shocks to compare, the Russia-

Ukraine war and the 2020 United States presidential election. On February 21, 2022, Putin ordered Russian troops into Ukraine; the full-scale offensive began on the 24th. The 2020 United States presidential election was held on November 3, 2020, and the vote to confirm Joe Biden as the 46th President was on December 14, 2020. The Russian-Ukraine war is negative news, but the US presidential election that elects a more suitable president based on the people's will is undoubtedly positive. The positive shock still carries uncertainty, because there's no guarantee that the new president will be better than the old one. By comparing the impacts caused by these two shocks, it is possible to speculate on the differences between the impacts of positive and negative events, which makes it easier to summarise the general pattern in subsequent studies.

I collect news data from three different websites, Financial Times (https://www.ft.com/), The Wall Street Journal (https://www.wsj.com/) and Reuters (https://www.reuters.com/). These new sites are some of the most authoritative websites in the world. Considering different news sites reduces the one-sidedness of news from a single site and makes judgements more comprehensive. However, these websites have strong protection mechanisms to prevent users from collecting news text data by web crawlers [18]. So I have to collect the news information by hand. I collect ten different pieces of news information for each day before and after the shocks on each website.

Text Normalization and Sentiment Analysis

Shock news has a lot of information to affect economic activities, including stock fluctuation. To study the impact of news, I use text mining to transform textual data into structured representations. Even if the textual information of news is much more standardised than that of social media, and does not require operations such as replacing word repetition with a single occurrence ("looook" to "look"), much work of text normalization still needs to be done. Like converting capital letters to lowercase, removing punctuation, removing non-words such as punctuations, and expanding abbreviations ("I'm" to "I am"). One of the specific tasks of tokenisation is removing stop words. Some words like "the" and "a" are useless when analyzing news information. The next step is stemming. I use 'SnawBallStemmer' to map different forms of the same word to a common token. After that, I get a list of words from the shock news.

Sentiment analysis is another key job of this project. Zhang and Skiena [19] proposed a method based on sentiment polarity.

$$\text{Polarity} = \frac{\text{positive} - \text{negative}}{\text{positive} + \text{negative}} \tag{1}$$

positive and *negative* is the number of positive and negative tokens in the textual information. Polarity is the percentage of the net positive occurrences among the total sentiment references. It indicates the sentiment of the news. It indicates the emotional direction of the news. The closer it is to 1, the more positive the news is; the closer it is to -1, the more negative the news is. The opinion lexicon provides specific emotional terms instead of syntactic or semantic prosperity. This calculates sentiment polarity more quickly and accurately. To get an overall indicator of shock news (*sentiment*), I calculate the mean for the sentiment polarities of the sample news on the same day to analyse the impact of news emotions on stock fluctuations.

Econometric Analysis Methods

Sentiment polarity is just a way to quantify emotion in the news. How to analyse its relationship with stock fluctuations still requires the use of some econometric analysis methods. To evaluate the shock news impact more exactly, I use both the sentiment method and the non-sentiment approach to analyse the effect of the shocks. These two approaches are event study methodology and cross-sectional regression method.

(1) Event study methodology. In 1997, Mackinlay [20] proposed the event study methodology to analyse the effects of a particular event on a financial market. The first step is identifying the shocks: the Russia-Ukraine war and the 2020 United States presidential election. I defined the event day of the Russia-Ukraine war as 22nd February 2022, when the two countries were in full swing; the event day of the United States presidential election was 14th December 2020, the date of announcement of voting results. The timing selection may be biased. However, I still chose the event windows around the shocks that happened to see stock fluctuations in the events. I define t as the date of the event day, and employ 10-day event windows [t - 3, t + 6]. t-3 is the date three days before the event day; t+6 means six days after the event day. I also select the estimation windows to analyse the characteristics of the market before the shocks. The intersection is [t - 183, t - 4], the 180 days before the event windows. The timeline is below as Figure 1.

Figure 1 Timeline for event study methodology

I employ the Capital Asset Pricing Model (CAPM) to estimate the expected return based on its risks. Sharpe [21] raised CAPM, which aims to maximise returns while minimising risks. The following CAPM was used to estimate the returns for each market index.

$$r_{i,t} = r_{f,t} + \beta_i (r_{M,t} - r_{f,t}) \quad (2)$$

$r_{i,t}$ *is the expected normal return for the stock of market i in date t.*

$r_{M,t}$ *is the return of the whole market, is the return of the whole market, which I use the mean of all the returns for 30 market indices in period t to present.*

$r_{f,t}$ *is the non-risk interest rate.*

Investors always consider treasury bills (T-bills) as risk-free assets and set the interest of T-bills as the non-risk interest rate. I combine 30 different market indices to see how the shocks influent the whole stock market. Many financial markets are volatile, and even T-bills are highly flammable. That means these interests of the T-bills cannot be considered non-risk interest rates. However, the T-bill of the United States is stable. It is a good reflection of the relative situation of the whole market. In that case, I set 3.88%, the 10-year yield of the US as the non-risk interest rate.

β_i measures the responsiveness of security in the market i to movements in the market portfolio. β_i is calculated using the following formula, market i's covariance with the whole market over the variance of these two markets.

$$\beta_i = \frac{Covariance(R_i,R_m)}{Variance(R_i,R_m)} \tag{3}$$

R_i = the return on the single market i.
R_m = the return on the overall market.
Covariance = how changes in a single stock market's return is related to changes in the whole market's return.
Variance = how far the market's data points spread out from their average value.

Then I calculate the abnormal return for the stock in the market i in period t.

$$ar_{i,t} = r_{i,t} - \widehat{r_{i,t}} \tag{4}$$

$ar_{i,t}$ is the abnormal return for the stock of the market i in date t.
$\widehat{r_{i,t}}$ is the actual return for the stock of the market I in date t.

Furthermore, I can calculate average abnormal return (AAR) and the cumulative average abnormal return (CAR) based on all abnormal returns for the whole market. AAR_t is the AAR in date t; CAR_t is the CAR in date t, the sum of the AARs from the start date to date t. I choose t from the event window, t-3 to t+6.

$$AAR_t = \frac{1}{n}\sum_{i=1}^{n} ar_{i,t} \tag{5}$$

$$CAR_t = \sum_{\gamma=1}^{n} AAR_t \tag{6}$$

n = the number of different markets.

Abnormal return (AR) t-test can be used to determine whether the AR of a security on a specific day is significantly different from zero. T-test helps to identify whether the event has a significant impact on the security's return.

$$t_{AAR,t} = \frac{AAR_t}{S_{AR_t}} \tag{7}$$

$$t_{CAR,t} = \frac{CAR_t}{\sqrt{n} S_{AR_t}} \tag{8}$$

(2) Cross-sectional regression method. The event study method can only analyse the outcome of an event, whereas the cross-sectional regression method can explore the importance of various factors in the occurrence of shocks. Event study methodology only deals with stock price information. But news text information, news sentiments, and stock volume all potentially affect stock volatility. I provide a multivariate analysis of abnormal returns. At the same time, I want to test whether the CAR is affected by various factors of the stock market, like sentimental representations, market sizes and risks. Equation (7) is my multivariate regression model.

$$AAR_t = a_t sentiment_t + b_t size_t + c_t \, risk_t + d_t \tag{9}$$

Where AAR_t is the average abnormal return of the whole market in period t; t is selected form the event window, t-3 to t+6;$sentiment_t$ is the overall qualified sentimental polarity of the stock market in date t;$size_t$ is the nature log of the mean of the total volumes for 30 different markets in period t. $risk_t$ is the standard deviation of the first ten days of the date t's returns. The parameters will be got by Ordinary Least Squares (OLS) method, calculated by taking data from two adjacent days.

ANALYSIS

Event study for the overall stock market around the world

Event study methodology is a method of analysing the impact of an event without analysing the content of the news, but focusing on the stock itself. I combine the approaches based on non-news and news simultaneously to evaluate the impact of shocks more accurately. To evaluate the shock news impact more exactly, I use both the sentiment method and the non-sentiment approach to analyse the effect of the shocks.

(1) Event study for the Russia-Ukraine war. First, I employ event study methodology in Russia-Ukraine war. Undoubtedly, the Russian stock market (reflected by IMOEX.ME, a capitalization-weighted index that tracks the performance of the largest and most liquid companies traded in Russia) was the hardest hit, and no further measurements were taken for IMOEX.ME after the war broke out. AAR and CAR can reflect the volatility of the stock market under the influence of shocks. The specific values of AAR and CAR during the event window time are shown in *TABLE I*.

To well understand the movement of the AAR and CAR, a graphical description of AAR and CAR in *TABLE I* is shown in *FIGURE I*. The overall curve is negative, meaning the overall estimated value is not as high as the actual value. Stocks remain within the normal range most of the time; At the same time, most of the P values of the AARs are less than 0.01. This means the influence of the shock is not significant to the stock price on most days at a 1% level of significance. The P-value of AAR and CAR are shown in *TABLE II.* However, there are still two peaks in the AAR and CAR curves and one P value doesn't pass the t-test.

1. The first peak is around t-2, February 22nd. AAR is 0.000051 and the CAR reaches to -0.000083, meaning the actual price of the stock is lower than the estimated price of the stock. The stock price dropped rapidly on that day. The reason behind the change is easy to understand. On February 21st, 2022, Putin ordered Russian troops to enter Ukraine. The news shocked the world. Even if the war is only between two countries, stock markets worldwide are hit. However, because the announcement time was at night, the impact of the shock on the market was postponed to the next day.

2. The second peak is around t+1, February 25th. On the 23rd and 24th, stocks fluctuated to gradually return to normal. This proves that unexpected events can make the entire stock market fluctuate, but it can still return to normal in a short time. However, AAR has risen rapidly to the highest value of 0.00026, and CAR changed from -0.00035 to -0.000091 on February 25th. The AAR is significant at the statistical level of 1%, which indicates a strong impact on the stock price in the whole market. Putin launched an all-out attack on Ukraine on the 24th. An all-out attack is the real start of the war. Any investor still hesitates and thinks about whether to give up or persist, knowing that war is inevitable. Most of them had to give away assets in the stock market. However, AAR&CAR's drastic change came a day after the shock. The one-day delay is no longer like the first peak because the announcement was made the night before. The impact of the shock of the Russia-Ukraine war on the whole stock market still has a one-day lag. But after AAR increased rapidly, the entire market is still adjusting rapidly to bring the overall trend back to normal. After all, even if the Russia-Ukraine war is the biggest in recent years, most stock markets still have relatively little correlation with Russia and Ukraine, and they will still make mediation as soon as possible to return to normal levels.

All in all, stock markets around the world would plummet the day after this negative shock. And the greater the event's impact, the greater the stock's decline. However, the entire market would still react as soon as possible and return to normal values.

	t-3 (2022-02-21)	**t-2 (2022-02-22)**	**t-1 (2022-02-23)**	**t (2022-02-24)**
AAR	-0.000134	0.000051	-0.000038	-0.000229

CAR	-0.000134	-0.000083	-0.000121	-0.00035
	t+1 (2022-02-25)	**t+4 (2022-02-28)**	**t+5 (2022-03-01)**	
AAR	0.000260	-0.000019	-0.000139	
CAR	-0.000091	-0.00011	-0.000249	

TABLE I CHANGES IN AAR AND CAR OVER TIME OF RUSSIA-UKRANIE WAR

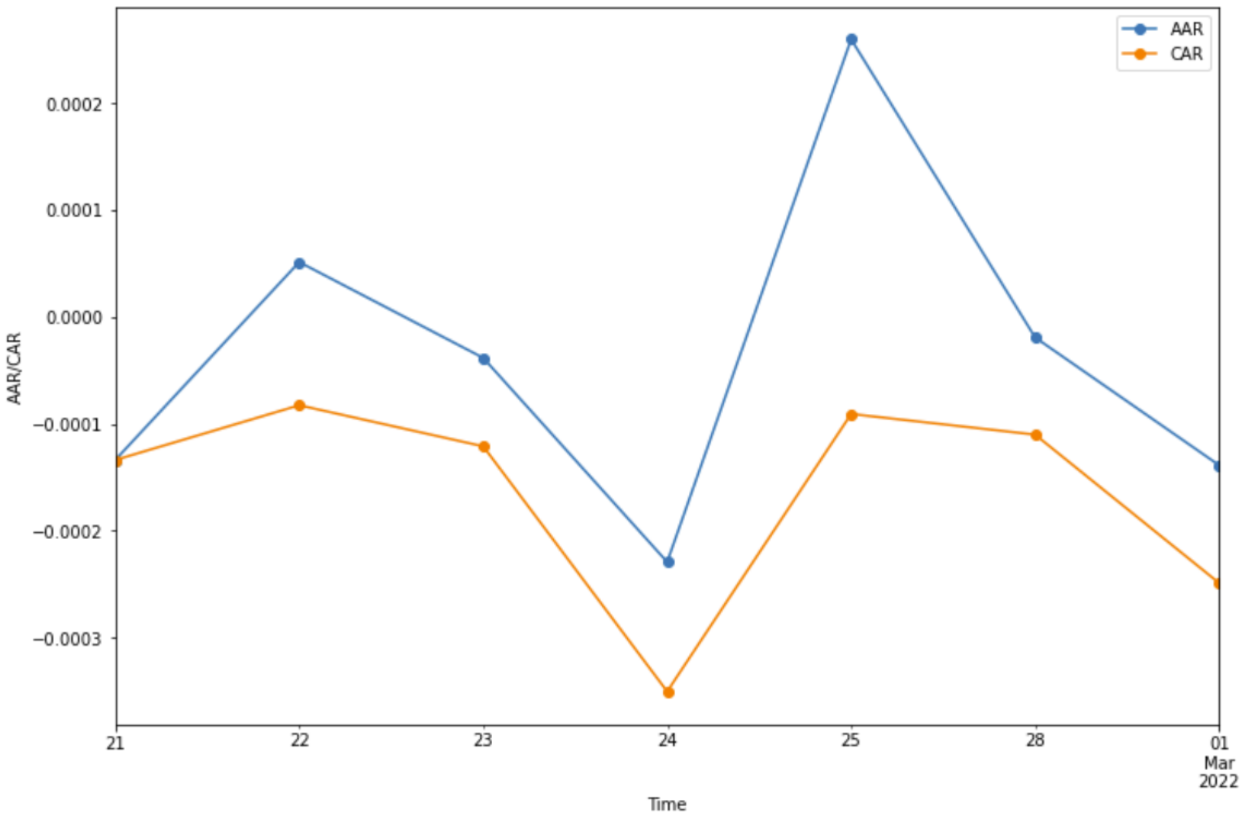

FIGURE I CHANGES IN AAR AND CAR OVER TIME OF RUSSIA-UKRANIE WAR

	t-3 (2022-02-21)	**t-2 (2022-02-22)**	**t-1 (2022-02-23)**	**t (2022-02-24)**
t_{AAR}	-0.005845	0.003145	-0.002559	-0.004796
t_{CAR}	-0.001067	-0.000928	-0.001474	-0.001338
	t+1 (2022-02-25)	**t+4 (2022-02-28)**	**t+5 (2022-03-01)**	
t_{AAR}	0.013405	-0.001282	-0.007540	
t_{CAR}	-0.000857	-0.001336	-0.002469	

TABLE II P VALUES FOR AAR AND CAR OF RUSSIA-UKRANIE WAR

(2) Event study for the US Presidential Selection 2020. I also use the event study method to analyze the presidential election's impact on the whole stock market. Because of non-working days, stock information is missing for both days t-1 and t-2. I add the information in the t-4 period to analyze the movement before the shock. The US stock market won't collapse like the Russian stock market (IMOEX.ME) did during the Russian-Ukrainian war. To better observe the changes in the AAR&CAR, I prepare *TABLE III* and *FIGURE II* to record the specific values and graphical description of AAR & CAR respectively. The CAR curve for the Russia-Ukraine war was always under the AAR curve, but the opposite for the US presidential election, where CAR was always above the AAR curve. That means the estimated returns are generally higher than the actual returns for the positive news. However, all the P values of the AARs are less than 0.01, indicating the influence of this shock is not significant to the stock price all days during event window at a 1% level of significance. One of the reasons may be that when negative shocks occur, the market will take timely measures to mediate; however, when positive shocks occur, the market may fluctuate freely and remain within the normal range. The P-value of AAR&CAR are shown in *TABLE IV.* There is one peak in the AAR and CAR curves.

The peak of AAR is around t, the exact date of the shock; the peak of CAR is a day later, on 15 December 2020. Biden's election to the president was announced on the 14th. Unlike the sudden start of the Russia-Ukraine war, the timing of the announcement of the U.S. election results was certain, and voters had their own guesses as to what to expect. So there is no lag in the impact of a positive shock on the stock market, and there will be a sharp movement on the day of the event. Furthermore, the AAR for the 15th remains at 0.000030, more than double that of the AAR on the 13th; and CAR reaches the maximum point, 0.000103. The overall market impact of positive shocks lasts for a few days and does not return to normal as quickly as negative news. However, the AARs still aren't significant at 1% significance, which means positive news doesn't impact the stock price in the whole market.

Overall, positive news causes immediate movement in the stock market and has a more lasting effect. But the fluctuations are always within normal limits.

	t-4 (2020-12-10)	**t-3 (2020-12-11)**	**t (2020-12-14)**	**t+1 (2020-12-15)**
AAR	0.000016	0.000011	0.000046	0.000030
CAR	0.000016	0.000027	0.000073	0.000103
	t+2 (2020-12-16)	**t+3 (2022-12-17)**	**t+4 (2020-12-18)**	
AAR	-0.000048	-0.000011	0.000027	
CAR	0.000055	0.000044	0.000070	

TABLE III CHANGES IN AAR AND CAR OVER TIME OF US PRESIDENTIAL SELECTION 2020

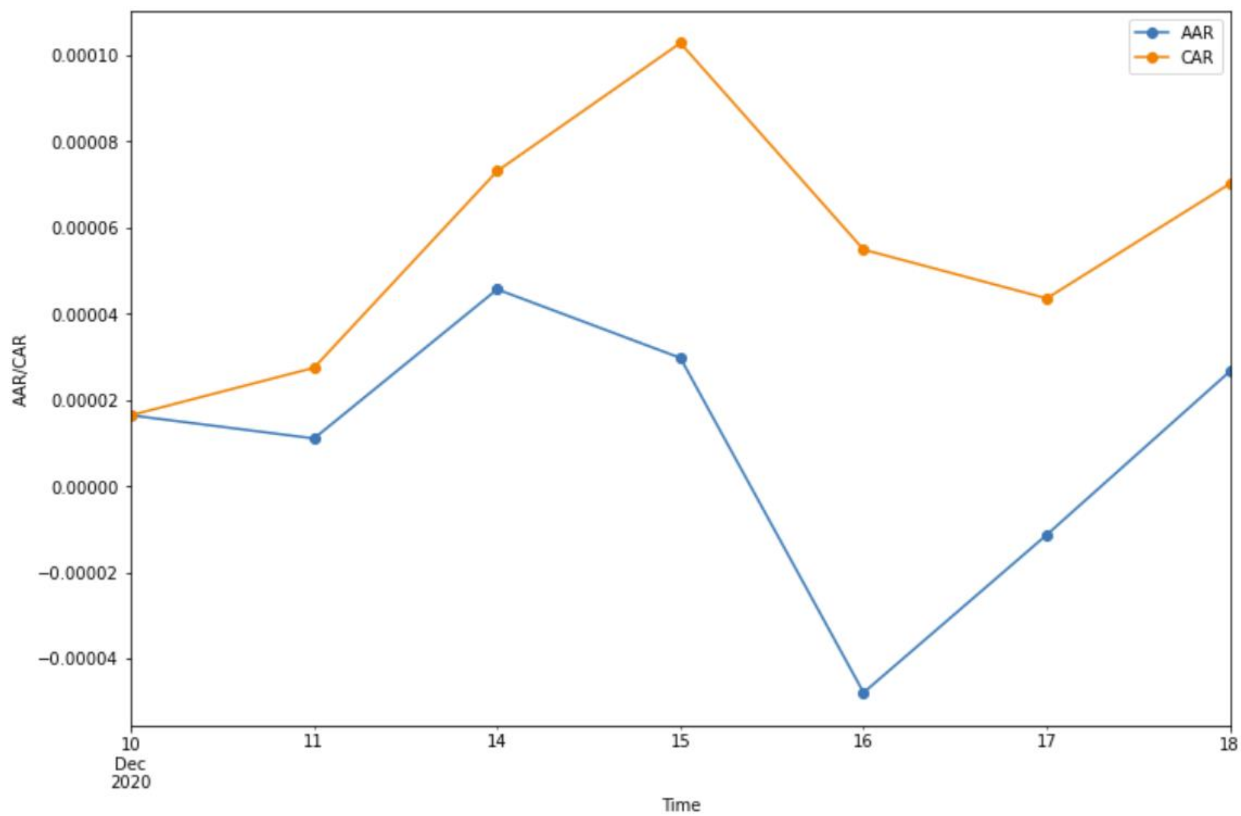

FIGURE II CHANGES IN AAR AND CAR OVER TIME OF US PRESIDENTIAL SELECTION 2020

	t-4 (2020-12-10)	**t-3 (2020-12-11)**	**t (2020-12-14)**	**t+1 (2020-12-15)**
t_{AAR}	0.000599	0.000502	0.002171	0.001162
t_{CAR}	0.000109	0.000228	0.000635	0.000734
	t+2 (2020-12-16)	**t+3 (2022-12-17)**	**t+4 (2020-12-18)**	
t_{AAR}	-0.001685	-0.000457	0.001040	
t_{CAR}	0.000352	0.000321	0.000501	

TABLE IV P VALUES FOR AAR AND CAR OF US PRESIDENTIAL SELECTION 2020

By comparing the impacts of the two shocks through the event study method, the following can be extrapolated:

i. The Russia-Ukraine war impacted the whole stock market more than the US presidential election 2020. The greater the magnitude of the event, the greater the impact.

ii. The impact of the Russia-Ukraine war is delayed by one day, while the effects of the US presidential election 2020 are immediate.

iii. The impact of the Russia-Ukraine war recovers within a day, but the impact of the US presidential election 2020 lasts for some time.

Cross-sectional regression for the overall stock market around the world

(1) Cross-sectional regression for the Russia-Ukraine war. *TABLE V* shows the parameters and variables of the multivariate regression model for Russia-Ukraine war. The parameters are got by Ordinary Least Squares (OLS) method. Because the parameters are calculated by taking data from two adjacent days, and no previous data is available for the t-3 period, the data for the t-3 period is not recorded.

$sentiment_t$ is always negative, indicating the emotions in the news about the Russian-Ukraine war are always negative. AAR and CAR show stock markets will return to normal as soon as the shocks hit them. However, emotions stay longer in the news. After the impact of the 21st, $sentiment_t$ was kept high from the 22nd to the 25th. On the 26th, $sentiment_t$ decreased slightly in the final. There is no lag in the reflection of emotions. When total war broke out on the 24th, $sentiment_t$ reached its lowest point, -0.931662. Instead of the stock market changing drastically the next day.

$size_t$ mostly stays the same overall. This proves that the overall world market size hasn't changed much because of the Russia-Ukraine war; $risk_t$ remain stable in the premise. After the outbreak of total war on the 24th, it began to rise rapidly. Investment risks are heightened globally following the start of the war. Even as news sentiment gradually stabilises, investors will be more cautious and not make easy choices to avoid further losses.

The absolute value of a_t is always the largest one for all parameters, meaning that news sentiments are very significant during the event window. $sentiment_t$'s importance rises rapidly under the influence of the shocks of the 24th, and a_t rises from -0.0009 to 0.0009. The significance of news sentiment is reflected at the first sign of a shock. However, it's still hitting its maximum impact the next day, like the stock market. The significance of a_t is kept for a while, even if the whole stock market return to the normal.

b_t's importance has remained relatively low. However, b_t reaches up to 0.00009304 on the 24th; the 25th was even more explosive, b_t goes straight up to 0.0013 with several orders of magnitude. The values of $size_t$ haven't changed much, but the significance of the volumes for the stock market still changes drastically as shocks occur. Meanwhile, c_t is more stable than b_t. c_t only rapidly rises to 0.003 on the 25th. Even if the significance of the risks has fallen a bit since then, c_t is still higher than the original values. The impact of the risks will continue for a while.

All in all, most drastic change due to the sentiments in the news about Russia-Ukraine war. Sentiments are the most significant indicator of stock fluctuations. No matter sentiments, sizes or risks, their significance peaked on the 25th, the day after the shock.

	a_t ($sentiment_t$)	b_t ($size_t$)	c_t ($risk_t$)	d_t	AAR_t
T -3 (2022-02-21)	(-0.414893)	(0.199564)	(0.012932)		
T-2 (2022-02-22)	-0.0004 (-0.832028)	-0.00006007 (0.200253)	-0.000003249 (0.013447)	-0.0003	-0.000051
T-1 (2022-02-23)	-0.0009 (-0.726822)	-0.0001 (0.198848)	-0.000007648 (0.012213)	-0.0006	-0.000038
T (2022-02-24)	0.0009 (-0.931662)	0.00009304 (0.203336)	0.00000784 (0.012174)	0.0006	-0.000229
T+1 (2022-02-25)	0.0118 (-0.891619)	0.0013 (0.201728)	0.003 (0.017480)	0.0105	0.000259
T+4 (2022-02-28)	0.001 (-0.621490)	-0.0001 (0.202585)	-0.00003098 (0.020865)	-0.0006	-0.000019
T+5 (2022-03-01)	0.0073 (-0.637628)	0.0014 (0.201701)	0.0006 (0.020029)	0.0042	-0.000139

TABLE V THE RESULTS OF MULTIVARIATE REGRESSION MODEL FOR RUSSIA-UKRANIE WAR

(2) Cross-sectional regression for the US Presidential Selection 2020. *TABLE VI* shows the parameters and variables of the multivariate regression model for US presidential election 2020.

Most $sentiment_t$s are positive, news remains optimistic about expectations for the U.S. election result. News positivity peaked at 0.450239 the day after the announcement of Biden's election, indicating news is pleased with Biden's election. However, negative news has a much stronger emotional bias overall than positive news. In both 17th and 18th, the sentimental polarity is negative, but not by much. It may be that after the excitement has worn off, all sorts of issues need to be addressed with a new president in office.

$size_t$ doesn't change too much during the event window. This proves that the whole market size mostly stays the same because of the U.S. presidential election 2020; $size_t$ drops from 0.0083 to 0.0069 at the time of the shock and remained even lower for several consecutive days. Positive shocks have little impact on market size, but can lead to a reduction and maintenance of risk. Investors become more confident in their investment behaviors.

The same as the Russia-Ukraine war, if all coefficients take absolute values, a_t is the largest. News sentiments are the most significant factors to analyze. However, emotions matter a lot less than the negative news. At the time of the events of the 14th, the importance of sentiment increased but not too much. On the 16th, the shock's joyous mood was still spreading, but the AAR was down to -0.000035, rising sharply to the maximum value of 0.0018. News sentiment becomes even more important as stocks return to normal after being mildly affected by positive shocks. Meanwhile, there is also a sudden rise in the significance of emotions the day after the worrying mood appears. The importance of news sentiment does not change much with positive news shocks. However, when the market returns to normal or begins to experience a negative emotion, sentiment spreads somewhat and becomes more significant.

$size_t$ is slightly more important than $risk_t$, but both remain low. Trends in b_t and c_t are similar to those in a_t, so I don't analyze too much about them again.

	$\boldsymbol{a_t\ (sentiment_t)}$	$\boldsymbol{b_t\ (size_t)}$	$\boldsymbol{c_t\ (risk_t)}$	$\boldsymbol{d_t}$	$\boldsymbol{AAR_t}$
T -4 (2020-12-10)	(0.048462)	(0.202008)	(0.008311)		
T-3 (2020-12-11)	-0.0000307 (0.336568)	0.000006596 (0.201714)	0.0000002742 (0.008273)	0.00003249	0.000024
T (2020-12-14)	-0.0001 (0.061793)	0.00001297 (0.201145)	-0.0000002323 (0.006903)	0.00006588	0.000060
T+1 (2020-12-15)	-0.00004028 (0.450239)	0.00001208 (0.201545)	0.0000005063 (0.006107)	0.00006028	0.000045
T+2 (2020-12-16)	0.0018 (0.404783)	-0.0001 (0.200827)	-0.00001730 (0.006389)	-0.0007	-0.000035
T+3 (2020-12-17)	-0.00008326 (-0.049463)	-0.0000003955 (0.200510)	0.000000005709 (0.006479)	-0.000001683	0.000002
T+4 (2020-12-18)	-0.0030 (-0.061663)	0.0008 (0.204025)	-0.00004027` (0.006322)	-0.0003	0.000042

TABLE VI THE RESULTS OF MULTIVARIATE REGRESSION MODEL FOR US PRESIDENTIAL SELECTION 2020

By comparing the impacts of the two shocks through the cross-sectional regression method, the following can be extrapolated:

i. News sentiments are important in both shocks, but the emotional intensity of the Russia-Ukraine war is higher and more significant for the stock market.

ii. US presidential election 2020 reduces market risk; the Russia-Ukraine war increases it.
iii. In times of deteriorating news expectations, news sentiment, market size and risk impacts are increased.

CONCLUSION

The research donates to analyze the impact of shocks on stock fluctuations in the worldwide market. Combination of sentimental and non-sentimental approaches, news-based and non-news-based approaches, resulting in more comprehensive analyses of stock market volatility. In particular, I chose the US presidential election 2020 as the positive shock and the Russia-Ukraine war as the negative shock. Few studies have talked about the impact of stocks on the overall market. Even though my research has only examined two shocks tentatively, it has been able to show many differences between the two types of events, and lay the groundwork for a more comprehensive study to follow. The Russia-Ukraine war impact the whole stock market more than the US presidential election 2020; news sentiments are important in both shocks, but the emotional intensity of the Russia-Ukraine war is higher and more significant for the stock market. My job can help macroeconomists and governments to understand that impact of positive and negative shocks on the stock market. The macroeconomists can consider the fluctuations causing by shocks to analyse economic performance, inform economic stabilization policies, evaluate policies and develop economic models; the governments can compare the difference in volatility between their own countries and the overall environment. Then they can decide whether to intervene in the stock market when shocks occur. For example, the governments may need to employ circuit breakers, trading halts, or temporary bans to calm the markets and prevent panic selling when negative shocks occur.

My research still has many shortcomings. For example, I just selected a limited number of news, because the financial websites have protection mechanisms. If large amounts of news could be collected, machine learning methods might make predictions more accurate; meanwhile, I have only selected the news in English. If considering multi-language texts, the analysis can be more comprehensive. However, the biggest problem is that I have only considered the impact of comparing two events. I cannot fully summarize the broad conclusions about the similarities and differences for the impacts of positive and negative shocks on the worldwide stock market. Analysing more shocks can make conclusions more convincing. These disadvantages can be tried to solve in subsequent research for more accurate analysis.

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