Role of Crude Oil, Natural Gas and Wheat Prices and the Impact of the Russian-Ukrainian War on the Investor Social Network Sentiment; Evidence from the US Stock Market

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13 May 2024

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Abstract

Through an empirical analysis of the impact of fluctuations in the international prices of crude oil, natural gas and wheat on the US stock market performance, the study seeks to show evidence of the investor social network sentiment effects post the Ukraine war declaration on February 24, 2022. A comparative approach was used for Ukraine's pre- vs post-war declaration period. The considered models are of the GARCH-X type. Founding show that only post-war declaration; investor sentiment as well as the economic factors such as the prices of raw materials (including crude oil and natural gas) and food (wheat) have caused the volatility of the S&P 500 index return, while market volatility (VIX) affect negatively the stock market return pre- and post-war declaration.

Key words: S&P500 stock index; American market volatility (the VIX index); American investor sentiment on tweeter, Ukraine War; commodity prices (crude oil, natural gas and wheat); GARCH-X model.

JEL classification: E44, G11, G15.

Conflicts of Interest: The authors declare no conflict of interest.

1. Introduction

This study aims to analyse the impact of investor sentiment, as expressed on Twitter, on the volatility of the American S&P500 stock index [1] in particular before and after the outbreak of war between Russia and Ukraine. By combining natural language analysis techniques with advanced statistical models, it aims to assess how investors' emotional reactions to major geopolitical events can influence US stock market.

The research sits at the intersection of international political economy and behavioural finance, providing an empirical framework for understanding the underlying dynamics of stock markets in a context of geopolitical crisis. It also examines how new technologies, particularly social media like Twitter, can provide a valuable source of real-time information on investor sentiment.

Social network sentiment is the sentiment extracted from the messages posted on social networks using, in most of the cases, some language processing software. This study analyzed the influence that social network sentiment has influence on S&P 500 Index's volatility, and see whether this influence was greater or lesser pre- or post-war declaration.

By dividing the study period into two distinct phases – pre-war and post-Ukraine war – the study takes a comparative approach to assess the evolving relationship between investor sentiment and market volatility. The results obtained provide important information for investors, portfolio managers and policy makers, illuminating market reactions to geopolitical events and enabling a better understanding of underlying financial dynamics.

This study contributes to the existing literature on the impact of investor sentiment on financial markets by focusing specifically on the S&P500 stock index in the context of the Russian-Ukrainian war. By providing valuable insights into the relationship between investor sentiment and market volatility, it offers avenues for more informed decision-making in a complex and ever-changing financial environment.

The paper has 5 sections. After the introduction, section 2 gives the theoretical foundation of the subject and a review of the literature on the effect of variables linked to the global environment and variables linked to the American stock market. Section 3 explains the data collection and the calculation of the sentiment variable and gives a descriptive analysis of the considered data. Section 4 presents the research methodology and the results of the considered models. We conclude in the last section.

2. Literature review and hypothesis setting

Financial markets respond to a wide range of *geopolitical events* such as the *wars*, invasions, terrorist attacks and periods of tension.

Though wars generally have a strong impact on financial markets (Izzeldin et al., 2023), …"the relevant literature is limited. Wisniewski (2016) found that wars result in widespread destruction of human and physical capital and stock markets fall. Hudson and Urquhart (2015) studied the effect of the second world war (WWII) on the British stock market and found that only one of the wartime events classified as important resulted in a structural break. Berkman, et al,. (2011) investigated 447 international political crises – but not all are wars. They find that the global stock market returns would have been higher by 3.6% per annum but for these events. Waldenström and Frey (2008) observed sudden shifts in sovereign debt yields and spreads in the Nordic bond markets during WWII. Frey and Waldenström (2004) compared sovereign debt prices on the Zurich and Stockholm stock exchanges and conclude that market efficiency has not been affected by WWII. Brown Jr and Burdekin (2002) studied German bonds traded on the London stock exchange during WWII and document a negative impact on only two events during the entire conflict course. Frey and Kucher (2001) analyzed government bond prices of Germany and Austria traded on the Swiss bourse during WWII. They show that war episodes are clearly reflected in government bond prices. Frey and Kucher (2000) examined the prices of the government bonds of five European countries during WWII. They found that the loss and gain of national sovereignty affected the bond prices of the countries."

Among the results of the most recent references on conflict or crisis effects, we present the following. Research conducted by Wu et al. (2023) found that conflict initially reduced stock volatility but increased it after Russia invaded Ukraine. Izzeldin et al. (2023) found a rapid reaction of stock and commodity markets to the Russian invasion, with less intense effects compared to other crises such as Covid-19 and the 2008 global financial crisis, particularly affecting products such as *wheat and nickel*. Kamal et al. (2023) observed significant negative *abnormal returns* in the Australian stock market following the event, especially for small and medium-sized and high-growth export-oriented *firms*. Arnd et al. (2023) studied the impact on *food and raw material prices*, showing increased vulnerability of agri-food systems and poverty to price increases. Liao (2023) highlighted the role of *renewable energy* in mitigating declines in *stock returns*. Umar et al. (2022) highlighted the co-movements between *sold stocks and beneficial* short-*term hedging* strategies. Yousaf et al. (2022) demonstrated the significant negative impact of the conflict on the *stock markets* of the G20 and other countries, with different reactions depending on the region. Finally, Boungou & Yatié (2022) documented a negative relationship between conflict and *global stock returns*.

Investor sentiment analysis on *social media* can provide a complementary perspective to traditional financial asset pricing models and provides a better understanding of emotional and behavioural influences on stock markets.

There are 5 *emotional and behavioural* aspects that influence financial markets that have been studied in the literature including:

- real-time information flows (Bollen, Mao et Zeng, 2011; Garcia et Schweitzer, 2015; Bollen, Mao et Pepe, 2011),

- peer reactions and social influence (Hong et Stein, 1999; Barber et Odean, 2001 ; Aral et Walker, 2012; Bollen, Mao et Pepe, 2011),
- contagion effects (Christakis et Fowler, 2009; Aral et Muchnik, 2013),
- confirmation bias (Christakis et Fowler, 2009; Aral et Walker, 2012; Bollen, Mao et Pepe, 2009; Tuckett et Taffler, 2011) and
- the effect on market liquidity (Bollen, Mao et Zeng, 2011; Sprenger et al, 2014).

The cited researchers among others have contributed to a better understanding of these phenomena and their impact on investment decisions and financial market dynamics.

Several studies have been conducted on the relationship between investor sentiment and stock market performance based on various sources such as social media (Twitter in particular). We present the main contributions. Recently, Nyakurukwa & Seetharam, (2023) used bibliometric analysis to examine the evolution of sentiment on social media, highlighting its multidisciplinary and structure within the stock market. Zeitun et al., (2022) studied the effect of Twitter-based sentiment on US sector returns, revealing varying causality and correlation across sectors. Ranjan & Majhi, (2022) developed a machine-learning model to predict the impact of sentiments expressed in tweets on stock values, concluding that this model has superior accuracy. Qing et al., (2022) examined the synergy between stock prices and investor sentiment, finding a positive synergy. Renault, (2019) evaluated the performance of different sentiment analysis methods in finance, concluding a correlation between investor sentiment and stock returns, but low predictive ability. Audrino et al., (2019) analysed the impact of sentiment and attention variables on stock market volatility, showing that these variables improve volatility forecasts. Cabarcos et al., (2019) studied the influence of social media sentiment on sustainability indices, highlighting its impact on sustainable business returns. Ranco et al., (2015) examined the relationship between Twitter and financial markets, identifying a correlation between tweet sentiment and stock returns, especially during peaks in volume.

The existing literature on the impact of the Ukraine-Russia war on stock returns has mainly examined the relationship between the geopolitical conflict and financial markets without considering effects related to both *commodity prices* and *investor sentiment*.

In this study, we will fill this gap by including specific variables related to the *commodity prices* as well as the *investor sentiment* effects. We believe that the inclusion of commodity prices (crude oil price, natural gas price, wheat price) will provide additional insight into the complex dynamics between war, commodity prices and U.S. stock index performance. Our approach will be based on three key aspects of geopolitical conflicts: geopolitical uncertainty and risk, financial contagion and commodity price fluctuations.

In this regard, we ask four questions:

Question 1: Is there a significant relationship between crude oil prices and the US S&P500 stock index volatility?

Question 2: Is there a significant relationship between the price of natural gas and the US S&P500 stock index volatility?

Question 3: Is there a significant relationship between the price of wheat and the US S&P500 stock index volatility?

Question 4: Does investor sentiment expressed on Twitter pre and post Ukraine war affect the fluctuations of the US stock index in the same way?

Then, we formulate the corresponding hypotheses as follows:

H1: there is no relationship between the price of oil and the volatility of the S&P500 stock market index.

H2: There is no relationship between the price of natural gas and the volatility of the S&P500 stock index

H3: There is no link between the price of wheat and the volatility of the S&P500stock market index.

and

H4: Investor sentiment expressed in tweets does not have an effect on the volatility of American stock index pre or post Ukraine war.

3. Data collection and preliminary analysis

In the current context marked by the war in Ukraine, financial markets are facing increased volatility and geopolitical uncertainties. This study aims to test the impact of investor sentiment extracted from Twitter on stock index returns, as well as the influence of crude oil price, natural gas price and wheat price fluctuations on the returns of the US S&P 500 index pre- and post-Ukrainian war declaration.

3.1 Data collection

Data includes daily prices of the US S&P 500 stock index (excluding weekends and holidays), the US VIX Volatility Index, and daily prices of crude oil, of natural gas and of wheat obtained from Yahoo Finance. The period of study extends from February 24, 2021 to February 24, 2023 (totalling 504 observations) covering the war declaration in Ukraine (February 24, 2022). The data are collected one year before and one year after Russia's invasion of Ukraine. The dependent variable is the daily return of the stock market S&P 500 calculated as:

$$\boldsymbol{R_t} = \Delta\log(\mathrm{SP}_t),$$

where $\Delta = 1 - B$ and B is the lag operator, SP = S&P 500.

The control variables include the US volatility index (VIX) for the mean evolution and the prices of crude oil (WTI), the natural gas price (NG) and the wheat price (WHEAT) as well as the Investor Sentiment Index (SENT) for the volatility fluctuations. Investor sentiment (SENT index) will be obtained from the the messages posted about S&P 500 Index explained in the following sub-section.

3.2 SENT index determination

Several recent works have used automatic processing models via natural language processes (NLP) to calculate the sentiment variable from messages published by investors in social media [2]. In this study, the approach used to calculate the SENT index from investors' tweets that is based on five different steps can be summed up as follows:

Step1. Importing the necessary packages into Python code: This step includes creating and activating an environment, installing the required packages via pip. The process begins with importing the necessary packages into a Python environment such as Anaconda. (see Figure 1).

```
In [1]:
import pandas as pd
import snscrape.modules.twitter as sntwitter
import re
import string
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
import transformers
import torch
from transformers import pipeline
from tqdm.notebook import tqdm
```

Figure 1: Importing the necessary packages into Anaconda

Step 2 Scraping the Tweets: This step involves searching and gathering tweets related to the S&P500 index using specific keywords like “S&P500” and “SPX”. The tweets are then stored in a data frame and exported to CSV format (se Figure 2).

```
In [2]:
#Researching tweets
query = '(S&P500 OR SPX) until:2023-02-24 since:2021-02-24'

#Creating list to append tweet data to
tweets = []

#Using TwitterSearchScraper to scrape data and append tweets to list
for i,tweet in tqdm(enumerate(sntwitter.TwitterSearchScraper(query).get_items())):
    data = [tweet.date, tweet.id, tweet.rawContent]
    tweets.append(data)

# Saving to a dataframe
df = pd.DataFrame(tweets, columns = ['Date', 'ID', 'tweet'])

# Export dataframe into a CSV
df.to_csv('S&P500.csv', sep=',', index=False)
```

…

```
In [7]: df.tail(10)
Out[7]:
```

	Date	ID	tweet
2237602	2021-02-24	1364683565649170432	*SPX*\nF *NIO*TSLA *LI*GM
2237603	2021-02-24	1364682996033462276	One of the most consistent bullish patterns is...
2237604	2021-02-24	1364682975250509825	Looks like also helping most indexes with DJI ...
2237605	2021-02-24	1364682916916326406	Impressive budget numbers and tweaks to lower ...
2237606	2021-02-24	1364682829423144960	@loveandthevoid Runners will always do the tri...
2237607	2021-02-24	1364682585671159808	From our email commentary yday 5:37pmET\n\nGo ...
2237608	2021-02-24	1364682494621192196	Cierre USA us (24/02/2021) \n\n$SPX 3925.3...
2237609	2021-02-24	1364682428900651013	#dax #fdax #DAX30 #dow #DowJones #NQ SQQQ @nas...
2237610	2021-02-24	1364682353289932808	@dapstats @andykatz19 @Celiwaves @DereckCoatne...
2237611	2021-02-24	1364364425042350082	#SPX - CORRECTION MAJEURE PROBABLE A LA BAISSE...

Figure 2: Scraping of tweets from tweeter

Step 3. Pre-processing the Tweets: The pre-processing step includes several steps such as data cleaning by elimination of irrelevant elements like hashtags and

URLs, tokenization to divide the text into tokens, elimination of stop words, usage of lemmatizes to normalize words, and cleaning to remove unwanted characters (see Figure 3).

```
In [ ]: # Create a function for tweet preprocessing

def preprocess_tweet(tweet):
    # Remove URLs, user mentions, hashtags, and punctuation
    tweet = re.sub(r'http\S+|www\S+|https\S+', '', tweet)
    tweet = re.sub(r'@\w+|\#\w+', '', tweet)
    tweet = tweet.translate(str.maketrans('', '', string.punctuation))

    # Tokenize tweet text
    tokens = word_tokenize(tweet)

    # Remove stop words and lemmatize tokens
    stop_words = set(stopwords.words('english'))
    lemmatizer = WordNetLemmatizer()
    clean_tokens = [lemmatizer.lemmatize(token.lower()) for token in tokens if token.lower() not in stop_words]

    # Join cleaned tokens back into a string
    cleaned_tweet = ' '.join(clean_tokens)

    return cleaned_tweet

In [ ]: #Apply the preprocess function
SP500['preprocessed_tweet'] = [preprocess_tweet(tweet) for tweet in tqdm (SP500['tweet'])]

In [8]: SP500= pd.read_csv('S&P500.csv', parse_dates = ['Date'])

In [9]: SP500.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2237612 entries, 0 to 2237611
Data columns (total 5 columns):
 #   Column              Dtype
---  ------              -----
 0   Date                datetime64[ns]
 1   ID                  int64
 2   tweet               object
 3   preprocessed_tweet  object
 4   sentiment_value     int64
dtypes: datetime64[ns](1), int64(2), object(2)
memory usage: 85.4+ MB
```

Figure3: Tweet preprocessing: tokenization, lemmitizer, token cleaning

Step 4. Sentiment Analysis: This step involves loading a NLP model for sentiment analysis using the Hugging Face library. A function is created to extract the sentiment value associated with each tweet, and the sentiment values per tweet are then aggregated to obtain one sentiment value per day (see Figure 4).

```
In [16]: model_path = "cardiffnlp/twitter-xlm-roberta-base-sentiment"

In [17]: sentiment_task = pipeline("sentiment-analysis", model=model_path, tokenizer=model_path)

In [19]: # create a function to extract sentiment value
def sentiment_analysis(tweet):
    output = sentiment_task(tweet)
    scores = output[0]['label']
    if scores == 'positive':
        return 1
    elif scores == 'neutral':
        return 0
    else:
        return -1
```

```
In [20]: SP500['sentiment_value'] = [sentiment_analysis(tweet) for tweet in tqdm(SP500['preprocessed_tweet'])]

  0%|          | 0/3486 [00:00<?, ?it/s]

In [23]: SP500.to_csv('S&P500_per_tweet.csv', index = False)

In [24]: SP500_per_day = pd.DataFrame(SP500.groupby('Date')['sentiment_value'].mean()).reset_index()

In [36]: SP500_per_day.to_csv('S&P500_per_day.csv', index = False)

Out[7]:
```

					nent_value
2237602	2021-02-24	1364683565649170432	SPX\nF NIOTSLA LIGM	spx f nio tsla li gm	0
2237603	2021-02-24	1364682996033462276	One of the most consistent bullish patterns is...	one consistent bullish pattern pullback 20 dma...	0
2237604	2021-02-24	1364682975250509825	Looks like also helping most indexes with DJI ...	look like also helping index dji spx rut healt...	1
2237605	2021-02-24	1364682916916326406	Impressive budget numbers and tweaks to lower ...	impressive budget number tweak lower financing...	0
2237606	2021-02-24	1364682829423144960	@loveandthevoid Runners will always do the tri...	runner always trick runner spx blew 2 12 googl...	0
2237607	2021-02-24	1364682585671159808	From our email commentary yday 5:37pmET\n\nGo ...	email commentary yday 537pmet go nqf nq go las...	0
2237608	2021-02-24	1364682494621192196	Cierre USA us (24/02/2021) \n\n$SPX 3925.3...	cierre usa us 24022021 spx 392535 113 qqq 1359...	0
2237609	2021-02-24	1364682428900651013	#dax #fdax #DAX30 #dow #DowJones #NQ $QQQ @nas...	qqq spy spx pues eso parte iii fin	-1
2237610	2021-02-24	1364682353289932808	@dapstats @andykatz19 @Celiwaves @DereckCoatne...	spx wird morgen noch ein neues ath machen min ...	0
2237611	2021-02-24	1364364425042350082	#SPX - CORRECTION MAJEURE PROBABLE A LA BAISSE...	correction majeure probable la baisse u 100 en...	1

Figure 4: Sentiment analysis and calculation

Practically, sentiment measurement is based on messages taken from tweeter social media site. Basically, from the https://huggingface.co/cardiffnlp/twitter-xlm-roberta-base-sentiment model [3], we get then 3 percentages of sentiment value (negative, positive and neutral) for each tweet. The sentiment obtained from each message can reach a score between – 1 and 1. For the highest %tage, we assign via phyton progam -1 for the negative sentiment, 1 for the positive sentiment, and 0 for the neutral sentiment. Then, the average of the daily sentiment is calculated as:

$$SENT_t = \frac{\sum_{i=1}^{m} S_{it}}{M_t},$$

where S_{it} is the sentiment of message i posted in moment t and M_t is the number of messages posted in moment t. We note by $SENT_t$ the daily sentiment. These values are transferred to a CSV file.

Step 5. <u>Filtering the SENT variable by dates in accordance with the other variables</u>: Sentiment values are filtered to match the dates of the other variables in the study, ensuring compatibility between different data sets. The filtered values are then saved to the main data file (see Figure 5).

Date	SP500	WTI	Wheat	VIX	NG	Sent
24/02/2021	3925,43	63,52	680,25	21,34	2,85	-0,07717303
25/02/2021	3829,34	63,39	671,75	28,89	2,78	-0,114550096
26/02/2021	3811,15	61,56	655	27,95	2,77	-0,090970808
01/03/2021	3901,82	60,23	643,75	23,35	2,78	0,040690506
02/03/2021	3870,29	59,39	663,25	24,1	2,84	-0,010017422
03/03/2021	3819,72	60,7	652	26,67	2,82	-0,083094556
04/03/2021	3768,47	64,19	649,75	28,57	2,75	-0,11687631
05/03/2021	3841,94	66,23	654	24,66	2,70	-0,076321551
08/03/2021	3821,35	64,86	646,5	25,47	2,66	-0,082357691
09/03/2021	3875,44	63,92	656,5	24,03	2,66	-0,035989717
10/03/2021	3898,81	64,64	650,75	22,56	2,69	-0,030385488
11/03/2021	3939,34	65,89	636,25	21,91	2,67	-0,031875212
12/03/2021	3943,34	65,54	631,75	20,69	2,60	-0,057884232
15/03/2021	3968,94	65,3	645	20,03	2,48	0,003909644
16/03/2021	3962,71	64,88	647	19,79	2,56	-0,056612529
17/03/2021	3974,12	64,58	640	19,23	2,53	-0,036852207
18/03/2021	3915,46	59,76	630,5	21,58	2,48	-0,058589079
19/03/2021	3913,10	61,46	627	20,95	2,54	-0,061780997
22/03/2021	3940,59	61,27	627,25	18,88	2,58	-0,044038668
23/03/2021	3910,52	57,53	634,75	20,3	2,51	-0,092334495

Figure 5: Filtering the "SENT" according to the dates of the data relating to the other variables of the study

3.3 Descriptive analysis

The considered sample is composed from 253 (251) observations for the pre (post-declaration) -war period.

From the evolution over time of these variables presented in Figure 6 (a) for the pre-war case and in Figure 6 (b) for the post-declaration case, we conclude that the three variables (crude oil price, natural gas price and wheat price) are non-stationary for the 2 sub-periods. It should be noted that the trend in the price of crude oil is upwards pre-war and downwards post-war. The same observation is true for the other two prices: natural gas price and wheat price.

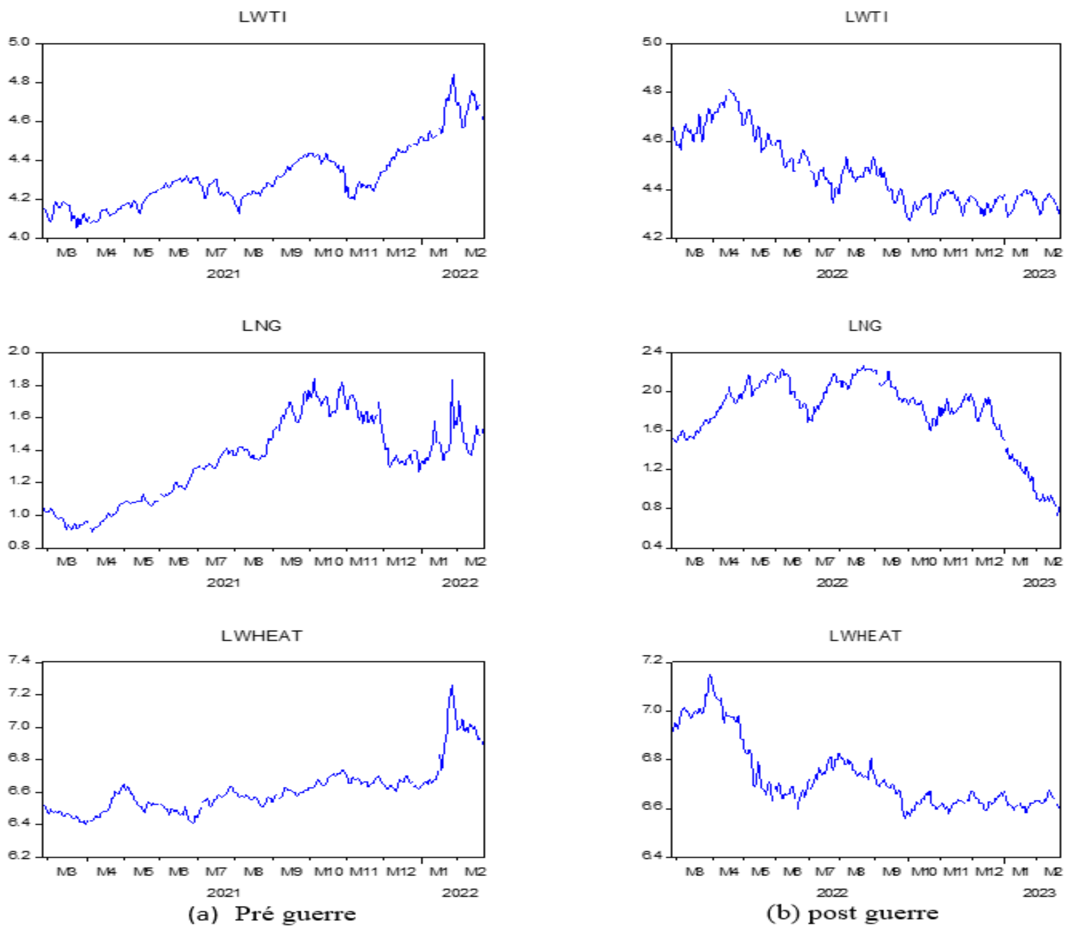


Figure 6: Evolution of oil price (WTI), natural gas price (NG), wheat price (WHEAT) in log.

For more reliable conclusion, we rely on the PP unit root test. PP test results are not reported here. All considered series are found to be non-stationary (I(1)) for the full, pre-war, and post-war declaration periods.

To avoid any problem of multi-collinearity, we analyse the correlations between the regressors for the entire period as well as for the two sub-periods. According to Table 1, the correlation between the natural gas price and the crude oil price is insignificant pre- and post-war, while the correlation between the natural gas price and the wheat price is only insignificant post-war declaration.

To check rigorously whether the behaviour of these variables changes or not with the Ukrainian war declaration, we propose the application of the Student's t and the ANOVA tests. From Table 2, it is clear that on average the crude oil price is significantly higher in the post-war declaration period. The same result is drawn for the other two prices.

Before proceeding for the remaining variables, it merits mentioning that these higher global prices in average are a signal of penury. Because of the Ukraine war, supplies of foods and energy on global markets were appreciably lower since February 24, 2022 than they would otherwise have been.

Now, according to Figure 7, the LSP = log(S&P 500) is non-stationary (figure (a)), while the first difference ΔLSP (US market return) is possibly stationary (LSP ~ I(1)). Also, from Figure 7 (b), ΔLSP, LVIX and SENT are found stationary (with stable mean and variance).

Table 3 presents the descriptive statistics (mean, min, max, standard deviation, Jarque-Bera test statistic of the Normality hypothesis and its p -value, the number of observations, ARCH-LM test for conditional heteroscedasticity, and PP test conclusion for unit root test). The statistics are calculated for the full period (Panel A), for the pre-war period (Panel B), and for the post-war declaration period (Panel C). All statistics are applied to the log of the series in level as well as to the yield series. For the dependent variable (R), we apply in addition the ARCH-LM (p) test to reveal the possible presence of conditional heteroscedasticity.

Table 1*:* Correlation matrices between WTI, NG and WHEAT

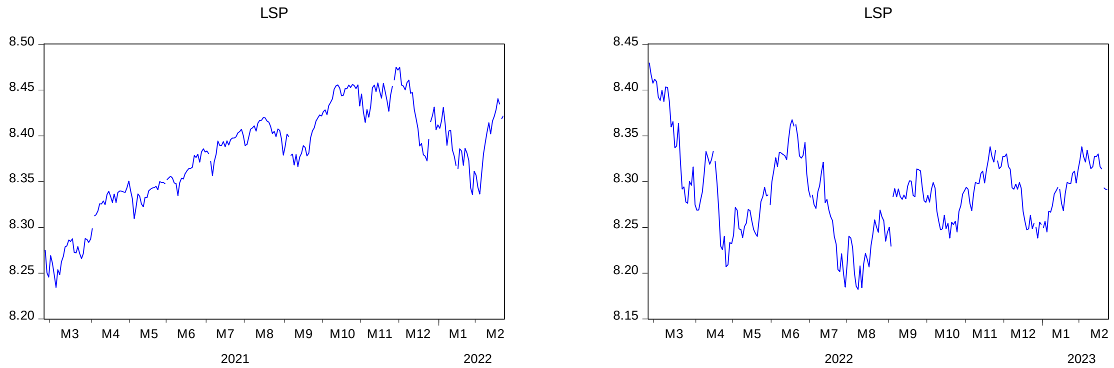
	Panel A: Full sample			**Panel B: Pre war**			**Panel C: Post declaration**		
	ΔLWTI	**ΔLNG**	**ΔLWHEAT**	**ΔLWTI**	**ΔLNG**	**ΔLWHEAT**	**ΔLWTI**	**ΔLNG**	**ΔLWHEAT**
ΔLWTI	1.000000			1.000000			1.000000		
	-----			-----			-----		
ΔLNG	0.022778	1.000000		0.052775	1.000000		-0.009119	1.000000	
	(0.6103)	-----		**(0.4042)**	**-----**		**(0.8859)**	-----	
ΔLWHEAT	0.279206	0.070658	1.000000	0.210515	0.196180	1.000000	0.359362	-0.073723	1.000000
	(0.0000)	(0.1135)	-----	**(0.0008)**	**(0.0018)**	-----	**(0.0000)**	**(0.2455)**	-----

Note: (.): are the p-values. LWTI: the price of crude oil in log, LNG: the price of natural gas in log, LWHEAT: the price of wheat in log.

Table 2: Results of the Student t and ANOVA tests

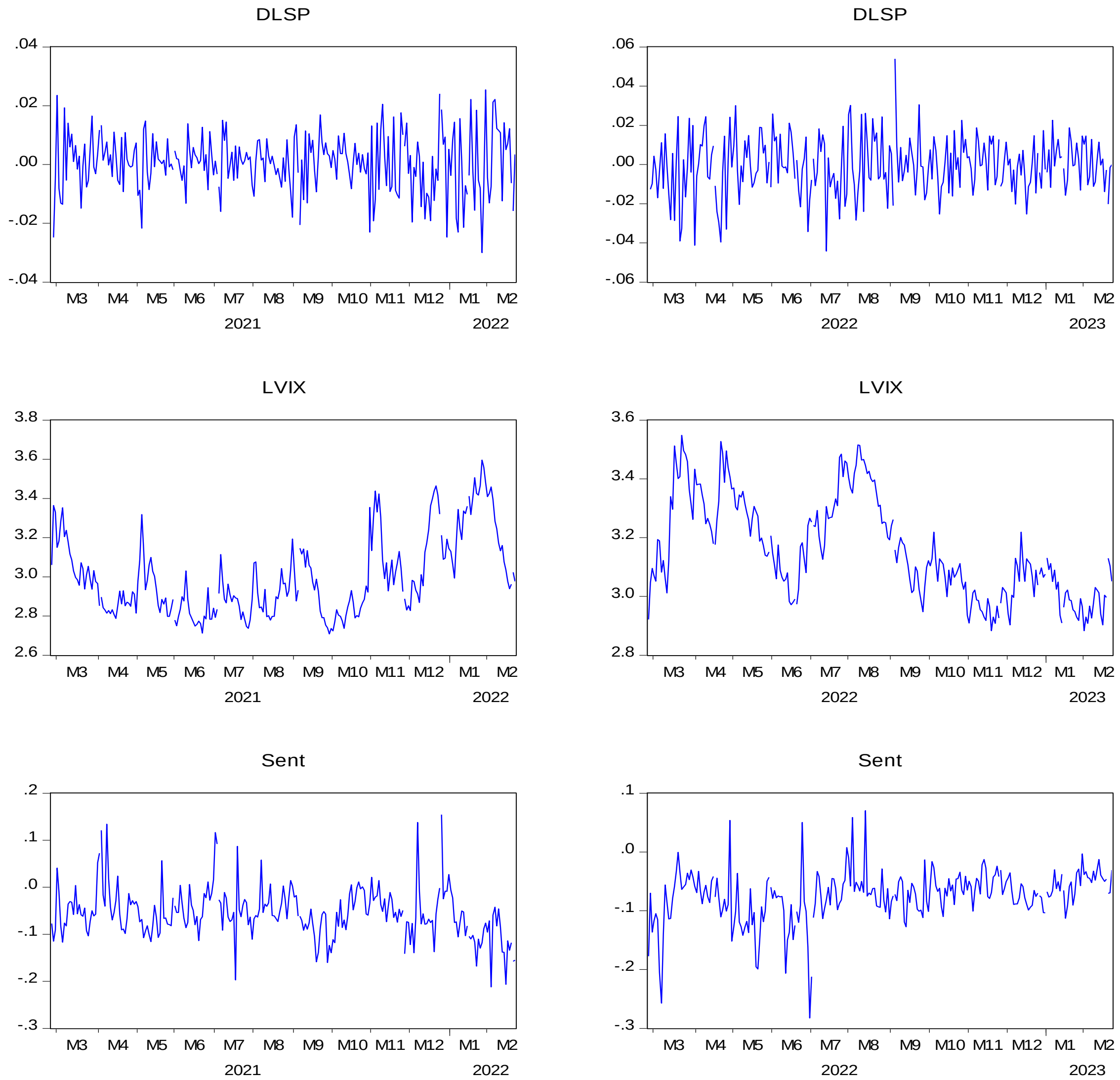
	LWTI	**LNG**	**LWHEAT**
Average **pre-war**	4.318563	1.341319	6.616101
Average **post-war**	4.473652	1.791455	6.732289
Student t	-11.27722	-16.2690	-8.777921
p-value	(0.0000)	(0.0000)	(0.0000)
ANOVA	127.1758	264.6809	77.05190
p-value	(0.0000)	(0.0000)	(0.0000)

Note: (.): are the p-values.



1. Pre-war 2. Post-war

(a) The index series at level



3. Pre-war 4. Post-war

(b) Stationary series (at level or in first difference)

Figure 7: Evolution of the USA series

Table 3: Descriptive statistics

Panel A: full period	LSP	LVIX	SENT	R
Mean	8.334154	3.079092	-0.064541	3.27E-05
Maximum	8.475024	3.595941	0.154289	0.053953
Minimum	8.182288	2.708717	-0.282481	-0.044199
Std. Dev.	0.067955	0.202180	0.049800	0.012501
Jarque-Bera	19.18759	23.00623	271.3470	22.58590
Probability	0.000068	0.000010	0.000000	0.000012
Observations	504	504	504	503
ARCH-LM (p)				18.88809(0,000)
PP test results	I(1)	I(1)	SL2	SL2
Panel B: Pre-war	**LSP**	**LVIX**	**SENT**	**R**
Mean	8.379791	3.000462	-0.054840	0.000582
Maximum	8.475024	3.595941	0.154289	0.025374
Minimum	8.234424	2.708717	-0.211967	-0.029963
Std. Dev.	0.054162	0.202978	0.053626	0.009995
Jarque-Bera	14.17192	32.47019	84.91337	2.062719
Probability	0.000837	0.000000	0.000000	0.356522
Observations	253	253	253	252
ARCH-LM (p)				13.16012(0,0003)
PP test result	I(1)	SL2	SL2	SL2
Panel C: Post-war declaration	**LSP**	**LVIX**	**SENT**	**R**
Mean	8.288153	3.158349	-0.074320	-0.000553
Maximum	8.430031	3.548180	0.070333	0.053953
Minimum	8.182288	2.883123	-0.282481	-0.044199
Std. Dev.	0.045845	0.167782	0.043587	0.014610
Jarque-Bera	9.012329	15.40802	214.2582	4.018292
Probability	0.011041	0.000451	0.000000	0.134103
Observations	251	251	251	250
ARCH-LM (p)				1.63648(0,2023)
PP test result	SL2	SL2	SL2	SL2

Note: (p) is the p-value of the LM test. The ARCH(1) test is applied to the residuals of the regression of R on the variation of LVIX. I(1): integrated at order 1. SL2:stationary in L2.

The LSP and LVIX in average are positive while the average of SENT is negative for the 2 sub-periods. On average, the volatility (measured by LVIX) is higher post-war (more risk), while LSP is lower post-war (fall in price), and the sentiment is more negative post-war (more pessimism post-war). The significance of these results will be rigorously studied via the Student's t and the ANOVA tests. Returns are on average is positive (negative) pre (post) war.

It is clear that the US stock market is negatively affected by the war. Based on Figure 7, it is clear also that the volatility of returns presents successively high and low fluctuations in amplitude. The ARCH test results confirm the presence of an ARCH effect in the volatility of US returns (see Table 3). All these series are stationary (SL2) pre- and post- the Ukraine war declaration except the LSP series, which is stationary, only post-war declaration (see Table 3).

Table 4 presents the correlations between the variables of interest (Panel A) as well as for the control variables (Panel B). For the pre-war period (Panel A1), it is clear that the yield is negatively linked with LVIX. In addition, the sentiment variable "SENT" is not linked to any of the three control variables: the natural gas price (ΔLGN), the wheat price (ΔLWHEAT) and the price of crude oil (ΔLWTI) pre- and post-war declaration (Panel B1). For the post-war declaration period (Panel A2 and B2), we obtain similar results.

Table 4: Correlation matrices

Panel A: Between the variables of interest

Correlation	**Panel A1: Pre-war**				**Panel A2: Post-war declaration**		
P-value	**ΔLSP**	**LVIX**	**SENT**		**LSP**	**LVIX**	**SENT**
ΔLSP	1			LSP	1		
	-----				-----		
LVIX	-0.278243	1		LVIX	-0.528369	1	
	0	-----			0	-----	
SENT	0.129691	-0.194629	1	SENT	-0.138853	-0.028572	1
	(0.0397)	0.0019	-----		0.0278	0.6524	-----

Panel B: Between control variables and the SENT variable

Correlation	**Panel B1: Pre-war**			**Panel B2: Post-war declaration**		
P-value	**ΔLWTI**	**ΔLNG**	**ΔLWHEAT**	**ΔLWTI**	**ΔLNG**	**ΔLWHEAT**
SENT	-0.033751	0.031571	-0.026113	0.093136	0.111317	0.031146
	(0.5938)	0.6179	0.6799	0.1420	0.0790	0.6240

Note: The correlation of the sentiment variable "SENT" is statistically zero with the three prices LWTI, LNG, and LWHEAT pre and post war. (.): are the p-values.

To see if the behaviour of the variables change post the Ukraine war declaration, we move on to the application of the Student t and the ANOVA tests. The test results as well as the empirical average of each variable pre- and post-war declaration are presented in Table 5 below. This involves testing the following hypothesis:

H0: the mean of the variable does not change.

Since all the p-values are less than 5%, we conclude that the difference in average between the pre- and post-war declaration is significant for each variable.

Table 5: Stability behaviour of the variables

	LSP	LVIX	SENT
Average **pre-war**	8.380709	3.000462	-0.054840
Average **post-declaration**	8.299192	3.158349	-0.074320
t de Student	16.23686	-9.513809	4.473012
p-value	(0.0000)	(0.0000)	(0.0000)
ANOVA	263.6355	90.51256	20.00783
p-value	(0.0000	(0.0000)	(0.0000)

Note: LSP: stock price in log, LVIX: market volatility in log, SENT: sentiment value from tweeter.

4. Research methodology and empirical results

Volatility is important for analyzing risk in financial markets. The increased availability of daily data has shift attention to modelling volatility measures. However, it is not directly observable. Realized volatility including GARCH-type models (Andersen, et al., 2003) has been shown to dominate several parametric approximations. It is well-known that volatility can be affected by economic shocks.

Two equations will be considered for yield modelling: one regression for the mean and another for the conditional variance. A GARCH $(p,\ q) - X$ model is proposed to analyse the volatility of stock index returns. These models have already been widely used to analyse index volatility (Schaeffer, et al. 2012; Cabarcos, et al., 2019, and Neifar, 2020). The conditional mean and variance equations take the following forms:

$$\boldsymbol{R_t} = \mathrm{C} + \boldsymbol{\beta}\ \Delta \boldsymbol{LVIX_t} + \boldsymbol{u_t}$$

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u^2{}_{t-i} + \sum_{i=1}^{q} \beta_i \sigma^2{}_{t-i} + \gamma' X_t$$

where,

R_t	Return of the SP500 index on date t,	
$\Delta LVIX$	Growth of the American market volatility index,	
$X_t =$	$(SENT, \Delta LWTI, \Delta LGN, \Delta LWHEAT)$,	
	$SENT$	Daily sentiment from tweeter,
	WTI	Price of crude oil,
	GN	Price of natural gas,
	$WHEAT$	Price of wheat,

if the elements of X_t are uncorrelated, $\sigma^2{}_t$ is the variance of the residuals u_t, c is the constant, α_i is the ARCH parameter, β_i is the GARCH parameter, γ is the coefficient vector of the exogenous variables vector X_t, and t is to indicate day t. The expected sign of the effect of each variable is presented in Table 6.

Table 6: Expected signs of the variable effects

Variable	Sign of the pre-war	Sign of the post-war	References
VIX	(−)	(−)	(Cabarcos, et al., 2019)
SENT	(−)	(−)	(Cabarcos, et al., 2019)
WTI	(+)	(+)	Our expectations
NG	(+)	(+)	Our expectations
WHEAT	(+)	(+)	Our expectations

To avoid multi-collinearity problem, different specifications based on correlation matrices will be considered. The adequacy verification of each multivariate model will be based on the Ljung-Box (LB) test statistics applied on the residuals and on the squared residuals of each model. In addition, the Wald test for the regressors significance (with respect to the independent variables in the variance equations) will be applied.

4.1 The Pre-war declaration case

Based on the correlation matrices in Table 1 (Panel B) and Table 4 (Panel A), we will then estimate two models whose mean behaviour admits the following specification:

$$R_t = \beta_0 + \beta_1 \Delta LVIX_t + u_t,$$

while the variance behaves either as

i) in the following GARCH-X1 model:

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u^2{}_{t-i} + \sum_{i=1}^{q} \theta_i \sigma^2{}_{t-i} + \gamma' X1_t + \varepsilon_t \quad (1)$$

Where

$$\gamma' X1_t = \gamma_1 SENT_t + \gamma_2 \Delta LWTI_t + \gamma_3 \Delta LNG_t,$$

with

$$X1_t = (SENT_t, \Delta LWTI_t, \Delta LNG_t)', \text{ and } \gamma' = (\gamma_1, \gamma_2, \gamma_3),$$

i) Or in the GARCH-X2 model:

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u^2{}_{t-i} + \sum_{i=1}^{q} \theta_i \sigma^2{}_{t-i} + \gamma' X2_t + \varepsilon_t \quad (2)$$

Where

$$\gamma' X2_t = \gamma_1 SENT_t + \gamma_4 \Delta LWHEAT_t,$$

$$X2_t = (SENT_t, \Delta LWHEAT_t)', \text{ and } \gamma' = (\gamma_1, \gamma_4).$$

The p and q lags determination is based on the AIC information.

Estimation results of each model by the maximum likelihood (ML) method is presented in Table 7 (Panel A) for the mean evolution, Table 8 (Panel A) for the volatility fluctuation, and Table 9 (Panel A) for the diagnostic check. Looking at Table 9, it is clear that both models (1) and (2) are well specified [4]. The errors behave well [non-autocorrelated (DW ≈ 2), homoscedastic and behave as taken from the Normal distribution. Additionally, using the Ljung-Box (LB) statistics [portmanteau test for white noise] on the residuals and squared residuals. Table 9 results confirm that there is no any inadequacy in models (1) and (2). Table 9 (Panel A) indicates also that each terms of the univariate ARCH and univariate GARCH is statistically significant for both models (1) and (2).

In accordance with hypothesis H1, H2, and H3, results revealed successively that fluctuations in the crude oil price (LWTI), in the price of natural gas (LNG), and in wheat price (WHEAT) do not have a direct impact on the American stock index volatility pre-war period. In addition, hypothesis H4 according to which investor sentiment (SENT) expressed in tweets would not have an effect on the volatility of American stock indices before the Ukraine war was not rejected. Then, in accordance with control variables: wheat price, crude oil price and natural gas price, the sentiment variable has insignificant effect on the S&P 500 index return volatility evolution during the pre- Ukraine-Russia war period (see Table 8 (Panel A)).

In accordance with previous results, Table 9 (Panel A) reports results of the Wald test against the null hypothesis that all coefficients of the independent variables in the variance equations are zero [Wald = 0.16329169 for Eq (1) and 0.17027068 for Eq (2) (p-value = 0.8435362 and 0.9209986 successively)]. Together, all considered independent variables have no effect on the American stock index volatility pre-war period.

However, results show as expected a significant negative relationship between the American VIX volatility and the US stock market volatility pre-war period. This means that contrarily to the volatility behavior, the average evolution of the American stock market returns was affected by the American VIX volatility (Table 7 and 8 (Panel A)).

Then, these results say that there are no emotions that reflect fear or anxiety on the behavior of American investors pre-war declaration. Even if the media have broadcast the probability of a near war between Russia and Ukraine this has not influence the sentiment of American investors and the information broadcast had not generate contagion effects or peer reactions.

Table 7: Results for mean evolution of R

Period	Panel A Pre-war period		Panel B Post-declaration war period	
Variable/Model	(1)	(2)	(3)	(4)
ΔLVIX	-0.081333* (-21.81613)	-0.081086* (-30.08187)	-0.160197* (-15.71842)	-0.159890* (-16.76727)

Note: *: 1% significance level. **: 5% significance level. ***: 10% significance level. (.) is the t statistic. LVIX: the volatility of the American stock market index.

Table 8: Volatility fluctuation Results

Period	Panel A Pre-war period		Panel B Post-declaration war period	
Variable/Model	(1)	(2)	(3)	(4)
SENT	3.13E-06 (0.366079)	3.90E-06 (0.488051)	0.000102 (1.435030)	7.47E-05** (2.356157)
ΔLWTI	-1.21E-05 (-0.258269)		0.000966* (4.844623)	
ΔLNG	-4.52E-06 (-0.173447)		9.43E-05 (0.994959)	0.000195* (4.510973)
ΔLWHEAT		7.51E-06 (0.187745)		0.000494* (4.035693)

Note: *: 1% significance level. **: 5% significance level. ***: 10% significance level. (.) is the t statistic. SENT: the sentiment variable, LWTI: the price of crude oil, LNG: the price of natural gas, LWHEAT: the price of wheat. Optimal lags for GARCH model: $p = q = 1$.

4.2 The Post-war declaration case

Again, using results on significant correlations from Table 1 (Panel C) and Table 4 (Panel B), we will estimate two models whose mean behavior admits the same linear specification as given in the previous sub-section, while the variance behaves as:

i) The GARCH-X3 model:

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u^2{}_{t-i} + \sum_{i=1}^{q} \theta_i \sigma^2{}_{t-i} + \gamma' X3_t \quad + \varepsilon_t \tag{3}$$

Where

$$\gamma' X3_t = \gamma_1 SENT_t + \gamma_2 \Delta LWTI_t + \gamma_3 \Delta LNG_t,$$

with

$$X3_t = (SENT_t, \Delta LWTI_t, \Delta LNG_t)' \text{ and } \gamma' = (\gamma_1, \gamma_2, \gamma_3),$$

ii) Or as in the GARCH-X4 model:

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u^2{}_{t-i} + \sum_{i=1}^{q} \theta_i \sigma^2{}_{t-i} + \gamma' X4_t + \varepsilon_t \quad (4)$$

Where

$$\gamma' X4_t = \gamma_1 SENT_t + \gamma_3 \Delta LNG_t + \gamma_4 \Delta LWHEAT_t,$$
$$X4_t = (SENT_t, \Delta LNG_t, \Delta LWHEAT_t)', \text{ and } \gamma' = (\gamma_1, \gamma_3, \gamma_4).$$

Table 7, 8, and 9 (Panel B) give successively the estimation results of both models (3) and (4) by ML method for the mean evolution, for the volatility fluctuation, and for the diagnostic check. Looking at Table 9 (Panel B), it is again clear that both models (3) and (4) are well specified. Indeed, the results of the LB test do not suggest any inadequacy of models (3) and (4). Table 9 indicates also that each terms of the univariate ARCH and univariate GARCH is statistically significant for both models (3) and (4).

Table 9 (Panel B) reports the Wald test against the null hypothesis that all coefficients of the independent variables in the variance equations are zero [Wald = 33.20805 for Eq (3) and 32.92307 for Eq (4) (p-value = 0.0000 for both statistics)]. This means that the sentiment variable as well as macroeconomic conjecture factors (such as crude oil price and natural gas price for Eq (3) and natural gas price and wheat price for Eq (4) have a significant effect on the volatility of the US stock market returns.

From Table 7 (Panel B), the results from the GARCH-X3 and GARCH-X4 specifications indicate that the growth of the US market volatility (ΔLVIX) has a negative impact on the S&P 500 return. An increase in the volatility of the US market is associated with a decline in the S&P 500 return. In addition, this market volatility has higher negative effect post-war than the pre-war effect.

Post declaration of the war, all macroeconomic conjecture factors (the crude oil price (ΔLWTI), the natural gas price (ΔLNG), and the wheat price (ΔLWHEAT)) showed a *significant* influence on the conditional variance of the LS&P500. However, even post war declaration, investor sentiment expressed in the tweets did not show any significant direct effect on US stock market volatility (Table 8 (Panel B)).

Table 9: Diagnostic check

Period	Panel A Pre-war period		Panel B Post-declaration war period	
Variable/Model	(1)	(2)	(3)	(4)
$\hat{u}^2{}_{t-1}$	0.090835***	0.086721**	0.112171**	0.014042**
	(0.0563)	(0.0467)	(0.0382)	(0.0384)
$\hat{\sigma}^2{}_{t-1}$	0.889858*	0.895016*	0.603127*	0.931138*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LB (10)	6.4763	6.3167	9.3406	8.9600
	(0.774)	(0.788)	(0.500)	(0.536)
$LB^2(10)$	4.3719	4.0576	7.0196	5.7193
	(0.929)	(0.945)	(0.724)	(0.838)
DW	2.003227	2.002777	2.165819	2.164876
ARCH	0.963739	0.881693	0.138183	0.536477
	(0.3262)	(0.3477)	(0.7101)	(0.4639)
Wald test	0.16329169	0.17027068	33.20805	32.92307
	(0.92099)	(0.8435362)	(0.000)	(0.000)

Note: (.) p-value. *: 1% significance level. **: 5% significance level. ***: 10% significance level.

5. Conclusion

In this study, we consider variables linked to the economic environment including the crude oil price (WTI), the natural gas price (NG) and the wheat price (WHEAT). We consider also a variable which measures the American market volatility (the VIX index), and the sentiment index "SENT" to check whether the ideas of investors expressed in tweets have a significant effect on the volatility of the S&P500 stock index.

By examining the relationships between the war, commodity prices and stock returns, we contribute to the existing literature by providing new perspectives and enriching our understanding of the financial consequences of the geopolitical crisis.

By focusing on the price of oil (WTI), the price of natural gas (NG) and the price of wheat (WHEAT), we take into account the export status of Russia and Ukraine in these commodities.

The results showed that investor sentiment helps to predict the volatility of daily returns of the American S&P 500 index post-war declaration. On the other hand, the other factors such as the market volatility, the variation in raw material (oil and gas) and food prices (wheat) effect the volatility of the index.

These results can be explained by several financial and economic factors as follow:

- Impact of market volatility: The growth in market volatility, measured by ΔLVIX, has a negative effect on the performance of the S&P 500 Index. This is because periods of high volatility are often associated with greater uncertainty and erratic movements in financial markets. Then, investors may become more cautious and reduce their exposure to risky assets, which may cause index returns to decline.
- Persistence of volatility: The persistence of volatility, measured by the coefficient of the conditional variance on the previous day (${\hat{\sigma}^2}_{t-1}$), suggests that past volatility continue to have an impact on current volatility. The persistence of volatility can amplify market movements and contribute to the volatility cycles formation. This may be due to momentum phenomena, which refers to the empirical observation that financial assets, that have had recent positive performance (negative performance) tend to continue to outperform (underperform) in the near future.
- Macroeconomic shocks: Geopolitical events can cause macroeconomic shocks, such as disruptions in production, exports, foreign investment, supply chains or commodity prices. Investors respond to these shocks by adjusting their expectations, which can lead to increased volatility in stock indices [5].
- Effects on the real economy: Wars can have a significant impact on the real economy, including production and trade and consumer confidence. Disruptions in these areas can affect company profits, growth prospects and investor expectations. Changes in corporate profits and changes in the economic outlook can result in fluctuations in stock prices and volatility in stock indexes.
- Investor sentiment: Although the exogenous variable "sentiment" (SENT) did not show a significant influence on the conditional variance of the S&P 500 index in the considered models, it is important to note that investor sentiment can play a role in shaping financial asset prices. In this study on the American stock market, the sentiment of the American investor was not too influenced by the Russo-Ukrainian war given the geographical distance from the USA. Similarly, investors may have

perceived that the Russian-Ukrainian conflict had no direct or immediate impact on the U.S. economy since Ukraine is not a major trading partner of the United States, and the economic ties between the two countries may be relatively limited.

These results highlight the importance of the volatility, volatility persistence, and exogenous factors in understanding and modeling stock market returns volatility. However, it should be noted that these results are specific to the post- declaration of Ukraine-Russia war and may not be generalizable to other periods or other financial markets. We can extend our study to other countries to better understand the role of investor sentiment in predicting stock market index returns during periods of major events.

Note:

1. The Standard and Poor's 500 (S&P 500) is a stock market index tracking the stock performance of 500 large companies listed on stock exchanges in the United States.
2. As an overview of the main methods for calculating the sentiment index, we give the more recent ones. Herrera et al. (2022) used a natural language processing (NLP) technique to extract investor sentiment from Twitter. Xiangn et al. (2022) developed a new improved semantic and syntactic neural model (SSENM) to infer bullish or bearish sentiments in the financial domain. Hodorog et al. (2022) used the NLP processing techniques to automatically detect real-time events in smart cities from Twitter messages to assess citizen satisfaction. Bapat et al. (2022) used FinBERT, a pre-trained NLP model for financial sentiment analysis, and calculated sentiment as positive, neutral, or negative, assigning corresponding weights. Sinha et al. (2022) used different learning and classification approaches to extract sentiments from financial news headlines, and then validated the economic effect of sentiments on overall market movements. Liu et al. (2022) used NLP processing techniques to construct an investor confidence index from investors' social media posts, relying on a Fourier transform to identify periods of sentiment fluctuation. Kevin et al. (2021) built a pipeline to predict stock prices using Twitter sentiment analysis, extracting public opinion, and predicting stock movement. Nguyen et al. (2020) presented BERTweet, a pre-trained language model for English Tweets, outperforming previous models on several NLP Tweet tasks. Zvonarev & Bilyi (2019) compared the performance of different text tone analysis techniques, showing that the convolutional neural network (CNN) performed best among the models tested for Russian-language tweets.
3. The index sentiment keywords are used to scrape tweet via python using snscrape library (sn: social network). Each tweet is pre-processed using pre-process function. To get sentiment value, each tweet is then treated by xlm-Roberta (multi-langage) model based on machine learning model developed by Cardiff NPL (natural language processing); see arXiv:2104.12250.
4. The value of R^2 is not reported in the table because the model is highly nonlinear, so R^2 is not a meaningful measure of goodness of fit.
5. This was specifically reflected in the GARCH-X3 model where changes in the crude oil price (ΔLWTI) and natural gas price (ΔLNG) showed a significant effect on the conditional variance of the S&P 500 index. Price fluctuations of these raw materials may reflect economic factors such as supply and demand in the global energy markets since movements in crude oil and natural gas prices can affect the production costs, business spending and investor confidence, resulting in greater volatility in the index performance.

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