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INTER-CONNECTEDNESS BETWEEN DEVELOPED AND VISEGRAD STOCK MARKETS DURING COVID-19 PANDEMIC AND RUSSIA-UKRAINE WAR

ABSTRACT

Purpose: The study checks relations between different developed and Visegrad stock markets and mainly concentrates on the analysis of the American market influence (reflected by S&P500) on other stock markets. It examines the influence of crisis situations such as COVID-19 pandemic and Russia-Ukraine war on the strength of the linkage between markets.

Methodology/approach: The study of changes in the dependence of stock market indices over 2018–2023 is conducted using rolling windows for the Pearson correlation coefficient. The similarity strength of indices is indicated using the DTW measure. The influence of the S&P500 index on other stock indices is examined by the Granger causality.

Findings: We show that both the COVID-19 pandemic and the war increased the linkage between stock markets, although for the latter this rule refers only to markets that are geographically close to the conflict zone. The research also shows that the American stock exchanges are the most strongly interconnected. Another important notice is that crises decrease the similarity of shapes between stock exchanges represented by market indices. Moreover, greater similarity between stock exchanges leads to lower volatility in correlations over time.

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Originality/value: The paper adds value in three aspects. The first one is that it examines changes in relations between indices, both in their correlations and their similarities strength during COVID-19 pandemic and Russia-Ukraine war – recent crisis situations. Contrary to the previous literature which is rather concentrated on the COVID-19 pandemic and its influence on stock markets, we show that such events that are not global also influence relations between stock markets close to the conflict zone. The second one is combining in one paper connections between both different indices from developed countries and Visegrad countries. The third one is using DTW method rarely used for financial time series analysis to examine shapes similarity between S&P500 index and so many stock markets, both from developed and Visegrad countries in one paper.

Keywords: stock markets, Visegrad, COVID-19 pandemic, Russia-Ukraine war

1. INTRODUCTION

Relations between stock markets in different countries are a vital issue because they influence decisions of investors, policy makers and portfolio managers. More important, highly correlated stock markets make international asset diversification difficult and may become a source of potential global crisis. While many stock markets are strongly correlated especially during special global events, it is the American one which seems to have the highest impact on other markets, both developed and developing ones.

We postulate that crisis situations increase relations between stock markets. The study checks relations between different developed and Visegrad stock markets and mainly concentrates on the analysis of the American market influence (reflected by S&P500) on other stock markets. In particular, it studies the influence of recent crisis situations such as the COVID-19 pandemic and the Russia-Ukraine war on the strength of the linkage between markets. We show that both the COVID-19 pandemic and the war increased the linkage between stock markets, although for the latter this rule refers only to markets that are geographically close to the conflict zone.

The study of the dependence of stock market indices and its changes over 2018–2023 will be conducted using rolling windows for the Pearson correlation coefficient. The similarity strength of indices will be indicated using the DTW measure. Additionally, the influence of the S&P500 index on other stock indices is examined using the Granger causality.

This paper extends the literature with the analysis of changes in relations between S&P500 index and other indices from developed and Visegrad countries during such crises times as the COVID-19 pandemic and the Russian-Ukrainian war, which have not received such attention in this context so far. The paper adds value in three aspects. The first one is that it examines changes in relations between indices, both in their correlations and their strength similarities during the COVID-19 pandemic and the Russia-Ukraine war – recent crisis situations. Contrary to the previous literature which is rather concentrated on the COVID-19 pandemic and its influence on stock markets, we show that such events that are not global also influence relations between stock markets close to the conflict zone. The second one is combining in one paper connections between both different indices from developed countries and Visegrad countries. The third one is using DTW method rarely used for financial time series analysis to examine strength similarity between so many global stock markets from both developed and Visegrad countries in one paper.

While (Wong et al., 2004) analyze changes of connectedness of stock markets during the Asian crisis, Akram et al., (2023) consider three financial crises of 1997, 2008 and 2010, (Tudor, 2011) (Barunik et al., 2016) (Panda et al., 2020) (Panda & Nanda, 2016) (Mensi et al., 2018) (Madaleno & Pinho, 2012) (Jebran, 2018) (Habiba et al., 2023) check how relations between different stock exchanges change during the global financial crisis change, we show that they also change when the crisis has no financial character (the COVID-19 pandemic and the Russia- Ukraine war). Although (Blahun & Bkahin, 2020) show that developed stock exchanges influence each other, we additionally consider Visegrad stock exchanges and extend the analysis over the period of the COVID-19 pandemic and the Russian-Ukrainian war. There are plenty of papers concentrating on the analysis of developed stock markets or developing markets (Hung, 2021) (Wong et al., 2004) (He et al., 2020), whereas it is hard to find papers where Visegrad countries are included. While (Huang et al., 2019) show that special events such as joining the EU may increase linkages between stock markets, we add to the literature that this is also true for other two particular events. Contrary to (Sakthivel & Kamaiah, 2012) we concentrate on differences in relations during special situations.

This paper proceeds as follows. Section 1 outlines the literature. Section 2 refers to the methodology and explains its adequacy in the literature context. Section 3 presents results. Section 4 concludes.

2. LITERATURE REVIEW

There are plenty of studies concerning relations between different stock exchanges. Authors use different methods such as descriptive statistics together with correlation coefficients, models from the GARCH group or VAR models. There are always some influences shown, however their significance and strength is different for different markets and for different periods ((Panda et al., 2019) for African and Middle-East countries) ((Panda & Nanda, 2017) for European countries).

Some authors concentrate on showing that relations between different markets change over time like (Mensi et al., 2017) who prove it for the connection between developed and BRICS stock markets. (Hung, 2021) analyses relations between stock markets in Gulf Cooperation Council countries in 2008–2019 and shows that correlation of returns varies during time but does not show any specific periods when these changes happen.

Authors also often check the influence of some distinctive events like financial crisis situations (Asian crisis, global financial crisis, European debt crisis) on stock markets relations. Some studies concentrate on developed markets only like (Barunik et al., 2016) who show that the linkage between different US stocks dramatically increased during the crisis of 2008. (Chiesnay, Jondeau, 2001) check correlations between main stock indices like S&P, DAX and FTSE in 1988–1999 and conclude that during turmoil times it really increases. We want to check if this rule still exists during the COVID-19 or the Russian-Ukrainian war. (Becker et al., 1990) show that American market reflected by S&P500 has a high impact on return on Japanese market represented by Nikkei index from 5 October 1985 to 28 December 1988, but this relation does not go in the opposite direction and the influence of Japan on America is pretty small. (Baur & Jung, 2006) check connectedness of returns between the US (Dow

Jones) and German (DAX) markets and find out that for both markets returns generated during the day are influenced by overnight ones. Thus, these two markets influence each other within a day. Other authors concentrate just on CEE countries like (Hung, 2020) that focusses on relations between some chosen countries from the mentioned group in 2008–2017, however it does not check relations with developed economies as we do and does not show changes during different time spans as we do.

The majority of studies in this field is devoted to showing the growing linkages between different markets during the global crisis of 2008, both for domestic inter-relations and internationally. It is done for different groups of countries and conclusions are similar. (Panda et al., 2020) check relations between stock markets in BRICS and developed countries from 2 August 2002 to 28 December 2017 and show that the linkage is twice higher in the crisis period than earlier. (Panda & Nanda, 2016) analyze relations between stock markets from different countries from South and Central America from August 1995 to December 2015 and notice that correlations increased in 2008 – 2010 and also conclude that they are generally higher at the end of the research period than at its beginning and suggest that market integration grows in time. (Habibi & Mohammadi, 2022) use weekly data from 2005 to 2017 to prove that during the crisis spillovers of volatility and returns between developed and MENA countries dramatically rise but they exist for the whole examined period. (Mensi et al., 2018) check volatility spillovers to examine interrelations between GIPSI countries (Greece, Ireland, Portugal, Spain and Italy) and the main EU markets such as France, Germany, UK. They find out that the global crisis 2008 intensified market connections. (Panda et al., 2023) analyze relations between BRIC countries and also find out that they are stronger during the crisis time. (Madaleno & Pinho, 2012) show that relations between FTSE100, DJIA30, Nikkei225 and Bovespa change during time especially during the global financial crisis when they increase. (Gilenko & Fedorova, 2014) check connectedness between BRIC markets themselves, BRIC markets with such countries as USA, Japan, Germany and MSCI emerging market index. Authors use BEKK-GARCH model to notice that these connections change depending on the studied time: pre-crisis, crisis or post-crisis on 14 April 2003–27 July 2012. Also (Habiba et al., 2023) concentrate on the financial crisis. (Tudor, 2011) uses data from 2006 – March 2009 to show that relations between CEE and American stock market vary in time. The author analyses the influence of the American crisis of 2007–2008 on the connectedness between these markets in two periods: pre crisis and post-crisis. We do the same but devote our analysis not only to CEE markets and we take the COVID-19 pandemic and the Russian-Ukrainian war time as crisis moments. Our conclusions are important because too strong influence of one market to another reduces possibilities of risk diversification for all kinds of investors.

Other publications dwell on other crises than the global ones like the Asian crisis or the COVID-19 pandemic. Some authors consider the COVID-19 pandemic in the examination of relations but do it for different stock markets than ours. (Lee & Kim, 1993) demonstrate that relations between stock markets were stronger after the crash from October 1987. (Akram et al., 2023) consider three financial crises of 1997, 2008 and 2010 to show rising spillovers between Pakistani stock markets and their trading partners. (Yousaf et al., 2023) show the rise of inter-connectedness between Chinese and ASEAN stock markets during the COVID-19 pandemic. Also (Wong et al., 2004) show the increasing dependence after the crisis event which was the Asian crisis of 1997. They study the interrelations between stock markets in developed countries and emerging Asian markets. They conclude that since the market crash of 1987, relations between these markets have increased and this process was intensified after the Asian crisis. Such conclusions let pose the question whether other particular events also make markets more connected. We verify this with the example of the COVID-19 pandemic and the Russia-Ukraine war. (Youssef et al., 2021) check relations between stock markets represented by indices from 2015 to 18 May 2020 in such countries as Germany, France, Italy, Spain, China, Russia, USA, and UK with the use of TVP_VAR model. They indicate that during COVID-19 the connectedness between indices was higher than in the ordinary time without any turmoil. (He et al., 2020) examine the impact of the COVID-19 pandemic on different stock markets. They use statistical measures such as returns different statistics or standard deviations to compare reactions of examined markets. Authors find out that there are interrelations in both directions between such markets as USA, Japan, Germany, Spain, France, Italy, China, and South Korea. They analyze a very short period from 1 June 2019 to 16 March 2020. Compared to previous studies, we use a different methodology, different groups of countries and additionally we make a comparative study of relation changes in different periods (pre-crisis, COVID-19 pandemic, Russia-Ukraine war), not just pandemic as the previous studies to see whether there are any differences in these relations in different periods of time.

3. METHODOLOGY

3.1. RESEARCH PERIOD AND INDICES USED FOR RESEARCH

The research covered the period from January 26, 2018, to September 29, 2023. This period was divided into shorter sub-periods as follows: I: January 26, 2018, to February 18, 2020; II: February 19, 2020, to January 2, 2022; III: January 3, 2022, to September 29, 2023. Due to S&P500 being the reference point for all analyses, the division points were determined based on the behavior of this index and ensuring similar durations.

Following (He et al., 2020) and (Youssef et al., 2021) we use daily data. We gather them from *investing.com* for many indices at one time, both from developed and Visegrad countries and check in what way the S&P500 index influences them, if there are some differences between these relations during turbulent times (the COVID-19 pandemic and the Russia-Ukraine war) and calm stock market situations. The following stock market indices were included in the study: WIG20 (Poland, comprising the 20 largest companies), SAX (Slovakia), PX (the Czech Republic, consisting of 14 companies that represent about 90% of the market capitalization), BUX (Hungary, including the top 12 companies by capitalization), S&P500 (USA, consisting of 500 companies representing the overall economy), NASDAQ (USA, comprising mostly technology sector companies), DJIA (USA, consisting of 30 major companies), Nikkei225 (Japan, comprising the top 225 companies by capitalization), FTSE 100 (UK, covering the top 100 companies), DAX (Germany, consisting of 30 major companies), CAC40 (France, comprising the top 40 companies by capitalization), Stoxx 50 (Eurozone index, including the 50 highest-capitalized companies from 8 countries: France, Germany, Spain, Netherlands, Italy, Belgium, Finland, Ireland).

3.2. PRELIMINARY STUDIES

The study was divided into several stages. The initial stage involved data preparation and completion. On days when there were no quotations, they were completed with data from the previous day. Subsequently, the closing price values were standardized to the same currency, USD, by dividing the quotes by the appropriate currency exchange rate. The logarithmic return rate was then calculated for the prepared data using the formula:

$$p_t = \ln(r_t) - \ln(r_{t-1}) \tag{1}$$

where r_t, r_{t-1} are the index quotations at time t, t-1.

In the first stage, the entire research period was divided into shorter sub-periods based on the trends of the S&P500 index to obtain periods of similar lengths. Preliminary analysis was conducted on the return values and standard deviation in rolling windows throughout the entire study period. Following (Peng et al., 2022) who examined relations between stocks from different sectors in China, we use Pearson correlation coefficients and construct time rolling windows. Pearson correlation coefficient is often used to show connectedness between markets. (Huang et al.; 2019) use it to check changes in relations between 35 European stock markets and conclude that there is an increase in the connectedness between examined markets existing in countries which joined the EU after the European Union was established.

In each sub-period, the Pearson correlation coefficient was calculated:

$$r_P = \frac{cov(p_X, p_Y)}{\sigma_{p_X}\sigma_{p_Y}} \tag{2}$$

where p is the return rate of index X for t=1,…T, $cov(p_X, p_Y)$, represents the covariance between p_X and p_Y, and σ_{pX} denotes the standard deviation of p_X.

The significance of the correlation coefficient was tested by setting hypotheses:

$H_0 : r_p = 0$ – the correlation coefficient is statistically insignificant

$H_0 : r_p \neq 0$ – the correlation coefficient is statistically insignificant

The test statistic, $t = \frac{r_S}{\sqrt{1-r_S^2}}\sqrt{n-2}$ (3)

follows a Student's t-distribution with n-2 degrees of freedom. a significance level of 5% was adopted.

3.3. SIMILARITY OF INDICES AND GRANGER CAUSALITY TEST

Next, the similarity of index quotation changes was examined using the DTW method (Dynamic Time Warping). DTW is a technique used to assess similarity between two time series. It involves determining the smallest distance between these series, while considering time shifts. DTW is also highlighted as a better measure for studying dependencies compared to, for instance, Pearson correlation coefficient, due to its consideration of the shapes of the series (Wang et al., 2012). This method is rarely applied to study linkages between financial time series (Bernardelli & Próchniak, 2023). (Miljkovic & Vatsa, 2023) use it to analyse relations between different commodity markets. (Han et al., 2019) (Thitaweera & Sinthupinyo, 2021) check relationships between single stock markets (the former for China, the latter for Thailand). The added value of our research is applying this method for so many global stock markets with the inclusion of Visegrad countries in one paper.

To align two paths, a matrix of Euclidean distances is constructed (Cassisi et al., 2012). Finding the best path is achieved by minimizing the cumulative sum of distances between them (Anh & Thanh, 2015).

The final stage involved observing the influence of the S&P500 index on the other indices. To do this, the Granger causality test was applied. Granger causality is often applied to check where the cause is for interconnectedness between both stock markets and other kinds of markets. (Pruchnicka-Grabias, 2022) analyses the relationship between the stock market and the crude oil market. (Al-Yahyaee, 2019) uses it to study causality between US stock market and those from GIPSI countries. (Żebrowska-Suchodolska & Piekunko-Mantiuk, 2022) analyze interrelations between sectoral stock market indices. However, before Granger causality test, the stationarity of the return series was examined using the Augmented Dickey-Fuller test (ADF), by setting the null hypothesis of non-stationarity against the alternative of stationarity (Dickey & Fuller 1979) (Dickey & Fuller, 1981). The Granger causality test is based on the VAR model (Granger, 1981):

$$y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i y_{t-i} + \varepsilon_t \tag{4}$$

$$y_t = \beta_0 + \sum_{i=1}^{k} \beta_i y_{t-i} + \sum_{i=1}^{k} \gamma_i x_{t-i} + \eta_t \tag{5}$$

where $\alpha_0, \beta_0, \beta_i, \gamma_i$ for $i = 1, 2, \ldots, k$ – coefficients estimated using OLS, k – lag order.

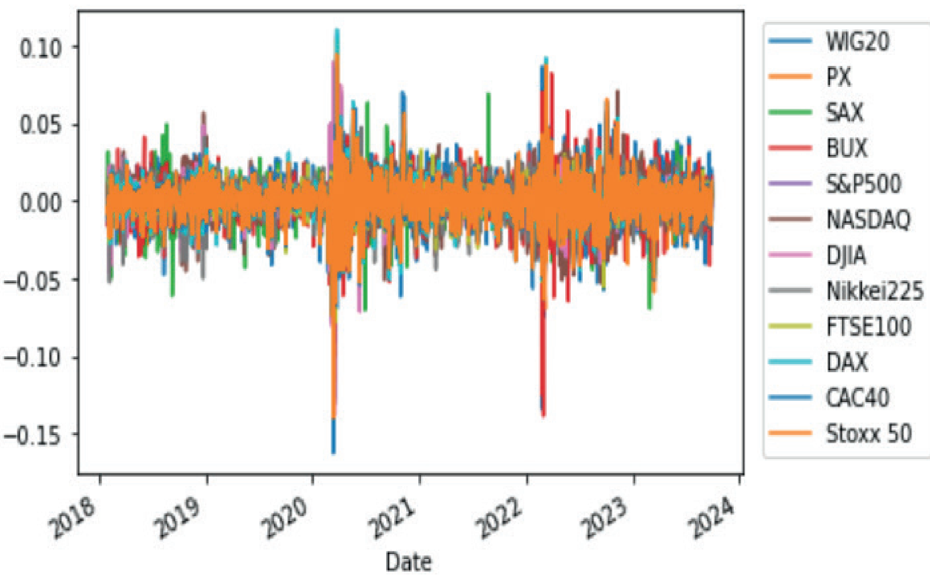
Testing the null hypothesis $\sigma^2(\varepsilon_t) = \sigma^2(\eta_t)$ against the alternative hypothesis $\sigma^2(\varepsilon_t) \neq \sigma^2(\eta_t)$ was carried out using the Wald test. The investigation involved determining whether the S&P500 is the cause of changes in the other indices up to a lag of 25.

4. RESULTS AND DISCUSSION

In the analysed period, significant differences in return rates can be observed at the beginning of 2020 and 2022 (figure 1). In the first instance, this was due to the outbreak of the COVID-19 pandemic, while in the second instance, it was due to the war in Ukraine. Before the pandemic, the logarithmic return rate ranged from -0.06 (for the SAX index) to 0.06 (for the NASDAQ index). The financial market uncertainty caused by the pandemic outbreak led to three times higher return rates. Throughout period II, the return rates fluctuated between -0.16 (for the WIG20 index) and 0.11 (for the DAX index). The smallest decrease in the return rate occurred for the SAX index, with a return rate of -0.07, while for the other indices, it ranged from -0.14 to -0.10. Following a massive decline, quotations were immediately corrected, bringing return rates to the range of 0.07 (WIG20) to 0.11 (DAX). The outbreak of the war in Ukraine caused the most turbulence in the markets of the countries closest to the conflict zone (Boungou & Yatié, 2022) (Ahmed et al., 2022). This was confirmed by the fluctuations in return rates at the onset of the war. It stood at -0.13 for WIG 20 and BUX. For the other indices, the return rate ranged from -0.07 (SAX, PX) to -0.04 (Nikkei225). The outbreak of the war had the strongest impact on the European stock exchanges, as evidenced by the Stoxx 50 index result (-0.06). This remains a highly uncertain period, indicated by a greater amplitude of fluctuations compared to the pandemic period, excluding its initial chase.

Figure 1

The logarithmic return rates of the examined indices for the period between January 26, 2018, and September 29, 2023



Note: Own work using the Pandas library in Python 3.0.

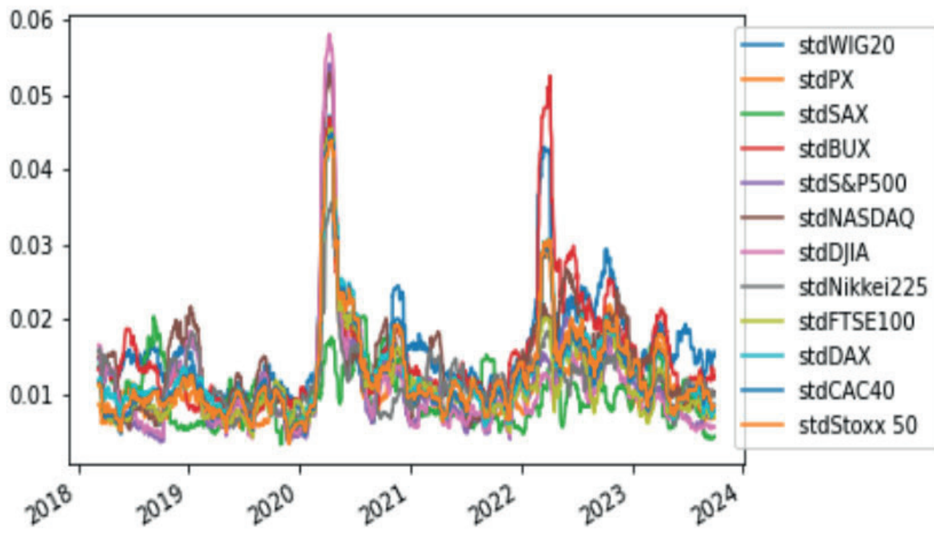
In Figure 2, the standard deviation over time is presented, considering 30 observations. Similar to the return rates, significant differences in the standard deviation size were observed in the first quarters of 2020 and 2022. High standard deviation values appeared in the initial phase of the pandemic for all indices. The American exchanges exhibited the greatest uncertainty, recording the highest standard deviation values (DJIA: 0.058, S&P500: 0.054, NAS-

DAQ: 0.053). Other indices ranged from 0.036 for the Nikkei225 index to 0.047 for the BUX and WIG20 indices. The lowest standard deviation value was 0.002 for the SAX index, despite having the highest return rates during this period.

From the beginning of 2021, there was a return of the standard deviation to levels seen in the first half of period I. Toward the end of period I, there was a rise in standard deviation values for the WIG20, BUX, S&P500, NASDAQ, DJIA, Nikkei225, FTSE100, DAX, CAC40, and Stoxx 50 indices. The onset of the war brought a substantial increase in standard deviation values, slightly lower than those at the beginning of the pandemic. The highest value was 0.052 for the BUX index, followed by the WIG20 index at 0.043. Standard deviation values ranging from 0.027 to 0.031 were reached by the NASDAQ, PX, CAC40, DAX, and Stoxx 50 indices. Standard deviation values ranging from 0.016 to 0.020 were reached by the SAX, DJIA, Nikkei225, and FTSE100 indices. Lower deviation values only began to appear at the beginning of 2023, but there was a subsequent increase in values in April.

Figure 2

The standard deviation of the return rates of the examined indices in the period from January 26, 2018, to September 29, 2023, in a rolling window of 30 observations



Note: Own work using the Pandas library in Python 3.0.

Table 1 presents the standard deviation values in individual periods. While in most indices (except WIG20 and BUX) the highest standard deviation values are in period II, period III is characterized by greater dynamic changes in standard deviation values, maintaining a high level for almost a year and a half.

Table 1
Standard deviation values in periods I, II, III

	Period I	Period II	Period III
WIG 20	0.0123	0.0190	0.0216
PX	0.0078	0.0157	0.0145
SAX	0.0099	0.0113	0.0099
BUX	0.0110	0.0178	0.0221
NASDAQ	0.0093	0.0167	0.0126
DJIA	0.0114	0.0181	0.0167
Nikkei225	0.0096	0.0176	0.0104
FTSE100	0.0104	0.0143	0.0126
DAX	0.0084	0.0164	0.0124
CAC40	0.0097	0.0170	0.0155
Stoxx 50	0.0090	0.0169	0.0152

Note: Own work using the Pandas library in Python 3.0.

The next step was to determine the Pearson correlation coefficient values between the return rates of the examined indices in each of the sub-periods. The Pearson correlation coefficient values between the return rates of the examined indices are presented in Figure 3.

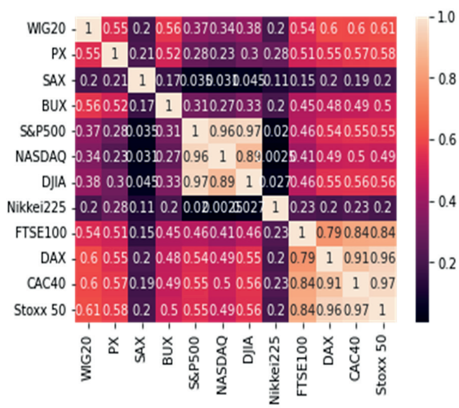
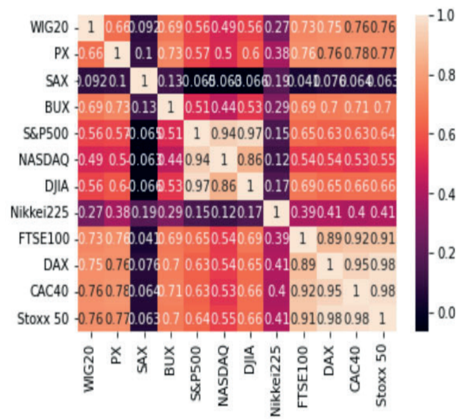
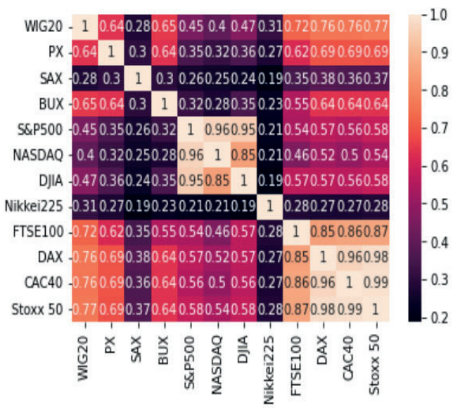
The obtained results of Pearson correlation coefficients between the indices differ. In the second period, during the COVID-19 pandemic, except for the SAX index, the rest of the coefficients were statistically significant. The relationships between the indices were strongest at that time.

During the period of war, strong dependencies are also noticeable. The correlation coefficient values were lower than during the pandemic period but higher than before the pandemic.

Additionally, distinct groups of highly correlated indices with each other are observed, regardless of the market situation. One group consists of the American exchanges. The second group comprises FTSE100, DAX, CAC40, and Stoxx 50. Tokyo and Slovakian markets represent distinct markets. The Nikkei 225 and SAX indices are weakly correlated with the other exchanges regardless of the period, although during the war period, their correlation is the highest among the three periods. Regarding the WIG20 index, it is most strongly correlated with the DAX, CAC40, and Stoxx 50 indices, and additionally with the FTSE100 in periods II and III.

Figure 3

Pearson correlation coefficient between the return rates of the examined indices for periods I, II, III

Period I	Period II
	
Period III	
	

Note: Own work using the Seaborn library in Python 3.0.

In the next stage, the focus was on the relationship between the S&P500 and the other indices. The results are presented in Table 2.

The strongest correlations between indices and the S&P500 were observed during the pandemic (period II). It was during this period that the Pearson correlation coefficient values were the highest (Table 2). Exceptions were seen with the SAX, NASDAQ, and Nikkei225 indices. Regarding the SAX index, this could stem from stronger local connections and delayed responses from the American market. The associations between the S&P500 and the NASDAQ index are consistently very strong across all sub-periods. However, the highest Pearson correlation coefficient value is observed for period III. Concerning the Nikkei225 index, its ties to the American market are strongest in period III. In all sub-periods, these values are very low and statistically insignificant in the period I. In the case of this index, regardless of the period, the low correlation coefficient values might be due to the fact that Asian markets react with a delay to the prevailing situation.

The weakest associations of the S&P500 index occur in the period I. During this period, all Pearson correlation coefficient values were the lowest among values for periods I, II and III. The strength of market associations increases during crisis periods, which is confirmed by the results observed during the COVID-19 pandemic and the Ukrainian war.

Irrespective of the research period, the strongest associations of the S&P500 occur with the NASDAQ and DJIA indices, while the weakest ones are with the SAX and Nikkei225.

Table 2

The Pearson coefficient values and their significance between the return rates of S&P500 and the other indices for all sub-periods

	Period i (p-value)	Period II (p-value)	Period III (p-value)
WIG 20	0.3677	0.5571	0.4483
PX	0.2812	0.5669	0.3527
SAX	0.0346	-0.0649	0.2602
BUX	0.3097	0.5058	0.3224
NASDAQ	0.9600	0.9438	0.9631
DJIA	0.9670	0.9729	0.9500
Nikkei225	0.0205	0.1517	0.2145
FTSE100	0.4579	0.6521	0.5397
DAX	0.5394	0.6290	0.5698
CAC40	0.5493	0.6291	0.5550
Stoxx 50	0.5453	0.6390	0.5844

Note: Own work using the Pandas library in Python 3.0.

When examining the changes in correlation over time, Pearson correlation coefficients were calculated for 30 return rates in rolling windows during periods I, II and III (Figure 4.1–4.3). The obtained results unequivocally indicate that correlation changes over time. In the first period, the lowest Pearson correlation coefficient values between the S&P500 index and WIG20, PX occurred from August 15th to October 1st, 2019 (the lowest value for WIG20 was -0.0896, and for PX, it was -0.1403). Earlier, negative values for the WIG20 index also occurred from June 28th, 2018, to August 9th, 2018, and for PX from February 6th, 2018, to March 19th, 2018, April 17th, 2018, to May 28th, 2018, and August 12th, 2019, to September 20th, 2019. For the Nikkei225 index, the lowest correlation coefficient value was -0.5351 from August 13th, 2019, to September 23rd, 2019. The relationship between

Nikkei225 and S&P500 was also negative from July 3rd, 2019, to February 18th, 2020. Negative correlation coefficient values between S&P500 and the SAX index appeared several times. These periods were February 6th, 2018, to May 17th, 2018, December 5th, 2018, to January 24th, 2019, June 5th, 2019, to September 10th, 2019, September 6th, 2019, to November 9th, 2019, and October 22nd, 2019, to January 7th, 2020. In the last period, the correlation coefficient reached its lowest value, -0.4934. Regarding the relationship between S&P500 and the BUX index, negative values appeared from June 20th, 2018, to August 9th, 2018 (the lowest coefficient value was -0.1612). The lowest correlation coefficient value between S&P500 and the NASDAQ index was 0.8289 (from May 14th, 2018, to June 22nd, 2018), and the DJIA index was 0.7906 (from June 19th, 2019, to July 30th, 2019). Similarly, the lowest positive return rates were observed for the FTSE100 index (0.0211 from March 26th, 2018, to May 4th, 2018), CAC40 (0.1107 from June 26th, 2018, to August 6th, 2018), DAX (0.1476 from April 17th, 2018, to May 28th, 2018), and Stoxx 50 (0.1362 from June 26th, 2018, to August 6th, 2018).

In the second period, strong dependencies with the S&P500 index persisted at the onset of the pandemic for all indices. For the WIG20 index, values between 0.4 and 0.6 persisted until January 12th, 2021. Other indices had shorter periods (PX, BUX: until July 21st, 2020, Nikkei225: until May 8th, 2020, FTSE100: until August 14th, 2020, DAX: until August 22nd, 2020, CAC40, Stoxx 50: until July 22nd, 2020). After the initial period, the coefficients often reached lower dependency values or exhibited fluctuations in their results. For the WIG20 and PX indices, the last six months of period II brought significant fluctuations in the coefficient results, occasionally reaching negative values (-0.0842 for WIG20, -0.0277 for PX, -0.1513 for BUX, -0.0298 for DAX). Regarding the Nikkei225 index, negative values occurred during the periods of May 13th, 2021, to July 29th, 2021, June 17th, 2020, to October 19th, 2020 and August 2nd, 2021, to November 9th, 2021. The lowest value was -0.3776 (from August 4th, 2020, to September 11th, 2020), and the highest was 0.6731. The SAX index behaved differently; correlation coefficient values were negative or close to zero until March 30th, 2021. Only after this period did the values increase, reaching the highest value of 0.6417 for the period from May 20th, 2021, to June 21st, 2021.

In Period III, during the Ukraine war, higher values of Pearson correlation coefficients persisted for many indices almost throughout the year, until the end of January 2023. For the PX, BUX, Nikkei225, FTSE100, DAX, CAC40, and Stoxx 50 indices, higher correlation values occurred in the middle of Period III. For the PX index, this was the period from August to November 2022, for the BUX index from June to October 2022, and for the SAX index from August to October 2022. Regarding the FTSE100, DAX, and CAC40 indices, a strong correlation with the S&P500 index lasted for a longer period, namely, for the FTSE100 index, it was from September 2022 to March 2023; for DAX, from November 2022 to January 2023; for CAC40, from August 2022 to February 2023; and for Stoxx 50, the period was from July 2022 to February 2023. So far discussed results are in accordance with other papers that show the rising strength of relations between other stock markets or for other crises (Madaleno & Pinho, 2012) (Habiba et al., 2023) (He et al., 2020).

Figure 4.1
Period 1 – the correlation of S&P500 with stock market indices in rolling windows of 30 data points

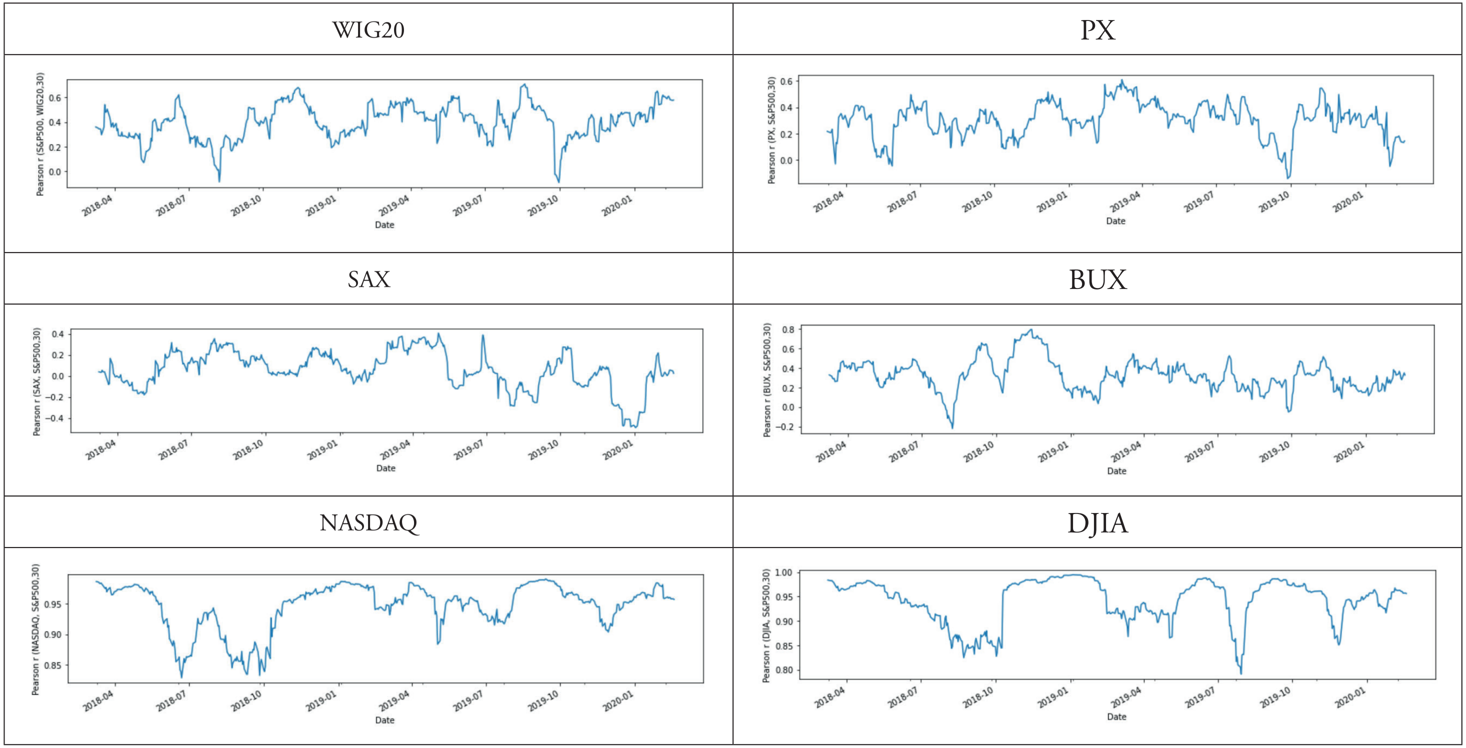
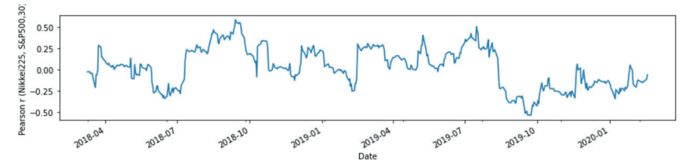
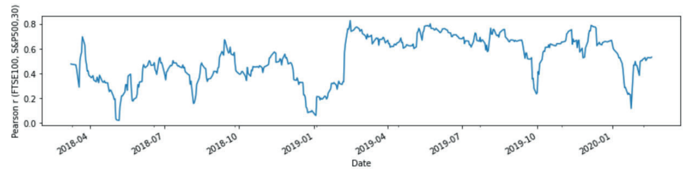


Figure 4.1 (continued)

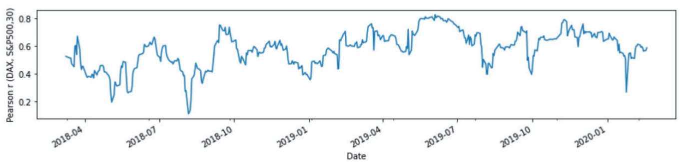
Nikkei225



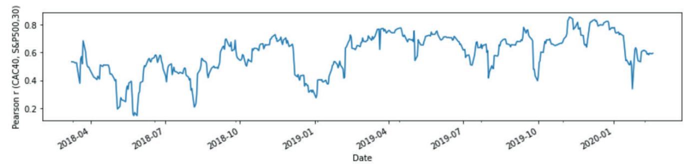
FTSE100



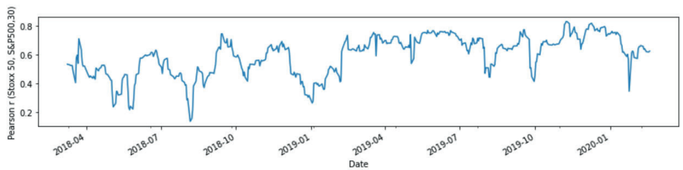
DAX



CAC40



Stoxx 50



Note: Own work using library in Python 3.0.

Figure 4.2

Period 2 – the correlation of S&P500 with stock market indices in rolling windows of 30 data points

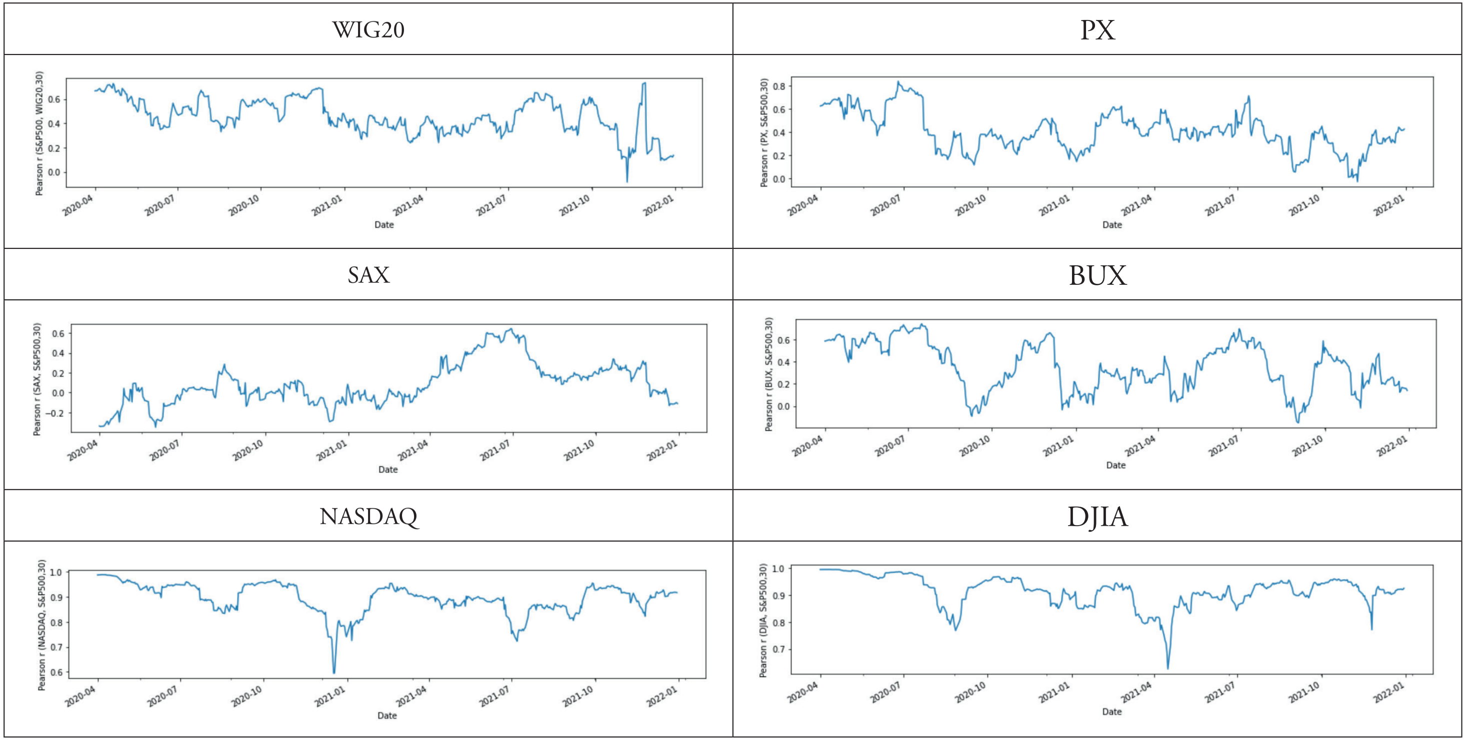
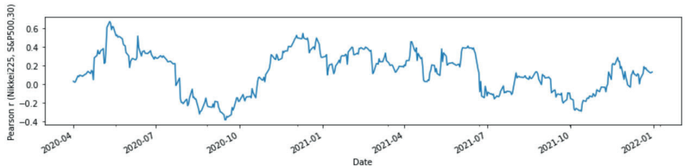
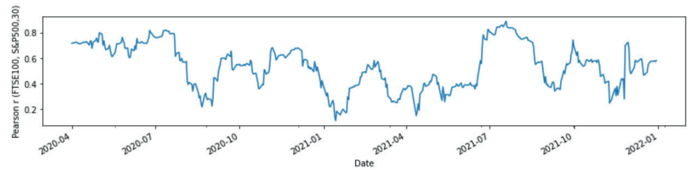
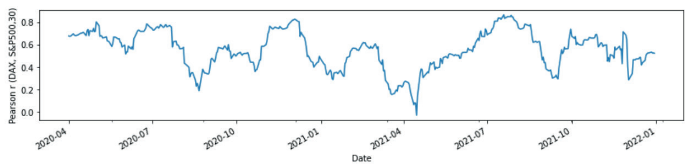
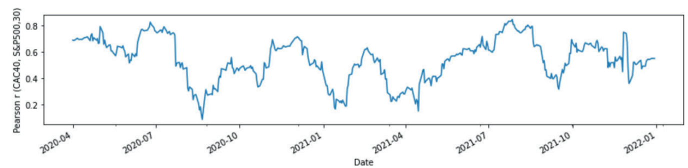
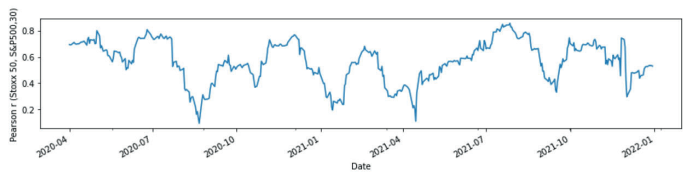


Figure 4.2 (continued)

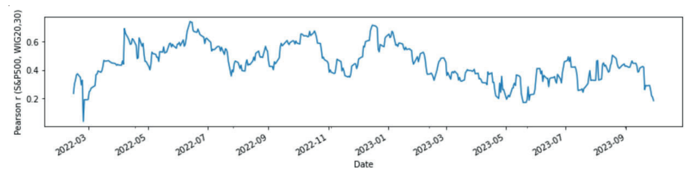
Nikkei225	FTSE100
	
DAX	CAC40
	
Stoxx 50	
	

Note: Own work using library in Python 3.0.

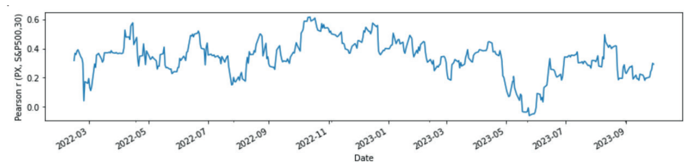
Figure 4.3

Period 3 – The correlation of S&P500 with stock market indices in rolling windows of 30 data points

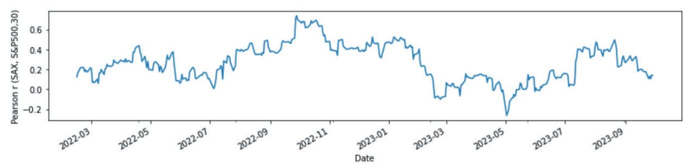
WIG20



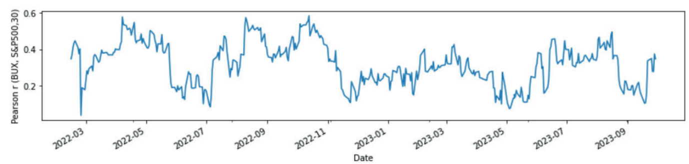
PX



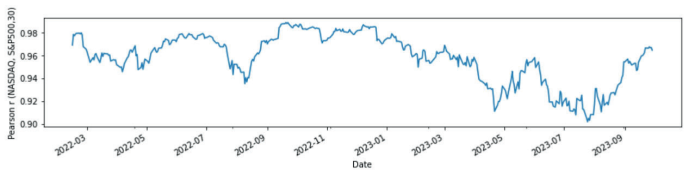
SAX



BUX



NASDAQ



DJIA

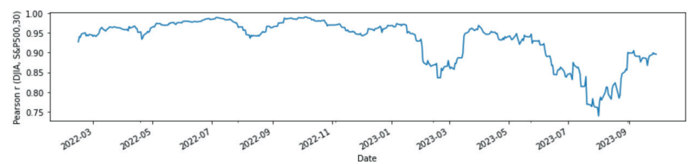
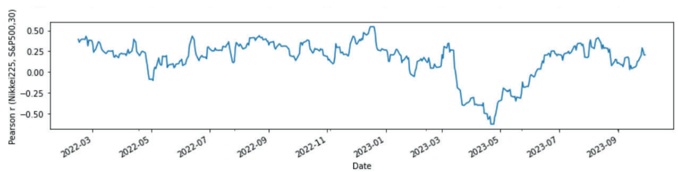
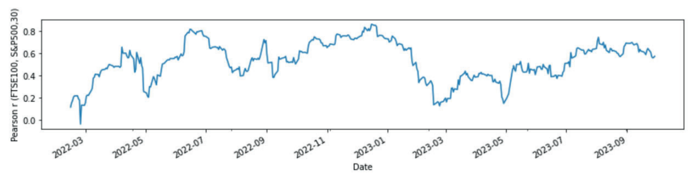


Figure 4.3 (continued)

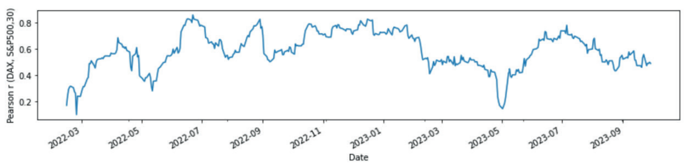
Nikkei225



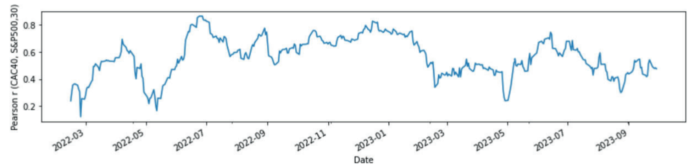
FTSE100



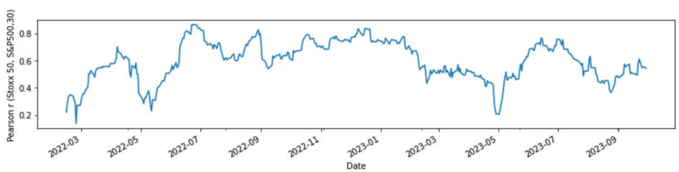
DAX



CAC40



Stoxx 50



Note: Own work using library in Python 3.0.

The next step was to determine the similarity between the S&P500 index and the other studied indices in the four periods. The results of the DTW measure are presented in table 3.

The obtained results indicate a low similarity between the shapes of curves representing the returns of the studied pairs in individual sub-periods. In all sub-periods, the S&P500 exhibits the closest resemblance in shape with the DJIA and NASDAQ indices and the least resemblance with the WIG20. Comparing the results obtained in sub-periods I, II, III, the highest similarity to the return rates of the S&P500 index occurs in period I. The lowest similarity, measured by the DTW measure, occurs between the return rates of the indices during the pandemic period (period II), except for the WIG20, BUX, and DJIA indices. In the case of the WIG20 and BUX indices, the proximity of the Ukrainian war actions and the different response strengths of the indices themselves to the situation caused by the war might have influenced such results.

Table 3

DTW minimum path with minimum distance in the periods I, II, III

	Period 1	Period II	Period III
WIG 20	3.6618	4.3906	4.9589
PX	2.6828	3.5982	3.4925
SAX	2.9736	3.9135	3.1453
BUX	3.2975	4.0430	4.8237
NASDAQ	1.4072	2.1038	1.9670
DJIA	0.9656	1.3680	1.4229
Nikkei225	2.8410	3.7865	3.1464
FTSE100	2,5565	3.4423	3.0380
DAX	2.7454	3.7240	3.3299
CAC40	2.6445	3.7203	3.3699
Stoxx 50	2.6024	3.6969	3.3721

Note: Own work using the DTW library in Python 3.0.

The final step involved examining Granger causality to test whether the S&P500 caused changes in the returns of the other indices. All return series were stationary (based on the ADF test), thus VAR models were constructed up to a lag of 25. The results in Table 4 present the lag numbers for which the results were statistically significant at a significance level of 0.05.

The highest number of statistically significant values occurred during Period II. The S&P500 was the cause of changes in the Nikkei225, FTSE100, DAX, CAC40, and Stoxx 50 indices for all examined lags (25). Therefore, even in the long term, the S&P500 influences changes in the other indices. For the PX, SAX, NASDAQ, DJIA indices, the

S&P500 caused changes in these indices for the first two weeks, then from the fourth week, except for DJIA and SAX. The impact of the S&P500 on the WIG20 and BUX occurred with a delay of one day for the WIG20 and five days for the BUX index.

During Period III, amid the Ukraine war, the S&P500 caused changes in the WIG20, PX, BUX, Nikkei225, FTSE100, DAX, CAC40, and Stoxx 50 indices. This influence extended up to a lag of 25 for the DAX, CAC40, and Stoxx 50 indices. Up to a lag of 12, the S&P500 caused changes in the WIG20, PX, Nikkei225, and FTSE100 indices. For these indices, the S&P500 was also a cause for their changes from a lag of 14.

During Period I, characterized by greater stability, the S&P500 was a shorter-term cause of changes in other indices (WIG20, BUX, FTSE100, DAX, CAC40, Stoxx 50). There were also periods where the S&P500 did not influence the indices, as was the case for DAX and CAC40. For the NASDAQ and DJIA indices, the S&P500 was not the cause of their changes.

Table 4
Granger causality test – delays at which causality occurs

S&P500→	I	II	III
→WIG 20	1–9, 23,24,25	2–25	1–12, 14–21
→PX	1–25	1–12, 14-25	1–12, 14–20, 25
→SAX	1–8	1–9	–
→BUX	1–2	5–25	1–9
→NASDAQ	–	1–7, 9, 15–25	–
→DJIA	–	1–2, 7–8	–
→Nikkei225	1–25	1–25	1–12, 14–25
→FTSE100	1–12, 15–20	1–25	1–12, 14–23
→DAX	1–20, 25	1–25	1–25
→CAC40	1–12, 15–16	1–25	1–25
→toxx 50	1–10	1–25	1–25

Note: Own work using the Statsmodels library in Python 3.0.

To sum up, the rising strength of connectedness between markets stays in accordance with other papers which show it for other crises or other stock markets or use different research methods (Habibi & Mohammadi, 2022) (Panda et al., 2023) (Youssef et al., 2021). Results add to the literature both by considering Visegrad countries together with developed markets and by using DTW method very rarely met in the literature devoted to financial time series (Bernardelli & Próchniak, 2023). Besides, in comparison to the discussed studies, we additionally consider the Russia-Ukraine war and its influence on the examined relations and show that it influenced relations in countries which are geographically close to the conflict zone, which is in line with results presented by (Boungou & Yatié, 2022) who do not concentrate on the influence of war on relations but on the stock markets themselves. Results are also in accordance with (Blahun & Bkahin, 2020) who prove that developed and less-developed stock markets influence each other but add to it changes in these relations during crisis times.

5. CONCLUSIONS

We checked the strength of relations between the S&P500 index and developed and Visegrad stock markets and its changes during crisis times such as the COVID-19 pandemic and the Russia-Ukraine war. Our thesis was confirmed.

The research shows that crises increase interdependencies between stock exchanges (most notably during the pandemic, followed by the war). Both the COVID-19 pandemic and the war increased the linkage between stock markets, although for the latter this rule refers only to markets that are geographically close to the conflict zone. It also makes it obvious that the American stock exchanges are the most strongly interconnected. Another important notice is that crises decrease the similarity of strength between stock exchanges represented by market indices. Moreover, greater similarity between stock exchanges leads to lower volatility in correlations over time.

The paper adds value in three aspects. The first one is that it examines changes in relations between indices, both in their correlations and their strength similarities during the COVID-19 pandemic and the Russia-Ukraine war – recent crisis situations. Contrary to the recent literature which is rather concentrated on the COVID-19 pandemic and its influence on stock markets, we show that such events that are not global also influence relations between stock markets but only these that are located close to the conflict zone. The second one is combining in one paper connections between both different indices from developed countries and Visegrad countries. The third one is using DTW method rarely used for financial time series analysis to examine shapes similarity between S&P500 index and many stock markets, both from developed and Visegrad countries in one paper.

Future research might concentrate on showing similar relations for other countries as well as on the usage of different research methods. It should also consider relations of volatilities. Together with time, they may also consider new crises.

Conclusions are important to investors because relations between markets and their changes over time influence the possibilities of diversification. If connectedness between markets rises during the turmoil, there arises a problem with international diversification. We find it the reason for flying to safe havens during such periods. Conclusions are also vital for portfolio managers and policymakers who can use this knowledge for their potential diversification advantages.

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