The Effect of Volatility on Risk Management Principles. A Case Study on Polish and Romanian Capital Markets

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Abstract
In the last decades, important progress has been made in risk assessment, in the value of risk exposure, in the ways of covering portfolios, in developing a range of systematic analysis for making operational and financial decisions, in order to obtain the best performing model. This paper proposes the analysis by theoretical and empirical methods of the relations between two countries in Central and Eastern Europe, where the main stock market indices are of the Romanian and Polish Stock Exchanges (BET and WIG), observing the important and primordial role of risk management. With each risk analysis, an empirically improved model is desired in order to reduce the risk, starting from the risk exposure, which is treated as a precise target and which must be effective in terms of actions and costs. In risk management, one of the main important concepts is given by risk assessment through the value of risk exposure, where the consequences are a combination of probability and impact, felt by the public entity in relation to the predetermined objectives, to the materialization of risk, where if the risk it is a threat, there would be negative consequences, and if the risk is an opportunity, this could lead to a positive outcome. The approach of the topic is made by using the daily data on the main stock market indices of the Romanian and Polish Stock Exchange and, from the obtained results, we will be able to observe the relationship between the two stock markets by transmitting, estimating, modeling the volatility processes and volatility transmission effect (spillover effect). We've also tested the occurrence of the clustering phenomenon (volatility clustering), which is the method of segmenting a data set (in the form of records or vectors) into several groups (clustering), as well as the transmission of volatility (spillover effect) from one market to another using tests such as VAR, Response to Colesky and Granger Causality.

Keywords
Volatility; Granger Causality; VAR; capital markets; risk management.

Introduction

Stock markets are a major element in the economy, as they are a long-term source of financing, being affected by both internal and external factors. Determined by the gains obtained, investors place their capital on the stock markets in both developed and emerging countries, taking into account stock prices, which are a decision factor due to portfolio diversification, leading to higher-than-expected gains.

Compared to 2020, given the COVID indicators, the launch of the vaccines and the vaccination of a large part of the population during the first half of the year shows that the stock market is strong. During this time, Tesla has become the most valuable car manufacturer and the sixth largest company in the world. It is also observed that most of the bad news that are transmitted on the stock market are related to the political influences rather than the corporate performance.

Volatility is a broad term, vaguely used by the financial world, sometimes referring to price movements, while other times being synonymous with risk. There are different uses for this concept, such as taking the volatility into consideration when planning investment strategies, so that volatility could be used to generate profit. Knowing that capital markets face problems related to the forecasting and modeling of time series volatility, which represents how much the price of an investment fluctuates over a period of time, often associated with risk (high volatility results in great uncertainty). It is desired that the present paper shows the relations between the main stock market indices of Romania and Poland (BET and WIG), the financial implications of the risk and opportunities, as well as the transmission of volatility.

The purpose of this paper is to highlight the connections between stock markets by forecasting the volatility based on EWMA (Exponentially Weighted Moving Average) and by testing the occurrence of the clustering phenomenon (volatility clustering), as well as the transmission of volatility (spillover effect), which is necessary to understand the financial risk.

The testing of correlation between the two series (BET and WIG) and their yields was performed by using: VAR calculation (autoregressive vector), followed by Granger Causality and Cholesky Response test. Those elements are used to show that the previous performance of the stronger index market always affects the return to the weaker market, just as the decrease of one of the indices also affects the other.

The paper is structured in three sections, namely: literature review, which highlights scientific papers that follow the volatility profile of stock indices on financial markets, the methodology, which presents techniques and models used in the paper, as well as the results of the study.

Literature review

Oikonomikou (2015) highlight the possibility of volatility links between different stock markets, which were part of economies in transition such as: Russia, Ukraine, Poland and the Czech Republic. What could be observed after the period of political crisis in

Ukraine was that the own effects of the return of the markets were much stronger, compared to the correlations between them. As a result, it was concluded that the four analyzed markets partially integrated in the European Union (Russia not being a member country of the EU), have links of cross-transmission of volatility, during the crisis, being stronger.

Mehmet Balcilar (2018) shows in his paper "On the risk spillover across the oil market, stock market, and the oil related CDS sectors: A volatility impulse response approach. Energy Economics" shows how strong is the magnitude of volatility transmission and the mechanism of risk spread on the financial market.

Luo and Shengquan (2019) show that volatility is important due to the direct involvement of the investor portfolio. Investors and stock market participants pay close attention to the properties of stock market volatility and profitability, such as time-varying volatility, volatility grouping, long memory, long-term dependence and leverage. Luo and Shengquan point out that stock volatility is a useful barometer or measure not only for the stock market, but also for the country's macroeconomic environment. The behavior of stock returns is very important in supporting the interests of current and potential investors for several reasons. As a measure of investment risk exposure, investors are more than interested in this indicator. Pricing primary assets, portfolio selection and diversification, and portfolio estimation and management show how important volatility is. Stock yield volatility models provide an important signaling effect for investments. Investors determine how time series respond to different types of news: symmetrical or asymmetric response. In essence, the relationship between economic information events and changes in stock volatility is a way in which corporate and public information causes changes in asset prices and values. Practically, the impact of news on volatility is studied.

Methodology of the paper

The stationarity of the data series, respectively for the WIG index and the BET index was achieved by the tests: Augmented Dickey – Fuller, Phillips – Perron and Kwiatkowski – Phillips – Schmidt – Shin.

The Augmented Dickey – Fuller test (ADF) is defined by testing the null hypothesis, in which a unit root is present in a time sample. The statistics of this test are negative numbers and the more negative they are, the greater the rejection of the hypothesis that there is a unitary root, at a certain level of confidence. ADF test calculation formula and assumptions:

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \qquad (1)$$

Where α is a constant, β represents the coefficient on a time trend, and p is the order of the autoregressive process lag.

The hypotheses of this test are: the null hypothesis (H_0) in which: γ = 0 (the series is non-stationary), and the hypothesis (H_1) in which γ ≠ 0 (the series is stationary).

The Phillips – Perron (PP) test tests the unit root and is used in the analysis of time series, to test the null hypothesis, in which the time series is integrated of order 1.

The Kwiatkowski – Phillips – Schmidt – Shin (KPSS) test is the only test that has the null hypothesis that the series is stationary around a trend, determined by the fact that it has a stationary trend compared to the alternative of a unit root.

The normality of the series distribution is analyzed by the tests: Jarque Berra (JB), Quantiles (Q-Q Plot) and Kernel Density. For a normal distribution of the series it is necessary: the asymmetry coefficient (skewness - which is a measure of the asymmetry of the probability distribution of a random variable, with real value in terms of average) with value 0, and kurtosis (excess or vaulting that measures the flattening of a distributions compared to a normal distribution) with a value of 3 and in this case the distribution is mesokurtic. If the indicator kurtosis has a value greater than 3, the distribution is leptokurtic, and if the value is less than 3 the distribution is platikurtic. The Jarque Bera (JB) test is a way to test the normality of the distribution.

JB test formula and its hypotheses:

$$\mathrm{JB} = \frac{n}{6}\left[s^2 + \frac{(k-3)^2}{4}\right] \tag{2}$$

The hypotheses of this test are: the null hypothesis (H_0) in which: the series of residues comes from a normal distribution (s=0, k=3), and the hypothesis (H_1) in which the residue series does not come from a normal distribution.

The normality of the series distribution can also be observed by Quantile (en. Q – Q Plot) with the help of the option: View Distribution Quantile Graph, from which the normal distribution is chosen or using Kernel Density. The method used compares with the graph the quantiles of the normal distribution, with the quantiles of the distribution being analyzed. The quantiles of the normal distribution are highlighted on the graph with a continuous line (theoretical), and the points represent the effective distribution and as far as they deviate from the theoretical distribution, it is concluded that the series is not normally distributed.

In the second case, in which the Kernel Density option is chosen, it can be observed that the densities do not coincide when the two lines do not overlap. Based on the graph, we see the phenomenon called volatility clustering, which occurs when large changes are followed by large changes in yields and vice versa when we are dealing with changes in low yields.

Series volatility using EWMA is calculated using the analytical VAR model.

The calculation formula is:

$$\hat{\sigma}_t^2 = (1-\lambda)r_{t-1}^2 + \lambda\hat{\sigma}_{t-1}^2 \tag{3}$$

where: λ represents a smoothing parameter with a standard value between 0.80-0.94 (RiskMetrics), most often used, for daily data and 0.97 for monthly data (lambda value varies over time); periodic return is: $t_i^2; t_{i-1}^2; t_{i-2}^2; t_{i-3}^2$; „Weight” : $(1-\lambda)\lambda^0(1-\lambda)\lambda^1(1-\lambda)\lambda^3$, where the parameter λ, shows how long the volatility of the financial asset lasts. The longer the persistence, the longer the shock in the market; The 1-λ parameter shows the rate at which asset volatility responds to a shock, regardless of direction. The response of volatility to shock is stronger, as the value of this parameter increases.

The results of the study

In order to highlight the modeling and transmission of volatility on financial markets, we used the data sets with daily observations (5 days / week) based on the closing prices of the two stock indices: BET (Bucharest Stock Exchange index) and WIG (stock market index Values from Warsaw), for the period 11 / July / 2016-06/ Aug / 2021. In the analysis of the two data series, we chose to use returns calculated on the basis of logarithm, because they are more likely to have a normal distribution, according to standard assumptions and to observe whether daily yields are normal or asymmetric (Skewness coefficient) distributed. Then we ran the series in Eviews 10 and tested their stationarity. Time series in reality are infinite as a domain of variation and therefore, a time series can be defined as stationary, if its variation is constant in time. A time series is non-stationary if its statistical properties depend on time. The tests for verifying the stationarity show that: the series characterized by constant mean and standard deviation over time is stationary. From an economic point of view, a series can be considered stationary if a shock applied to the series is temporary. The series' stationarity verification tests are: Augmented Dickey-Fuller (ADF), Phillip Perron (PP), which in turn are verified by the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

Table 1. Augmented Dickey-Fuller (ADF) test statistic

Augmented Dickey-Fuller (ADF) test statistic	BET	WIG	Prob
Null Hypothesis: BET_YIELD has a unit root	-38.16786	-33.90294	0.0000
1% critical value	-3.433912	-3.435428	
5% critical value	-2.863000	-2.863670	
10% critical value	-2.567594	-2.567954	

Own calculation made in EViews 10

Table 2. Phillips –Perron (PP) test statistic

Phillips –Perron (PP) test statistic	BET	WIG	Prob
Null Hypothesis: BET_YIELD has a unit root	-34.85310	-34.00685	0.0000
1% critical value	-3.435428	-3.435428	
5% critical value	-2.863670	-2.863670	
10% critical value	-2.567954	-2.567954	

Own calculation made in EViews 10

Table 3. Kwiathowski –Phillips –Schmidt –Shin (KPSS) test statistic

Kwiathowski –Phillips –Schmidt –Shin (KPSS) test statistic	BET-LM-Stat	WIG-LM-Stat
Null Hypothesis: BET_YIELD has a unit root	0.071243	0.142700
1% critical value	0.739000	0.739000
5% critical value	0.463000	0.463000

10% critical value	0.347000	0.347000

Own calculation made in EViews 10

Normality of distribution - Jarque-Bera test

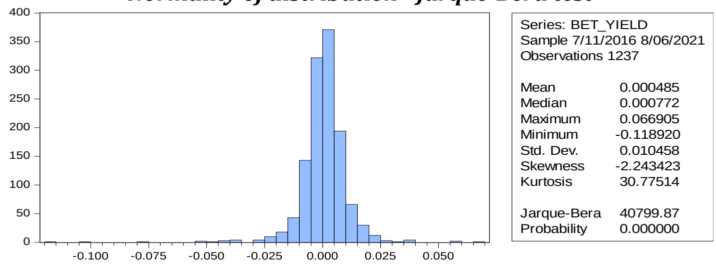


Figure 1. Jarque-Bera test applied to BET-Return
(own calculation made in EViews 10)

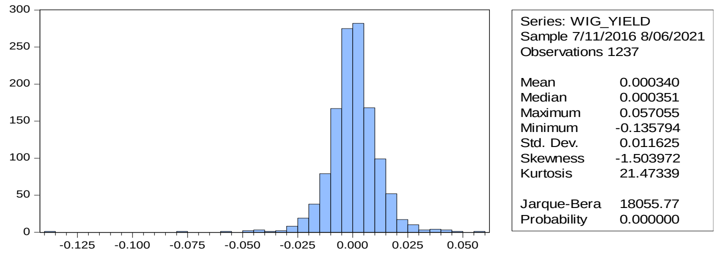


Figure 2. Jarque-Bera test applied to WIG-Return
(own calculation made in EViews 10)

From the two figures above it can be seen that the results obtained on the BET and WIG data series have a probability of 0.0000, lower than the allowed threshold of 0.05, which shows that null hypothesis (H_0) is rejected, and the residue series does not come from a normal distribution. For BET, the Kurtosis coefficient with the value of (30.77) exceeding the threshold of 3, shows that the series of residues comes from a leptokurtic distribution, and the asymmetry is to the left, due to the negative value of the Skewness coefficient with different value and less than 0 (- 2.24).

For WIG, the Kurtosis coefficient with the value of (21.47) shows as in the case of BET that the residue series comes from a leptokurtic distribution, and the asymmetry is to the left, due to the negative value of the Skewness coefficient (-1.50), different value even more, less than 0.

Another way to test the normality of the distribution is to use Quantiles and Kernel Density.

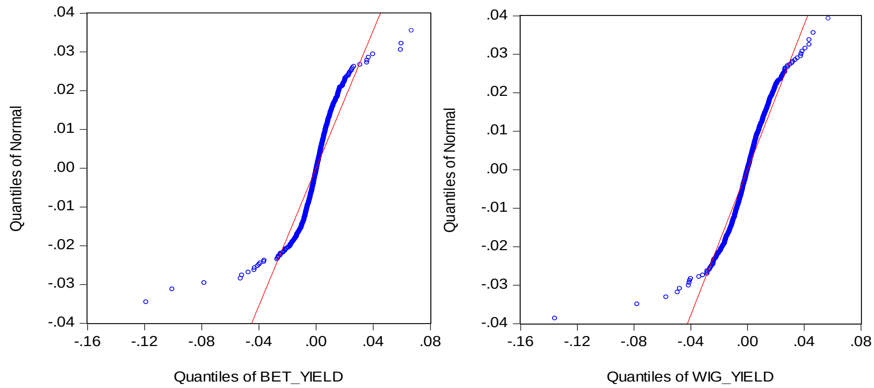


Figure 3. QQ-Plot applied to BET and WIG-Return
(own calculation made in EViews 10)

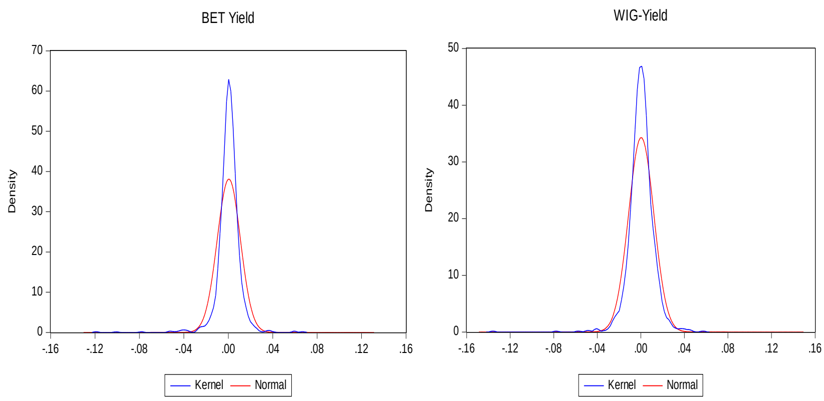


Figure 4. PP-Plot applied to BET and WIG-Return
(own calculation made in EViews 10)

Through this methodology, the quantiles of the theoretical, normal distribution are represented graphically, versus the quantiles of the distribution which are analyzed as follows: with a continuous line the quantiles of the normal distribution are represented, and with dots, those of the effective distribution are represented. As the latter deviate more from the theoretical ones, the distribution is not normal. Thus, if, in the first graph (Figure 3) analyzed it can be seen that the distribution of the series of the natural logarithm applied on the BET closing price is not normally distributed, in the second graph (Figure 4) with the Kernel Density option, it is highlighted that the densities do not coincide when the two lines do not overlap. In the second graph (Figure 3) analyzed it can be seen that the distribution of the series of the natural logarithm applied on the WIG closing price is not normally distributed, in the second graph with the Kernel Density option (Figure 4), it is highlighted that the densities do not coincide when the two lines they do not overlap.

The occurrence of the volatility clustering phenomenon in the case of BET and WIG

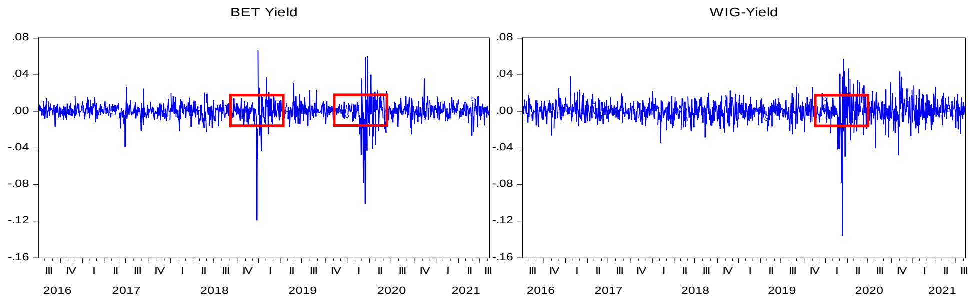


Figure 5. Volatility clustering phenomenon in the case of BET and WIG
(own calculation made in EViews 10)

From the two graphs illustrated above you can see the trend of clustering in different periods of time such as those marked in red. According to the graphs above, it can be seen that in the period 2016-2018 there are no sharp decreases or increases in stock market share prices, therefore we can almost see a linear trend, except for the end of 2018 when it comes to the BET index, where there was a significant decrease in December due to some changes of the laws that impacted the future revenues of the main companies of the Romanian Capital Markets. Volatility and influences between international markets and implicitly between the two stock indices WIG and BET can be seen in the financial information collected, especially in 2020, because as the coronavirus spreads worldwide, the impact on the two exchanges is growing. From March 4, it is observed that the WIG20 index decreases systematically until March 12, and the reason for the stock market falls is none other than the visible fear during three weeks of the epidemic. Thus, the first quarter of 2020 was the worst in the history of the index worse than the end of 2008, when the financial crisis broke out. Two days later, the BET index, the main index of the Bucharest Stock Exchange, between 6-13 March 2020 experienced massive decreases in trading, as a result of the VIX (no fear index) registering very low values not seen since 2008. There were large decreases in international markets, which also spread to BVB.

EWMA (exponentially weighted moving average)

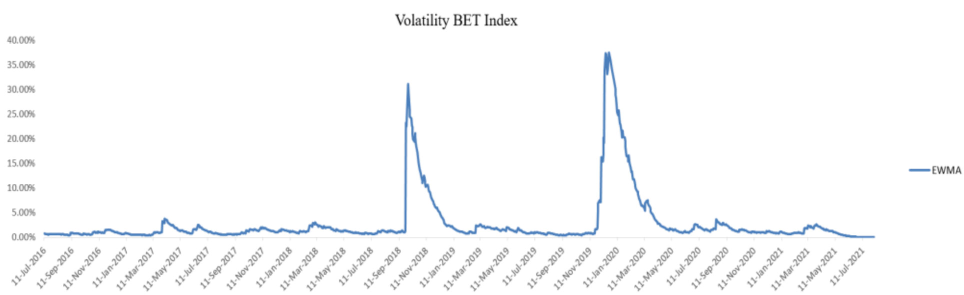


Figure 6. Volatility BET Index
(own calculation made in Excel)

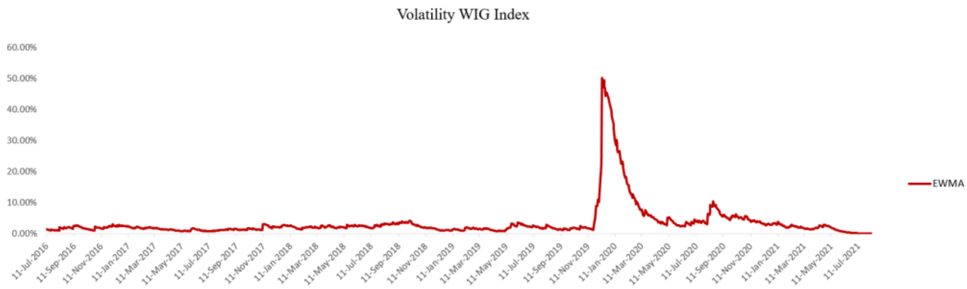


Figure 7. Volatility WIG Index
(own calculation made in Excel)

Following the calculations in Excel, for BET the EWMA model calculated on the basis of daily data over a period of 60 days with relevance level 1, has a value of 0.000027, and for WIG calculated in the same way over the same EWMA time interval, it has a value of 0.000047.

Minimum and maximum BET and WIG indices

Table 4. Stats table BET and WIG

Stats tabel BET and WIG	*BET*	*WIG*
Mean	0.000485	0.000340
Median	0.000772	0.000351
Maximum	0.066905	0.057055
Minimum	-0.118920	-0.135794
Std.Dev.	0.010458	0.011625
Skewness	-2.243423	-1.503972
Kurtosis	30.77514	21.47339
Jarque-Bera	40799.87	18055.77
Probability	0.000000	0.000000
Sum	0.600458	0.421149
Sum Sq. Dev.	0.135191	0.167048
Observations	1237	1237

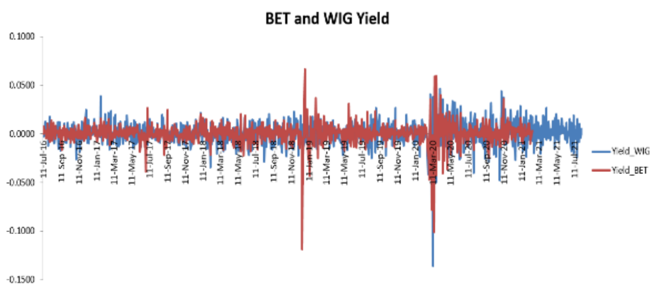


Figure 7. Return BET VS WIG
(own calculation made in Excel)

According to the graph above, it can be seen that there is data in which both stock indices BET and WIG registered significant decreases on the same day, 11.03.2020, due to the pandemic. Through Table 4 above we wanted to highlight the minimums and maximums of the two indices and what can be said is that the minimum for BET is on 19.12.2018 followed by 16.03.2020 the date when the stock market fell due to the pandemic, and the maximum is given on 27.12.2018 when the number of shares increased for some of the main companies, such as Fondul Proprietatea (FP), Banca Transilvania (BT) and Petrom. For the WIG index, a drastic decrease can be observed in March 2020, as in the case of the BET index based on the pandemic. The maximum of the WIG index was registered on 17.03.2020.

Testul Pairwise Granger Causality and VAR (vector autoregresiv)

Table 5. Granger Causality test

Pairwise Granger Causality Tests-Lags:2	Obs	F-Statistic	Prob.
Null Hypothesis:			
WIG does not Granger Cause BET	1235	5.62266	0.0037
BET does not Granger Cause WIG		3.82647	0.0220

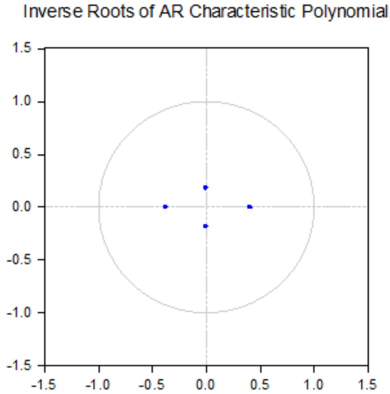
Own calculation made in Excel

From the results of the Granger Causality test, it is observed by the probabilities obtained that in both BET and WIG the hypotheses are rejected by which: WIG does not influence BET and conversely BET does not influence WIG, because the probabilities are below the threshold of 0.05. The Granger causality test shows the existence of direction and influence from BET to WIG with a probability of 0.0220 and vice versa from WIG to BET with a probability of 0.0037.

Table 6. VAR

Vector Autoregression Estimates	*BET*	*WIG*
BET(-1)	0.007483	0.040746
	(0.03068)	(0.03434)
	[0.24386]	[1.18652]
BET(-2)	0.084939	0.086184
	(0.03070)	(0.03436)
	[2.76632]	[2.50798]
WIG(-1)	0.001249	0.016281
	(0.02763)	(0.03092)
	[0.04519]	[0.52650]
WIG(-2)	0.092542	0.034315
	(0.02761)	(0.03090)
	[3.35178]	[1.11052]
C	0.000405	0.000258
	(0.00030)	(0.00033)
	[1.37102]	[0.78113]

Figure 8. Inverse Roots of AR



(own calculation made in Excel)

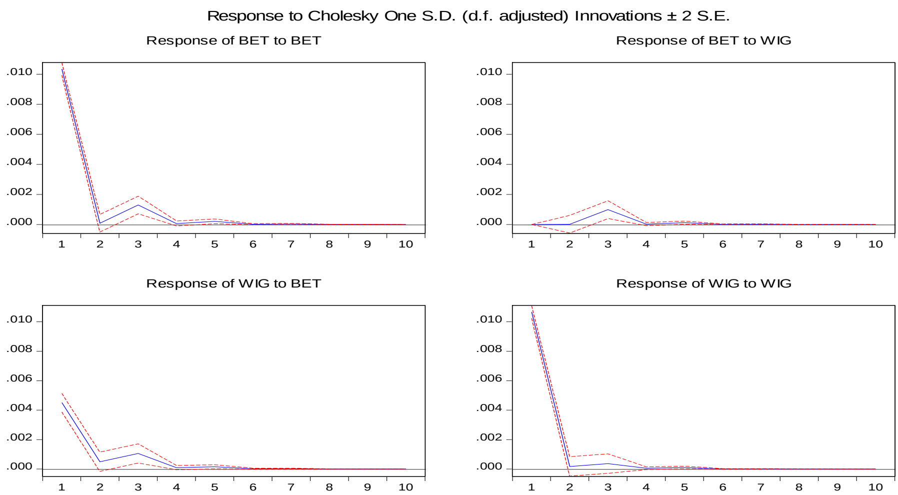


Figure 8. Impulse response
(own calculation made in Excel)

From the obtained results, it can be observed from the second equation from table 6 that the BET index influences the WIG index having the statistically significant t-value of 2.5 (in absolute terms), which exceeds the allowed threshold of 2. The last equation from table 6 showcases that the WIG index influences the BET index, having a statistically significant t-value in absolute terms of 3.35 that exceeds the allowed threshold of 2. We tested whether autoregressive vectors are stable, having variables that are not influenced by shocks, because the effects of these shocks diminish, usually about 4 periods. Following this analysis, we found that the VAR model applied on the BET-WIG data series describes autoregressive links between the Polish and Romanian capital markets, respectively between the main indices, BET and WIG. By applying this model, four impulse responses emerged (see Figure 8).

The Inverse Roots of AR Characteristic Polynomial test shows that the four points are very close to the center of the circle, even on its diagonals, indicating the stability between the two stock indices BET and WIG. The Cholesky method tests if there is a contagion effect between the two stock exchanges and the result obtained, enforcing, in this paper, the fact that the BET stock index influences the WIG stock index and, conversely, the WIG index influences the BET index. It can be seen that between BET and WIG, according to the graphs, there is a distance between the red and blue lines, which shows that there is a correlation between the two indices.

Conclusion

In essence, the results obtained showcases the relationship between the two stock markets and volatility, which leads to changes in stock prices due to the impact of pandemic news. From the results obtained, it can be said that the coronavirus pandemic caused a distortion in the capital markets. The data implies a minor correlation between the two indices, based on the global coronavirus pandemic, reason why investors should be careful when investing in the markets that are linked with one another in order to better diversify their portfolio to reduce the risks to which they are exposed.

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