Proceedings of STRATEGICA International Conference October 24-25 2024, Bucharest, Romania

Analysis of the Relationship Between the VIX Index and the Stock Index

Maria-Cristina ZWAK-CANTORIU
Doctoral School of Finance, Bucharest University of Economic Studies
11 Tache Ionescu St., Sector 1, 010352 Bucharest, Romania
maria.cantoriu@fin.ase.ro

Lucian Claudiu ANGHEL
National University of Political Studies and Public Administration
30a Expoziției Blvd., Sector 1, 012104 Bucharest, Romania
lucian.anghel@facultateademanagement.ro

Pompei MITITEAN
National University of Political Studies and Public Administration
30a Expoziției Blvd., Sector 1, 012104 Bucharest, Romania
pompei.mititean@facultateademanagement.ro

doi: 10.25019/STR/2024.049

Abstract
The paper analyzes the role of the VIX (Volatility Index) and its impact on financial markets, focusing on how changes in this index influence investors and stock indices. The VIX, or volatility index, measures the expected volatility of financial markets and reflects investor sentiment regarding short-term economic uncertainty. The study uses a mixed-methods approach, combining empirical analysis and econometric modeling. Specifically, the research uses descriptive statistical methods, including mean, standard deviation, skewness, kurtosis, confidence intervals, and econometric techniques such as linear regression, Spearman correlation, and Granger causality tests. These methods investigate the interaction between the VIX and key stock indices, as well as prominent international indices such as the FTSE, DAX, and Nikkei. By analyzing these relationships, the study provides insights into how changes in VIX volatility signal shifts in market conditions, thereby influencing investment decisions. The results suggest that VIX volatility serves as a critical indicator of market uncertainty, capable of directly affecting the price of stock indices. In addition to theoretical implications, the results provide practical information for investors, helping them to understand market dynamics better and anticipate future trends. This research contributes to the existing literature by highlighting the importance of the VIX in assessing market volatility and by providing a comprehensive framework for predicting stock market movements.

Keywords
VIX (Volatility Index); Spearman Correlation; Linear Regression; Granger Causality Test.

Introduction

In analyzing financial markets, assessing their current and future state is essential to making informed investment decisions. In this context, the VIX (Volatility Index) serves as a barometer of investor sentiment and short-term volatility expectations. This index reflects anticipated fluctuations in financial markets, providing an overview of the level of uncertainty or investor confidence. For a complete understanding of the context of the markets, it is essential also to analyze reference stock indices, such as the S&P500 index, a key indicator of the performance of the American economy, which measures the performance of the shares of 500 of the largest companies listed on the stock exchanges in the US, the Dow Jones Industrial index Average (DJIA), comprising 30 of the most influential companies, and the NASDAQ Composite index, known for its concentration in the technology sector. By combining VIX analysis with the performance of these stock indices, investors can gain a more detailed picture of the current state of the markets and possible risks and opportunities. This approach allows for a more accurate assessment of market sentiment and the potential impact of economic and political factors on investments. The VIX measures the market's expectations of the short-term volatility of the S&P500. When the VIX is high, it suggests increased market volatility, usually associated with economic or geopolitical uncertainties.

An analysis of the relationship between the VIX and other international stock indices can highlight how a rising VIX tends to coincide with declines in global indices, such as the FTSE (Financial Times Stock Exchange), the UK's main stock index, representing the 100 largest companies listed on the London Stock Exchange (LSE), DAX (Deutscher Aktienindex) the main stock index in Germany which includes the 30 largest companies listed on the Frankfurt Stock Exchange, or Nikkei known as (Nikkei 225) the main stock index in Japan which represents the largest 225 companies listed on the Tokyo Stock Exchange. To carry out this work, daily data were collected of the stock market indices: S&P500, DJIA, NASDAQ, FTSE, DAX, and Nikkei, as well as the VIX index, known as the volatility index, over a period of approximately 5 years (October 2019- August 2024), using Yahoo Finance and Reuters as sources. Stock markets and the VIX are currently in a transition phase following one of the fastest and most coordinated rate hikes by central banks in developed economies since 2022-2023. Aggressive interest rate hikes aimed at combating high inflation led to increased market volatility as investors reassessed the risks and economic impact.

Studying this topic is essential because changes in the VIX significantly affect investors and financial markets, and understanding these interactions allows investors to anticipate market movements better and make more informed decisions. The paper's main objective is to analyze the relationship between the VIX index and the stock indices chosen for analysis to understand the impact of volatility and investor sentiment on global financial markets.

The paper is structured as follows: introduction, specialized literature, research methodology, results and discussions, conclusions, and bibliographic references.

Literature review

In the literature, stock indices and the VIX volatility index have been extensively studied for their ability to provide essential information about market sentiment and anticipated volatility. They are often used as predictive tools for future stock market movements. Chow, Jiang, and Li (2020) challenge the VIX's accuracy as a measure of expected volatility, arguing that, without imposing a structure on the underlying process, the VIX reflects a linear moment combination rather than actual market volatility. They introduce a model-free generalized volatility index (GVIX) derived from the log-return variance and show that VIX typically understates actual volatility, especially during highly volatile market conditions. The spread between GVIX and VIX follows a mean-reverting process. Ding, Mazouz, and Wang (2021) investigate the profitability of simple short-term trading strategies based on the implied volatility index (VIX) in the stock market. The strategies proposed in their paper involve holding stocks sensitive to market sentiment when the VIX is low and stocks resistant to sentiment when the VIX is high, achieving significantly higher excess returns than benchmark long-short portfolios that do not consider the VIX. The authors' findings align with the delayed arbitrage theory and the timing problem proposed by Abreu and Brunnermeier (2002).

Campisi et al. (2024) use volatility indices to predict the stock market's future direction by applying various machine learning methods. The dataset analyzed includes stock index returns and US market volatility indices spanning a significant period. The performance of the models is evaluated by three metrics: accuracy, area under the ROC curve, and F-measure, and the results show that the machine learning models outperform classical linear regression in predicting the direction of S&P500 returns. Another study on the relationship between the VIX index and various stock indices is Wang (2019), whose results indicate that the VIX index and its components significantly affect stock market volatility. Also, the author concludes that the VIX improves the accuracy of market forecasts, and the robustness tests confirm these conclusions. However, Bonaparte, Chatrath, and Christie-David (2023) find that the VIX is not as reliable a predictor of 30-day forward S&P 500 volatility, with limited accuracy across sample periods. They propose an alternative method based on asymptotic distribution theory, which demonstrates significantly improved performance and reveals that the superior outcome is due to the method accounting more comprehensively for idiosyncratic risk, while options prices, on which the VIX is based, fail to fully capture stock market volatility patterns.

Through their study, Qadan et al. (2019) show that aggregate market volatility risk, as measured by VIX, influences the relationship between stock returns and idiosyncratic volatility. Specifically, the authors' study highlights that increasing VIX leads to a negative relationship between idiosyncratic volatility and future returns. At the same time, a decrease in VIX is associated with a positive relationship, suggesting that investors are becoming more risk-averse and diversifying their portfolios when The VIX is rising. These results are consistent with the results of the present work, which show that an increase in the VIX by one percentage point leads to a decrease in all the analyzed stock markets. Similarly, Vergili and Çelik (2023) explore the relationship between volatility and sustainability in emerging markets. Using the ARDL bounds test on monthly data for 7 years, they find a long-term cointegration relationship between the VIX and the Dow Jones Sustainability Emerging Markets Index. Their findings reveal a negative relationship, suggesting that as the VIX increases, the performance of companies in the Dow Jones Sustainability Emerging Markets Index decreases. The authors' results also highlight the relevance of the VIX for long-term investors in sustainable markets, aligning with the broader understanding of the impact of the VIX on market dynamics.

Whaley (2000) is the one who created the VIX index in 1993, and his work, besides the importance of the VIX index, explains the mechanism behind this index and its importance in measuring the feeling of fear and uncertainty in the financial markets. It turns out that the VIX is the "investor fear indicator," given its construction, the name fits the measure's name, as it can be considered a measure of volatility and expected stock market risk. In their paper, Bollerslev, Andersen, and Diebold (2002) discuss methods of measuring market volatility, including implied volatility derived from the VIX. The paper helps understand the statistical and econometric techniques applied to volatility analysis. A paper that provides an academic study of the relationship between market volatility and derivative prices, and explains in detail how the VIX works and how it can be used to predict stock market fluctuations, is Mele (2008).

In their work, Tauchen and Zhou (2011) examine jumps in financial markets and their impact on market volatility, finding the VIX index useful for understanding the sudden evolution of volatility and its effects on other economic indicators. Carr and Wu (2009) investigate how investors demand a premium for the additional risk associated with future volatility, and the authors analyze the risk premium associated with market variance, a concept related to implied volatility and the VIX. Following these studies, Hansen et al. (2024) demonstrate that the realized GARCH model provides an explicit formula for both the volatility index (VIX) and the volatility risk premium, which is powered by return and volatility shocks, explaining the time variation of volatility risk premium through different dynamics between physical and risk-neutral measures. Empirical results show that the realized GARCH model significantly outperforms conventional GARCH models. Similarly, using quantile-on-quantile spillover analysis, Altinkeski et al. (2024) analyze the relationship between the VIX and global stock market returns. Their study, covering both developed and emerging markets over a significant period of 28 years, finds that high stock returns typically occur at low VIX levels, while low returns correspond to high VIX levels. They observe that spillovers are particularly strong at extreme quantiles, suggesting that investors might need to consider alternative investment strategies for diversification, especially in periods of elevated market volatility. Their findings further underline the critical role VIX plays in understanding market dynamics across varying conditions.

To apply and explore the effects of the VIX index on stock markets more profoundly, our study uses a methodological approach that integrates empirical analysis and econometric models. By applying these methods, we aim to verify and extend the understanding of the impact of VIX on stock market volatility and returns, thus providing additional insights into stock market dynamics.

Methodology

For this research, daily data were analyzed over a period of approximately 5 years (October 2019-August 2024) regarding the evolution of the stock market indices S&P500, DJIA, NASDAQ, FTSE, DAX, and Nikkei and the VIX index, also known as "volatility index," data collected from official sources such as Yahoo Finance and Reuters. To ensure coherence between the specialized literature and the methodology, we integrated the concepts and approaches found in the theoretical sources within the descriptive statistical analysis. This included applying data description techniques that reflect trends and variations discussed in the literature, such as measures of centrality and dispersion, to provide a detailed and grounded picture of the phenomena under study.

The descriptive statistics used in this work, such as mean, standard deviation, coefficients of Skewness, Kurtosis, minima, and maxima, as well as the Jarque-Bera test, are of great importance in the analysis of the data series used since the trend of the time series used can be observed. With the help of the standard deviation, the volatility of the time series can be more easily observed. With the coefficients of Skewness (the coefficient of asymmetry) and Kurtosis (the coefficient of vaulting), it is possible to detect the type of asymmetry as well as the degree of concentration of the data around the average, thus providing a clearer picture of the distribution and behavior of the time series. The Jarque-Bera test (Jarque & Bera, 1980) shows through its formula whether the data used in the analysis have Skewness and Kurtosis coefficients in accordance with the normal distribution. The Jarque-Bera test formula is:

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right) \tag{1}$$

where: n represents the number of observations, and S and K represent the coefficients of asymmetry (S) and vaulting (K).

Spearman's coefficient, also known as Spearman's rho correlation coefficient (Spearman, 1904), and used in this paper, is a non-parametric measure employed to evaluate the strength and direction of the monotonic relationship between two ordinal or continuous variables. Unlike the Pearson correlation coefficient, which measures the linear relationship between two variables and assumes that the data are normally distributed, the Spearman coefficient can be used even when the data does not meet this assumption. Spearman coefficient values range between -1 and 1. A positive value indicates a monotonically increasing relationship between the variables, meaning that as one of the variables increases, the other tends to grow as well. A negative value indicates a monotonically decreasing relationship. The formula for calculating this coefficient is:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{2}$$

where: ρ represents the Spearman coefficient, d_i represents the difference between the ranks of two variables (x_i) and (y_i), and n represents the number of observations.

To determine the relationship between variables, we used one of the econometric models that illustrate important results, namely, simple linear regression, characterized by the formula:

$$Y = a + b \cdot x + \varepsilon \tag{3}$$

where: Y represents the dependent variable, and x the independent variable; coefficients a and b represent the constant (a) and the slope of the line (b).

The Granger causality test (1969) used shows the causality relationship between the variables used and their hypotheses: the null hypothesis, which shows that the variable x respectively y does not Granger cause the variable y respectively x and the hypothesis H_1 which shows that the variables Granger each other.

Results and discussion

To carry out the work, we collected the closing prices with daily frequency for the S&P500, DJIA, NASDAQ, FTSE, DAX, and NIKKEI stock indices as well as for the VIX index, over a period of approximately 5 years (October 2019-August 2024). Following data collection, which was equalized so that the data reflected the same trading days and where all variables collected were expressed in USD, except for the Japan index (expressed in JPY), which we applied currency conversion to using historical data of the JPY/USD exchange rate collected from the Investing.com platform. After the data manipulation, the daily returns of the indices were calculated by applying the logarithmic formula: $\left(ln\ ln\ \frac{P_1}{P_0}\right)$.

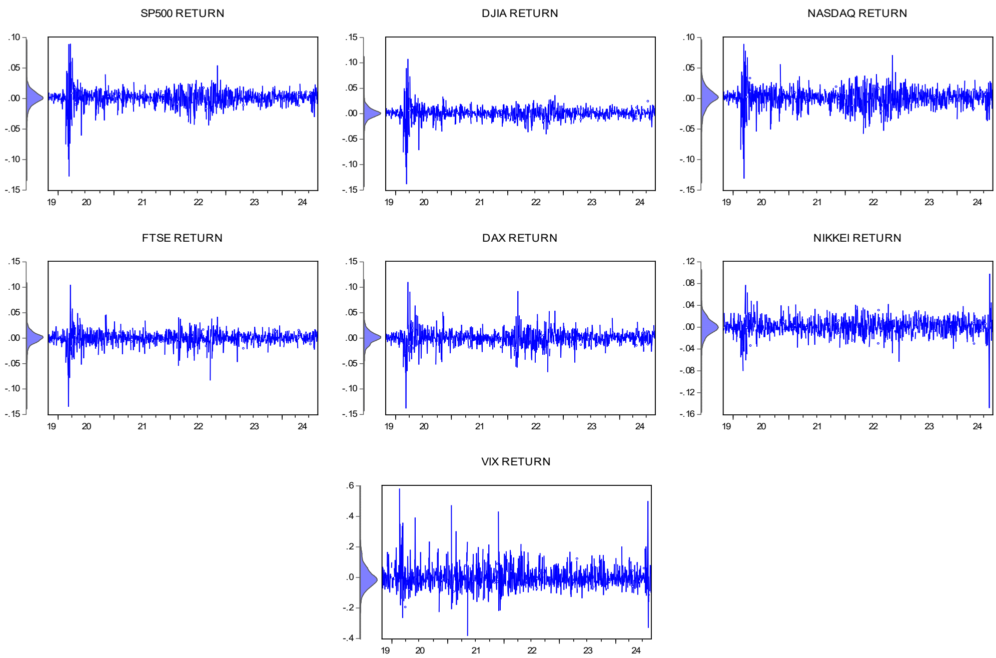

Figure 1. Evolution of stock market indices and the VIX index
(data collected from Yahoo Finance and Reuters- own processing and calculations)

From the graphs presented in Figure 1, where we have illustrated the daily evolution of capital market returns and the VIX index during the period October 2019 - August 2024, the trends of the stock markets and the VIX index are clearly highlighted. An increase in volatility is noted during this period, followed by a stabilization of yields, indicating a tendency to calm the markets. The VIX index reflects the fluctuations of other stock market indices, confirming through its high levels periods of heightened volatility. The onset of the pandemic (late 2019 – early 2020) generated significant fluctuations in both stock indices and the VIX, reflecting the impact of uncertainty on markets. The charts of the three major US indices (S&P500, DJIA, NASDAQ) show similar behavior, with sharp fluctuations between 2019 and 2020, followed by a relative stabilization.

European and Asian indices such as the FTSE, DAX, and NIKKEI initially show strong fluctuations, but their amplitude gradually decreases as the period progresses. On the other hand, the VIX index, which measures volatility, shows pronounced fluctuations, especially during periods of increased uncertainty, thus confirming the link between market volatility and sudden movements in stock indices. This development is consistent with previously observed trends, where high volatility is followed by a period of stabilization. Thus, from the graphs, we find significant oscillations, which reflect sharp variations in returns, influenced by the high volatility of the markets, and we note that, during the COVID-19 pandemic, both the stock indices and the VIX index were strongly affected.

VARIABLES	MEAN	STDEV	MAX	MIN	SKEWNESS	KURTOSIS	JARQUE-BERA	NR. OBS
SP500 RETURN	0.06%	1.44%	8.97%	-12.77%	-1.02	16.74	8420 (0.000)	1047
DJIA RETURN	0.04%	1.41%	10.76%	-13.84%	-1.18	23.46	18504 (0.000)	1047
NASDAQ RETURN	0.07%	1.70%	8.93%	-13.14%	-0.73	9.87	2152 (0.000)	1047
FTSE RETURN	0.02%	1.45%	10.46%	-13.47%	-0.97	15.98	7511 (0.000)	1047
DAX RETURN	0.04%	1.61%	11.03%	-13.80%	-0.34	13.45	4786 (0.000)	1047
NIKKEI RETURN	0.08%	1.66%	9.82%	-14.83%	-0.65	11.90	3526 (0.000)	1047
VIX RETURN	0.02%	8.12%	0.58%	-0.38	1.31	10.34	2651 (0.000)	1047

Table 1. Descriptive statistics results (Source: Yahoo Finance and Reuters - own processing and calculations)

From the results obtained after applying descriptive statistics on returns, we observe that all indices have a positive mean, which suggests a long-term growth trend. The NASDAQ and NIKKEI indices show the highest averages, indicating better performance relative to the other indices. Compared to the rest of the indices, the FTSE index illustrates the lowest average, which shows a relatively weaker performance.

From a standard deviation perspective, the NASDAQ, NIKKEI, and DAX indices exhibit higher volatility (characterized by higher standard deviation) compared to the S&P500 and DJIA indices, suggesting that these markets are more volatile. The VIX index has the most significant standard deviation (8.12%), reflecting large swings in volatility.

Regarding skewness, all stock indices show negative skewness, suggesting a longer-tailed distribution on the downside (more pronounced declines than gains). The DJIA index has the largest negative skewness, which shows a greater risk of extreme decreases, and the VIX index has a positive skewness, which suggests that it is more likely to experience sharp increases. From the perspective of the skewness coefficient, all indices have high kurtosis values. High values of the kurtosis coefficient (or kurtosis) indicate that the analyzed distributions have thicker tails than a normal distribution, significantly greater than 3, which suggests that the distributions are leptokurtic, that is, a higher probability of observing extreme values (outliers) compared to a normal distribution and at the same time a distribution in which rare and extreme events are more frequent. Distributions with high kurtosis values have a greater tendency to generate extreme events, i.e., very large or very small values, compared to a normal distribution and indicate high volatility. Descriptive statistics results clearly show that the distributions have much thicker tails than a normal distribution, suggesting that extreme events are more frequent than expected, and the DJIA index records the highest coefficient of kurtosis, thus highlighting a high probability of such events.

The minimum and maximum values in Table 1 show that all indices experienced both large gains and losses. The most significant loss in the analyzed period is -the DAX index registers 14.83% registered by the NIKKEI index, and the biggest gain at 11.03%. In contrast, the VIX index has a much smaller variation between the maximum and the minimum. The high and low of the two financial markets are confirmed. Public information and data show that Japanese stocks entered a bear market on August 5, 2024, when all markets in the Asia-Pacific area ended trading with massive declines. The Nikkei index of the Tokyo Stock Exchange had the biggest drop since the "Black Monday" of 1987. The maximum point in the analyzed period is that of the main DAX index of the Frankfurt Stock Exchange, which reflects the performance of 40 German companies, reached on March 14, 2024, because of maintaining low interest rates in the USA, a favorable monetary policy, with a positive impact on international financial markets, including the main European stock indices.

Table 2. Spearman correlation coefficient results (Source: Yahoo Finance and Reuters - own processing and calculations)

VARIABLES	VIX RETURN	SP500 RETURN	DJIA RETURN	NASDAQ RETURN	FTSE RETURN	DAX RETURN	NIKKEI RETURN
VIX RETURN	1.00						
SP500 RETURN	-0.74	1.00					
DJIA RETURN	-0.67	0.91	1.00				
NASDAQ RETURN	-0.69	0.93	0.74	1.00			
FTSE RETURN	-0.43	0.53	0.57	0.43	1.00		
DAX RETURN	-0.46	0.57	0.57	0.49	0.82	1.00	
NIKKEI RETURN	-0.10	0.19	0.18	0.15	0.18	0.20	1.00

In the context of the analysis of stock indices and the VIX, we opted for the Spearman coefficient due to the data's non-linear nature and non-normal distribution, confirmed by the Jarque-Bera test.

The interpretation of the results using the Spearman correlation coefficient reflects the monotonic dependence relationships between the analyzed variables (VIX and the returns of various stock indices. The results obtained from Table 2 indicate a strongly negative relationship between VIX and S&P500 (-0.74) and VIX and DJIA of (-0.67) When the VIX rises, the returns of the S&P500 and the DJIA tend to fall, an expected relationship since the VIX is often seen as an indicator of fear in the stock markets where it is highlighted how the increase in VIX also has a negative impact on the European markets, although the effect is less compared to the US markets.

The Japanese market seems less influenced by the volatility perceived in the US markets, having a correlation of (-0.10) between the VIX volatility and NIKKEI yields.

After analyzing the correlations between stock indices, we can state that our analysis of the results of the correlation coefficient highlights that VIX has a strong negative correlation with most of the American stock indices (S&P500, DJIA, and NASDAQ), confirming that an increase in perceived volatility in the markets tends to be associated with declines in stock market returns. The correlation between US stock indices is very strong, indicating that these markets move similarly, reflecting their economic interdependence. These results confirm the role of VIX as a risk indicator for US markets and, to a lesser extent, for European markets, but less relevant for Asian markets.

On the other hand, the European market (FTSE and DAX) is less influenced by the VIX, where there is a moderate negative relationship, suggesting that the volatility in the US markets also affects the European markets and the Japanese market (NIKKEI) has a very weak correlation with the VIX and the other stock indices, suggesting that it is less influenced by perceived volatility in international markets or that it has stronger internal drivers of returns.

Table 3. Regression results (Source: Yahoo Finance and Reuters - own processing and calculations)

DEPENDENT VARIABLE	SP500 RETURN	DJIA RETURN	NASDAQ RETURN	FTSE RETURN	DAX RETURN	NIKKEI RETURN
INDEPENDENT VARIABLE: VIX RETURN						
Coefficient	-0.12	-0.11	-0.14	-0.08	-0.09	-0.05
Prob.	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.48	0.40	0.47	0.19	0.20	0.06
Durbin-Watson stat	2.40	2.41	2.28	1.99	2.02	2.08

Interpreting the results of the simple regressions presented, since each individual regression has only one dependent variable (the return of a stock index such as the S&P500, DJIA, etc.) and one independent variable (VIX) provides valuable information about the relationship between market volatility and the performance of these indexes. The coefficients obtained are negative for all indices: S&P500:(-0.12), DJIA: (-0.11), NASDAQ: (-0.14), FTSE: (-0.08), DAX:(-0.09), NIKKEI: (-0.05); which means if we keep in mind that a negative coefficient indicates that there is an inverse relationship between the VIX and the returns of these stock indices, that in simple terms, as the VIX increases (indicating higher volatility or increased uncertainty in the market), the returns of these indices tend to decrease. These coefficients vary in size, suggesting that the NASDAQ has the highest sensitivity to VIX changes (-0.14) and the NIKKEI the lowest (-0.05).

The probability (P-value) for all coefficients is (0.000). It indicates that the relationships between the VIX and the returns of each index are highly statistically significant (well below the usual significance level of 0.05). In other words, there is very strong evidence that the VIX has a significant impact on the returns of these indices. Regarding R-squared, its values range between (0.06) NIKKEI and (0.48) S&P 500. As an interpretation, it is known that a higher R-squared (closer to 1) indicates that the model explains well the variation in returns. In this case, the model explains 48% of the variation in the S&P500 return and 47% of the variation in the NASDAQ, suggesting a fairly strong relationship between the VIX and these indices. However, lower values such as (0.06) for the NIKKEI indicate that The VIX explains only a tiny portion of the variation in the NIKKEI return, suggesting that other factors may have a more significant influence on this index.

The results of the Durbin-Watson test fall between (1.99) for the FTSE and (2.41) for the DJIA, and given that the values of this test vary between 0 and 4, where 2 indicates no autocorrelation (residuals are independent), and values lower than 2 suggests positive autocorrelation and values greater than 2 suggest negative autocorrelation, we note that in this analysis the values are close to 2, which suggests that there is no significant autocorrelation of the residuals, that is, a positive sign for the validity of the regression model.

As an analysis of the results, we highlight that the VIX has a negative and statistically significant impact on the returns of all the analyzed stock indices. Returns tend to decrease as market volatility increases (indicated by a higher VIX). The R-squared varies considerably, suggesting that the model explains better the variation in returns for some indices (S&P500, NASDAQ) than for others (FTSE, DAX, NIKKEI), and the Durbin-Watson test values suggest that there are no significant autocorrelation problems in residual data, strengthening the validity of the model. This analysis suggests that market volatility, as measured by the VIX, is an important predictor of stock index returns, but the magnitude of this impact varies across indices and does not fully explain variations in returns, suggesting that other factors also contribute.

Table 3. Granger Causality test
(Source: Yahoo Finance and Reuters - own processing and calculations)

Pairwise Granger Causality Tests		
Sample: 10/30/2019 8/23/2024		
Null Hypothesis: VIX->SP500_Return	F-Statistic	Prob.
VIX does not Granger Cause SP500_RETURN	5.67	0.00
SP500_RETURN does not Granger Cause VIX_R	2.39	0.09
Null Hypothesis: VIX->DJIA_Return	F-Statistic	Prob.
VIX_R does not Granger Cause DJIA_RETURN	6.37	0.00
DJIA_RETURN does not Granger Cause VIX_R	2.45	0.08
Null Hypothesis: VIX->NASDAQ_Return	F-Statistic	Prob.
VIX_R does not Granger Cause NASDAQ_RETURN	1.80	0.17
NASDAQ_RETURN does not Granger Cause VIX_R	0.64	0.52
Null Hypothesis: VIX->FTSE_Return	F-Statistic	Prob.
VIX_R does not Granger Cause FTSE_RETURN	18.96	0.00
FTSE_RETURN does not Granger Cause VIX_R	2.34	0.10
Null Hypothesis: VIX->DAX_Return	F-Statistic	Prob.
VIX_R does not Granger Cause DAX_RETURN	15.80	0.00
DAX_RETURN does not Granger Cause VIX_R	0.63	0.53
Null Hypothesis: VIX->NIKKEI_Return	F-Statistic	Prob.
VIX_R does not Granger Cause NIKKEI_RETURN	69.25	0.00
NIKKEI_RETURN does not Granger Cause VIX_R	0.21	0.81

The Granger causality test was applied to see if VIX (volatility index) can "cause" the returns of different stock indices and vice versa. The results obtained between VIX and S&P 500 with VIX do not Granger Cause S&P500_RETURN, with F-statistic = 5.67, and prob = 0.00 shows that at the 5% (or even 1%) significance level, the null hypothesis that VIX does not Granger cause S&P500 returns is rejected, but this means that there is statistically significant evidence that VIX variations help predict of the S&P500 return, the null hypothesis that the S&P500 returns do not Granger cause the VIX cannot be rejected at the 5% significance level, but it is close to significant at the 10% level, suggesting that although there is a relationship, it is not as strong.

Analyzing each causality separately from the obtained results, we can say that VIX has a significant causal influence on the returns of most of the analyzed stock indices (S&P500, DJIA, FTSE, DAX, and NIKKEI), which suggests that market volatility (measured by VIX) can be used to predict the performance of these indices. In most cases, the returns of these indices do not have a significant causal influence on the VIX, indicating that the VIX tends to be a precursor rather than a result of market movements with some exceptions, such as the NASDAQ index, where there is no significant evidence that VIX Granger causes NASDAQ returns, which might suggest that other factors are more important for this index. Thus, it can be said that the VIX index is important as a predictive indicator for stock markets, but this relationship is not reciprocal but rather unidirectional in most cases.

Conclusions

Based on the results obtained in this paper, we can say that the VIX (volatility index) is an anticipatory, significant factor for most of the analyzed stock indices (S&P500, DJIA, FTSE, DAX, and NIKKEI). This means that changes in market volatility, as measured by the VIX, significantly impact the future returns of these indices. Although the VIX can be used to anticipate market trends, it does not have a significant causal relationship with NASDAQ returns, suggesting that the NASDAQ may be influenced more by other factors specific to the technology sector and not as much by general market volatility. Stock returns are observed to have no significant causal influence on the VIX, indicating that the VIX functions as a leading indicator rather than a reaction to market movements. This emphasizes the role of the VIX as a measure of market expectations of future volatility, rather than a direct result of stock market price changes. International indices, such as FTSE, DAX, and NIKKEI, show a significant causal relationship with VIX, especially the relationship between VIX and NIKKEI, which is extremely strong and could show the sensitivity of the Japanese market to global volatility or financial events that directly influence global risk perception.

Because of its ability to predict future market returns, the VIX can be a valuable risk management tool for investors and portfolio managers. Monitoring the VIX can provide early indications of possible market movements, thereby allowing for strategic portfolio adjustments to minimize risk. The obtained results underline the importance of tracking the VIX not only in the context of the US market, but also for international markets. Global investors should factor in the anticipated volatility of the VIX in their investment strategies, especially in markets that have shown a strong correlation with the VIX, such as the FTSE, DAX, and NIKKEI. The S&P500 and DJIA are significantly influenced by the VIX, reflecting that these markets are sensitive to overall market risk perception changes. The European indices, FTSE and DAX, show a significant causal relationship with the VIX, which suggests that US market volatility has a notable impact on European markets and reflects the global interconnectedness of financial markets and the importance of the US as a global financial center. Also, the extremely strong connection between the VIX and the NIKKEI indicated a particular sensitivity of the Japanese market to global volatility, making it more susceptible to international financial shocks.

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