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The Relationship Between the Volatility of the S&P 500 and CBOE Volatility Index (VIX)

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ABSTRACT

This study investigates the bidirectional Granger causation between the CBOE Volatility Index (VIX) and the volatility of the S&P 500 Index utilizing data obtained from Yahoo Finance. The GARCH (1,1) model is employed for the estimation of conditional volatility. This study employs Granger Causality Tests to determine whether the volatility of the S&P 500 can be forecasted by the VIX Index and vice versa. The results show significant bidirectional Granger causality, indicating that the VIX Index and the S&P 500's historical volatility may be accurately predicted from each other. This study contributes to a better understanding of the dynamic relationship between the volatility of the S&P 500 and the VIX Index.

Keywords: volatility, CBOE Volatility Index, S&P 500

Introduction

Volatility is a crucial concept in financial markets, reflecting the degree of fluctuation in the price of financial instruments over time. It is a fundamental indicator of uncertainty and investor sentiment. A higher volatility means higher risk; this provides investors with crucial information to estimate fluctuations in financial markets. Understanding volatility provides investors with a successful portfolio allocation. This study investigates the relationship between CBOE Volatility Index (VIX) and the volatility of S&P 500 indexes. We derived the data from Yahoo Finance. The study uses a GARCH (1,1) model for modeling S&P 500 volatility. The study intends to determine whether fluctuations in the VIX have an impact on the volatility of the S&P 500. The S&P 500, one of the most widely followed stock market indices, represents the performance of 500 leading companies in the US market. Traders, analysts, and policymakers closely monitor the volatility of the S&P 500, using it as a barometer of the overall U.S. economy.

The CBOE Volatility Index (VIX) is a metric that indicates market expectations regarding volatility in the upcoming 30 days. Investors frequently refer to it as a fear index because of its tendency to rise when they anticipate increased market volatility or uncertainty.

A higher VIX value indicates higher expected volatility, while a lower VIX value suggests a more stable market. The investigation of causality between the S&P 500 and VIX can be helpful in determining whether changes in the volatility of the S&P 500 can predict future changes in VIX, and vice versa. This predictive capability has the potential to improve the decision-making process of risk management. In other words, a better understanding of whether changes in the VIX Index affect the volatility of the S&P 500 can help people come up with better risk management techniques. It might help people come up with the best way to hedge their investments. Furthermore, investors may modify their strategies in anticipation of market conditions. To investigate the relationship between these two financial markets is important for policymakers in order to ensure market stability. Therefore, this paper aims to make a significant contribution to the field of empirical finance. It helps fill the gaps in understanding market dynamics and provides an important insight for investors, financial analysts, and policymakers. The results of this paper shows significant two-way Granger causality, indicating that past volatility in the S&P500 can help forecast the VIX Index. This paper enhances our comprehension of the correlation between VIX and S&P 500 volatility.

This paper proceeds as follows: Section 2 provides information on existing literature, Section 3 highlights the empirical findings, and Section 4 concludes the paper.

Literature Review:

Numerous studies have examined the relationship between the stock market, instability, and the overall economy across various countries and years. In 2011, Oseni and Nwosa used EGARCH to look at GDP, inflation rate, interest rate, and stock returns in the context of stock market instability. Their findings show a significant relationship between volatility and macroeconomic variables. Similarly, Shaar and Nikmanesh (2016) examined Malaysia and Indonesia, finding that trade openness has a statistically significant effect on market volatility. Other researchers have concentrated on the US market, utilizing volatility indexes like the CBOE Volatility Index (VIX). For example, Lin and Lee (2010) show that there is a two-way causality between S&P 500 returns and VIX. They stress how important VIX is for predicting stock market volatility, especially during times of crisis. Vuong et al. (2022) show that the VIX has significant effect on corporate leverage.

The most common methods in volatility modeling are GARCH approaches. The literature widely uses GARCH models to predict volatility based on historical data (Oseni and Nwosa, 2011;

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Shaar and Nikamesh, 2016). Roszyk and Ślepaczuk (2024) also used different models, such as LSTM and GARCH. They emphasized that combining LSTM and GARCH works much better than standard methods for predicting S&P 500 volatility. From a different point of view, Ishida et al. (2011) looked at stochastic volatility models that make forecasts more accurate. Ahoniemi (2008), on the other hand, used the ARIMA-GARCH model to predict the direction of VIX and found 58% accuracy.

Sector-specific studies have also highlighted how specific assets respond to volatility. Jubinski and Lipton (2013) emphasize that gold and silver positively responded to increases in VIX, while oil had a negative response. Grosvenor and Greenidge (2013) explored the effects of volatility spillover between different markets by studying the Caribbean stock exchange and its co-movements with the NYSE. Their findings suggest significant volatility spillover between regional and developed markets. Several papers have researched the impact of policy uncertainty on market volatility (Prasad et al., 2022; Shaikh, 2020).

This study is different from existing research in a number of important ways. First, it focuses on the Granger causality. Second, the paper uses a strong method to model how volatility changes over time. Previous research looked at how volatility was affected by larger economic factors or sector-specific factors. This study, on the other hand, focuses on how the VIX and the S&P 500 interact with each other.

The comprehensive literary summary table (Attachment-1) is presented in the attachment. The table provides extensive evidence on the method used in existing studies, the period, countries, samples, and the determinant of volatility.

Empirical Findings

Data

We obtained data from Yahoo Finance for selected financial instruments such as US Stock Market Index (ticker symbol: S&P 500) and CBOE Volatility Index (ticker symbol: VIX), covering daily closing price for selected period from 01/02/1990 to 06/05/2024. Within this selected period of time, there were 8263 observations

Descriptive Statistics

Table 1. Descriptive Statistics

	VIX	Volatility of S&P 500	VIX Return	S&P 500 Return
Mean	19,514900	0,000132	-0,000036	0,000311

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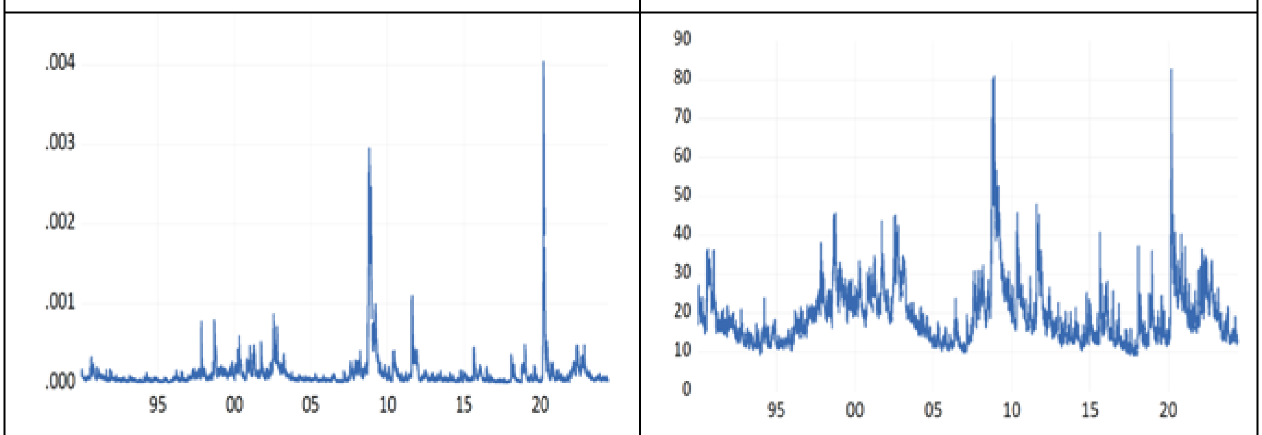
Median	17,660000	0,000073	-0,003969	0,000573
Maximum	72,690000	0,004033	0,768245	0,109572
Minimum	9,140000	0,000000	-0,350589	-0,127652
Std. Dev.	7,886037	0,000234	0,066724	0,011416
Skewness	2,168970	7,974644	0,954694	-0,395436
Kurtosis	11,399300	86,787550	9,290812	13,672890
Jarque-Bera	32281,8	2627997,0	15616,9	41385,7
Probability	0,000000	0,000000	0,000000	0,000000
Sum	169194,2	1,140770	-0,311157	2,700362
Sum Sq. Dev.	539121,4	0,000475	38,604510	1,130050
Observations	8670	8670	8672	8672

Note: Jarque-Bera statistic is used to determine if data comes from normal distributions.

This table provides descriptive statistics for VIX and S&P 500 index. The VIX has 8670 observations with a mean of 19.5149 and a standard deviation of 7.886, ranging from a minimum of 9.14 to a maximum of 72.69. The S&P 500's volatility has 8670 observations with a mean of 0.0001 and a standard deviation of 0.0002, ranging from a minimum of 0 to a maximum of 0.0040. The VIX Index returns 8672 observations with a mean of -3.58E-05 and a standard deviation of 0.0667, ranging from a minimum of -0.3506 to a maximum of 0.7683. The S&P 500's return has 8672 observations with a mean of 0.0003 and a standard deviation of 0.0114, ranging from a minimum of -0.1277 to a maximum of 0.1096. The figure below, Fugure-1, presents the volatility dynamics over time.

Figure 1: Volatility of S&P 500 and VIX

Panel a. Volatility of S&P 500	Panel b. VIX



Note: Graph is the volatility of S&P 500 versus year (Scale for volatility: 1 to 1000000)	**Note**: Graph is the VIX values versus year (Scale for VIX: 1 to 1000000)

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Table 2. Granger Causality Results

Null Hypothesis	**Lags**	**Obs**	**F-Statistisc**	**Prob.**
SP500_Volatility does not Granger Cause VIX	3	8667	11.7354	0.000
VIX does not Granger Cause SP500_Volatility	3	8667	341.979	0.000
SP500_Volatility does not Granger Cause VIX	4	8666	13.7014	0.000
VIX does not Granger Cause SP500_Volatility	4	8666	264.956	0.000
SP500_Volatility does not Granger Cause VIX	5	8665	10.6848	0.000
VIX does not Granger Cause SP500_Volatility	5	8665	233.457	0.000
SP500_Volatility does not Granger Cause VIX	6	8664	9.23152	0.000
VIX does not Granger Cause SP500_Volatility	6	8664	209.063	0.000
SP500_Volatility does not Granger Cause VIX	7	8663	12.3642	0.000
VIX does not Granger Cause SP500_Volatility	7	8663	183.893	0.000
SP500_Volatility does not Granger Cause VIX	8	8662	12.8268	0.000
VIX does not Granger Cause SP500_Volatility	8	8662	163.106	0.000
SP500_Volatility does not Granger Cause VIX	9	8661	13.2444	0.000
VIX does not Granger Cause SP500_Volatility	9	8661	145.269	0.000
SP500_Volatility does not Granger Cause VIX	10	8660	11.8018	0.000
VIX does not Granger Cause SP500_Volatility	10	8660	135.078	0.000

The Granger Causality Test examines whether one time-series can predict another. In our empirical findings, we have conducted tests between the volatility of S&P 500 and VIX Index with a sample of 8623 observations and 10 lags. Since the p-value (Prob.) is lower than 0.05, we reject the null hypothesis for all cases. This means that the volatility of S&P 500 does Granger Cause VIX Index, suggesting that the past volatility values of the S&P 500 can predict the VIX Index. The results indicate that there is a bidirectional Granger Causality between the volatility of S&P 500 and VIX Index, implying that past values can be used to predict each other. These findings suggest interconnectedness of these two financial instruments.

Conclusion

The causality relationship between the volatility of the S&P 500 index and the CBOE Volatility Index (VIX) was investigated in this study using the Granger-Causality Test. The result demonstrates a significant two-way Granger causality, which suggests that the volatility of the S&P 500 in the past can be used to predict the price of VIX in the future, and vice versa. This

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relationship emphasizes the dynamic nature of these financial instruments, where change in one can help forecast another.

This predictability can enhance risk management strategies and improve investment decision-making. Investors can use this insight to adjust their portfolio and improve their hedging strategies. For policymakers, understanding this dynamic helps to design and stabilize financial markets during periods of high volatility.

These findings can be expanded by studying how GDP, interest rates, and exchange rates affect S&P 500 and VIX volatility. The relationship between volatility indices in global stock markets can be examined via cross-market research. Moreover, the effects of major global events could also be explored.

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Appendix 2. Litrature Review Table

Name of Authors	Year	Country/Region	Variables	Main Finding	Methods	Period
Isiaq Olasunkanmi Oseni, Philip Ifeakachukwu Nwosa	2011	Nigeria	GDP, İnflation Rate, İnterest Rate, Stock Returns	Stock market volatility and real GDP have a relationship; stock market volatility and interest rate and inflation rate volatility have no relationship.	Co-Integration And Multi-Variate Vector Error Correction Model Approach	1986-2010
Abu Hassan Shaar Mohd Nor, Lida Nikmanesh	2016	Malaysia and Indonesia	Consume Price İndex, Exchange Rate, İnterest Rate, İndustrial Production İndex, Money Supply, Trade Openness	Stock market volatility and trade openness explains 81% of volatility in Malaysia and 75% in Indonesia.	GARCH	1998-2013
Chi-Tai Lin, Yen-Hsien Lee	2010	United States	S&P 500, VIX, İmplied Volatility	Significant jump-diffusion process and bi-directional casual relationship between S&P 500 returns and VIX changes.	CBP-GARCH	2001-2009
Isao Ishida, Michael McAleer, Kosuke Oya	2011	United States	S&P 500, VIX Index, High-Frequency İntraday Data	Proposed new method for estimating leverage parameter in stochastic volatility models, which delivers more accurate estimates compared to existing methods.	Continuous-Time Stochastic Volatility Model, GMM	2003-2007
Natalia Roszyk, Robert Ślepaczuk	2024	United States	S&P 500 İndex, VIX, Log Returns, Lagged Volatility	Hybrid LSTM-GARCH significantly outperforms traditional GARCH models in predicting S&P 500 volatility	GARCH, LSTM, Hybrid LSTM-GARCH With VIX	2000-2023
Angelos Kanas	2012	United States	VIX Squared, Conditional Variance, S&P 500 Returns, VIX	Adding VIX squared in the conditional variance equation of GARCH models uncovers a positive risk-return relation.	GARCH(1,1)-M, GARCH With And Without VIX Squared	1990-2006

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Giang Thi Huong Vuong, Manh Huu Nguyen, Wing Keung Wong "	2022	United States	VIX, S&P 500 Returns, NASDAQ Composite Returns, Market Leverage, Long-Term Market Leverage, Short-Term Market Leverage	Increase in VIX postively impacts corporate leverage, particulary long-term market leverage	Panel Model, OLS Regression, Two-Stage Least Squares (2SLS)	2000-2019
David E. Allen, Michael McAleer, Robert Powell, Abhay K. Singh	2013	United States	S&P 500 Returns, VIX	Non-parametric and entropy-based measures reveal changing patterns in the relationship between the S&P 500 and VIX, particularly around the Global Financial Crisis. There is significant uncertainty and asymmetry in the distributions of both indexes, with varying information flow over time	Non-Parametric Tests, Entrophy-Based Quantile Regressions	1990-2011 (focus on 2003-2011 with new VIX)
Stavros A. Degiannakis	2008	United States	S&P 500 Returns, VIX, Realized Volatility (İnterday, İntraday), Conditional Volatility	Implied volatility from the VIX index alone provides all the necessary forecasting information for the next day's VIX value. Neither realized volatility nor conditional volatility adds incremental predictive value	Fractionally Integrated ARMA	1990-2003
Irena Vodenska, William J. Chambers	2013	United States	S&P 500 Index, VIX, 1-Month And 3-Month T-Bill Rates	VIX tends to overestimate S&P 500 volatility during stable market periods and underestimates it during high volatility periods. VIX is better related to past S&P 500 volatility than predictive of future volatility	Regression Analyses, Correlation, R-Squared Values	1990-2009

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Akhilesh Prasad, Priti Bakhshi, Arumugam Seetharaman	2022	United States	Economic Policy Uncertainty İndices, Gold Price, USD Index, Crude Oil Prices, Financial Stress İndex, M2, TED Spread, İnitial Claims, Fed Rate	U.S. macroeconomic variables such as the Economic Policy Uncertainty (EPU) indices, gold price, and the USD index are strong predictors of VIX movements (unidirectional). The TED spread and Financial Stress Index are positively associated with the VIX	Machine Learning Classification (Light GBM, Xgboost, Logistic Regression)	2007-2021
Fabio Bellini, Lorenzo Mercuri, Edit Rroji	2020	United States	S&P 500 Returns, İmplicit İnterexpectile Differences, VIX	Negative dependence between the S&P 500 and both implied volatility indices (VIX and interexpectile differences), and a positive dependence between VIX and interexpectile differences. The dependence structure displays asymmetry and strong tail dependence, which aligns with the leverage effect	ARMA-EGARCH, Copula Modeling	2003-2013
Ming Jing Yang, Meng-Yi Liu	2012	Taiwan	TVIX (Taiwan Volatility Index), İmplied Volatility, Trading Volume, Put-Call Ratios	The TVIX is a strong predictor of future stock market volatility, outperforming GARCH models and historical volatility in Taiwan's emerging market.	Regression Analysis, Volatility Forecasting Models	2006-2010
Daniel Jubinski, Amy F. Lipton	2013	United States	Gold, Silver, Oil Futures Returns, VIX, S&P 500 Volatility, USD İndex	Gold and silver respond positively to implied volatility (VIX), while oil has a negative relationship with implied volatility. These effects are amplified during recessions.	GARCH Models, Contemporaneous And ımplied Volatility Analysis	1990-2010
Łukasz Markowski, Jakub Keller	2020	United States	80 Macroeconomic Variables İncluding U.S. Unemployment Rate, ISM Manufacturing PMI, GDP, Core PPI	Variables related to the labor and housing markets have the strongest impact on VIX, especially the U.S. Unemployment Rate and ISM Manufacturing PMI. Differences between forecast and actual data significantly affect market volatility.	Correlation Analysis, Logit Modeling	2009-2019

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Katja Ahoniemi	2008	United States	VIX, S&P 500 Returns, Trading Volume, Macroeconomic İndicators (E.G., LIBOR)	The ARIMA(1,1,1) model with GARCH errors predicts VIX direction correctly on over 58% of trading days. S&P 500 returns have explanatory power, but trading volume does not.	ARIMA-GARCH Model, Simulation	1990-2007
Tiffany Grosvenor, Kevin Greenidge	2013	Caribbean (Barbados, Trinidad and Tobago, Jamaica)	Composite İndex Of Each Stock Market, NYSE İndex	Significant volatility spillovers exist between regional stock exchanges and the NYSE, indicating regional stock market co-movements with developed markets	Univariate And Multivariate GARCH Models	2005-2010
Katherine Smith, George Sofianos	1997	Global	NYSE Listing, Trading Volume, Stock Prices, Turnover Ratios, 128 Non-US Stocks	NYSE listing leads to a 42% increase in combined trading value, with a 24% increase in home-market trading. NYSE listings benefit both the U.S. and home markets.	Regression Analysis	1985-1996
Roni Bhowmik, Shouyang Wang "	2018	Emerging Asia and Developed Countries (India, China, Bangladesh, Malaysia, Philippines, South Korea, USA, UK, Japan, Singapore)	Stock Returns, Volatility, Financial Crisis İmpact (GFC, Brexit)	Strong volatility and return linkages exist between emerging Asian and developed markets, with the US having the most significant influence. Neighboring markets influence volatility.	GARCH Family Models, VAR, Cross-Correlation Function (CCF), Causality Tests	2007-2016
Imlak Shaikh	2020	United States	VIX, economic policy uncertainty index (EPU), commodity prices, exchange rates, interest rates	Policy uncertainty increases volatility in equity, commodity, and currency markets. The 2008 financial crisis and elections significantly impacted the volatility indices.	GARCH Models, Correlation Analysis	2000-2018

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Appendix-2. Volatility of SP500-GARCH (1,1) Model

Dependent Variable: Return of SP500
Method: ML ARCH - Generalized error distribution (GED) (BFGS / Marquardt steps)
Sample (adjusted): 1/05/1990 6/05/2024
Included observations: 8670
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000738	7.71E-05	9.562175	0.0000
RETSP(-1)	-0.034769	0.010838	-3.207963	0.0013
RETSP(-2)	-0.025596	0.010403	-2.460416	0.0139
Variance Equation				
C	1.28E-06	1.96E-07	6.551290	0.0000
RESID(-1)^2	0.098110	0.007125	13.77064	0.0000
GARCH(-1)	0.893290	0.007351	121.5170	0.0000
GED PARAMETER	1.316571	0.024098	54.63339	0.0000

R-squared	0.002959	Mean dependent var	0.000313
Adjusted R-squared	0.002729	S.D. dependent var	0.011417
S.E. of regression	0.011401	Akaike info criterion	-6.598168
Sum squared resid	1.126617	Schwarz criterion	-6.592462
Log likelihood	28610.06	Hannan-Quinn criter.	-6.596223
Durbin-Watson stat	2.090955		