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EMPIRICAL ANALYSIS OF THE CAUSAL RELATIONSHIPS OF SPILLOVERS IN THE VOLATILITY OF THE S&P-500 INDEX

Abstract

The volatile nature of the relationship between the stock index and the stocks which stand for it, is revealed. The directions of volatility spillovers are studied in the context of the transformation of causal relationships. The article analyses the interrelationships and volatility spillovers between the S&P-500 index and the shares of META and GOOG (technology sector), JPM and BAC (financial sector), MRO and OXY (oil and gas sector), which are included in the index. The research methodology is based on the GARCH (1,1) model, which allows considering the development of variance over time and the dynamics of conditional volatility of time series. The identified interdependencies are focused on forecasting volatility spillover shocks from the S&P 500 to stocks and vice versa.

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spillover of volatility; Granger causality; GARCH (1,1) model; S&P-500 index; conditional volatility.

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4 figures, 1 table, 15 references.

Problem Statement and Literature Review

On the one hand, the volatility of stock market indices' returns has led to a large number of empirical studies, and on the other hand, it has created the demand for new scientific approaches that would allow identifying and substantiating the directions of the causal relationships.

Empirical studies using Norwegian data on the returns of the OSLO All-Share stock index and Brent crude oil show that their causality is time-varying (Raifu, 2023). Isiaka Akande Raifu's study argues that monthly and weekly stock returns show a one-way casual effect on monthly and weekly oil returns, i.e., fluctuations in stock market trading affect the price of oil, yet not vice versa. However, for daily returns, the causal relationship is bilateral. Other studies have found a bilateral causal relationship between the oil price and the stock market index using monthly data from Russia and China (Ghedira & Nakhli, 2023).

In some studies, symmetric and asymmetric causality is tested, while taking into account different data frequencies, where the stock market is one of the variables (Yilanci et al., 2021; Demirtaş et al., 2021; Hatemi-J, 2022). The results of the Toda-Yamamoto test for dynamic Granger causality confirm the absence of any relationship between stock prices and exchange rates using Iranian data (Siami-Namini, 2017). Using the Granger causality test for the time series of return volatility of the RKLCI (Malaysia), RLQ (Indonesia), and RSET (Thailand) stock market indices, the existence of a two-way causality is revealed (Lim et al., 2023).

The aforementioned relationships are complemented by similar studies, showing a bilateral causality between the Nifty stock market index (India) and the USD/INR currency pair and oil prices, as well as a unilateral causality between the Nifty index and gold, Bitcoin, and government bond yields (Rawlin et al., 2022). This means that each variable contains useful information for predicting the Nifty index. However, the unidirectional causality between stock indices and cryptocurrencies may disappear during periods of high volatility (Mgadmi et al., 2024).

A modified Granger causality test based on the types of GARCH models can be used to identify the effects of volatility spillovers in international markets, which creates opportunities for risk diversification (Zarezade et al., 2024; Yadav et al., 2023). The direction of Granger causality changes depending on the phases of economic cycles, which affects volatility spillovers (Yadav et al., 2023; Jiang et al., 2022; Ozdemir, 2020). The usage of methods and models that take into account the development of variance over time allows for more accurate results in assessing causality rather when it is assumed that the variance is a constant (Ozdemir, 2020).

The existing empirical evidence on the causal relationships between stock market indices in different countries and some other variables (other asset classes and their markets) contains inconsistent results to draw a clear conclusion. Among the research papers mentioned previously, the most similar to the problem raised in this article is the study by Dong Tung Lim et al. (Lim et al., 2023). However, they focused on the causal relationships of volatility between stock indices of some Southeast Asian countries, while this article is devoted to the study of the causal relationships of volatility of the S&P-500 (US) stock index, not with other indices, yet with the stocks included in the S&P-500.

The purpose of the article is to reveal the interdependencies of volatility between the S&P-500 stock index and its constituent stocks in the context of the information technology, financial and oil and gas sectors of the economy.

Methodology

The problem in anticipating the volatility dynamics of stock indices, including equities, is that their returns do not follow the normal Gaussian and Laplace distribution law. The violation of the normal law of the distribution of returns is a subject of debate in the field of financial economics in general, and portfolio investment theory in particular. Heavy tails in the distribution of returns indicate the emergence of sharp extreme deviations from its mean in the price dynamics. Stock market participants are more concerned with extreme negative returns, since such values are directly related to a possible loss from an investment. In the portfolio investment paradigm (Sortino F., 1994), the emphasis was shifted from total risk to downside risk. Calculating that part of the volatility (standard deviation) which contains a series of values of only negative returns is an important task, as it provides information on how much return is attributable to each unit of downside risk.

Extreme negative returns characterise financial crashes on stock exchanges. It may happen that they (crashes) occur simultaneously on several exchanges. The question may arise as to whether one of the exchanges can be a harbinger for another. The necessity to monitor the fluctuations of the stock exchange index not only of one market, as well as of others, can be justified by the fact that current deviations of the stock exchange index may be the result of news from another exchange. In other words, one stock exchange can interpret the behaviour of another.

The pairwise modelling of the casual relationship between stock indices and stocks fits well into the Granger's paradigm of testing causality between two variables. As shown by (Granger, 1969), using two regression equations, it is possible to test time series for causality. The establishment of casual relationship between two variables helps to ensure the existence of cases when the variance of Y_t can be explained by its past values and the past values of X_t included in the model, which should improve this explanation. In this article, we use the Granger causality test, a procedure for evaluating the casualness of relationships between dynamic time series.

Let us consider a causal connection between X_t and Y_t. The model will have the following form:

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t \ ,$$

$$Y_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + w_t \ ,$$

where X_t, Y_t – variables, the causal relationships of which are being investigated;

a_j, b_j, c_j, d_j – autoregressive coefficients;

ε_t, w_t – inaccuracies.

Dependency testing will allow us to analyse the causal relationships of the S&P 500 index volatility in terms of the following hypotheses:

1. There is a one-way causal relationship between X_t and Y_t. That is, the volatility of the stocks included in the S&P 500 index determines the volatility of the index itself, but not vice versa.

2. There is a two-way causal relationship between X_t and Y_t. That is, the volatility of the stocks included in the S&P 500 index determines the volatility of the index itself and vice versa.

3. There is no causality between X_t and Y_t according to the Granger causality test.

Granger causality is confirmed by accepting the alternative hypothesis that X_t has an effect on Y_t and, accordingly, rejecting the null hypothesis that X_t does not affect Y_t. For the alternative hypothesis to be true, the p-value of the examined pair of stock indices must be less than the significance level of 0.05.

The conditional volatility in the GARCH model is described by the equation:

$$\sigma_t^2 - \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 \ldots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_p \sigma_{t-q}^2$$

where q – number of lagged variances;

p – number of lagged residuals.

The article identifies the causal relationship between the volatility of the S&P-500 stock index and the volatility of the stocks included in its calculation in the context of three sectors of the economy, namely: Meta Platforms, Inc. and Alphabet Int. (information technology sector); JPMorgan Chase & Co and Bank of America (financial sector); Occidental Petroleum and Marathon Oil Corporation (oil and gas sector). The closing prices of the indices are extracted from Yahoo Finance. The time period covered is from 2018-01-01 to 2023-12-31.

Research Results

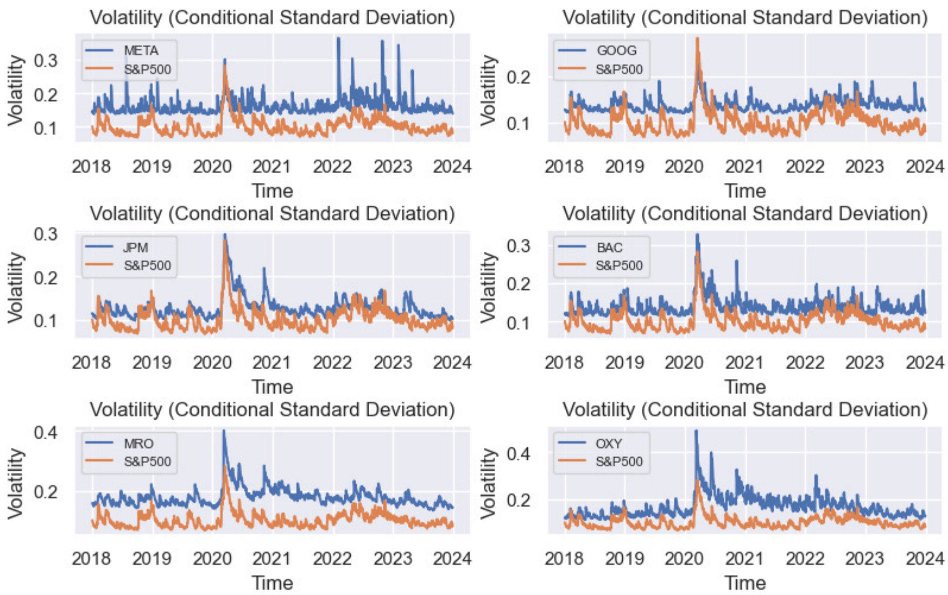
Volatility dynamics, or as well referred to as fear dynamics, is one of the main indicators of financial markets. It reflects the level of risk, so determining the processes of volatility spillovers between markets is an important task from both a practical and theoretical point of view. The problem of difficulty in predicting possible spillovers of volatility shocks in financial markets makes us think about the causal relationships that exist in the patterns of market development. In making investment decisions, it is crucial to have an understanding of volatility spillovers not only between individual assets and stock indices, but also between an index and its constituent stocks, as this understanding may serve as a signal for making the right investment decision and can help to anticipate certain undesirable volatility transitions.

A sudden change in the level of concern among stock market participants about the prospects for a particular sector of the economy may affect all other sectors included in the calculation of a stock index. In addition, changes in the volatility of stocks may have different effects on the volatility of a stock index. In general, the system of relationships between stock volatility and the index is manifested through the spillover effect, which increases the overall volatility of the stock index. Comprehension of the spillover effect of volatility shocks based on GARCH and Granger causality models helps investors to grasp the interdependencies in such complex systems as stock indices.

To determine the relationship between the volatility of the S&P-500 index and the volatility of the stocks that represent this index, the GARCH (1,1) model of the orders is applied. Based on the results of estimating the GARCH (1,1) model, we have plotted the dynamics of the conditional volatility of the S&P-500 index and its constituent stocks. As shown in Figure 1, during the recession caused by the COVID-19 pandemic, which occurred in the US in the second quarter of 2020, there was a rapid increase in the volatility of the index and stocks.

Figure 1

Conditional volatility determined by the GARCH (1,1) model



Source: Author's own calculations.

In addition, it is worth noting that the conditional volatility of META's stock, compared to other stocks and the S&P 500 index, shows higher fluctuations in 2022-2023. The increase in volatility can be explained by the fact that in the fourth quarter of 2022, the company's net profit more than halved. However, it might be assumed that this happened due to the spillover of volatility from other stocks, for which, for instance, investors' positive expectations have declined. Theoretically, the current variance of META stock can be described by its past values and past return shocks, as well as by the past variance and past return shocks of the S&P 500 index. Thus, there is a necessity to find out the interdependence of volatility of META stock and the S&P-500 index, which may reflect the general market sentiment. In order to identify the direction of the causal relationship of volatility, the Granger causality test was used. The results are shown in Table 1. As can be seen, the assumption is false, since the S&P 500 index is not a Granger causality for META, i.e. the index does not affect META and there is no spillover of volatility from the S&P 500 to META.

Table 1

Results of Granger causality estimation based on the GARCH (1,1) model

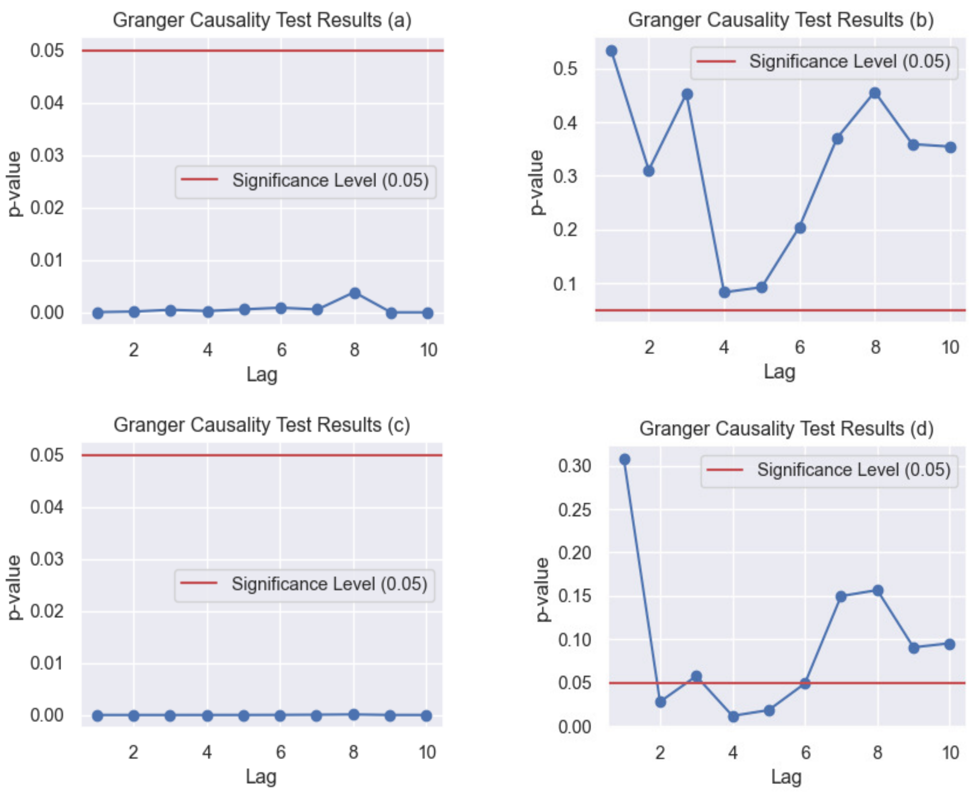
Economy Sector	Null hypothesis	p-value	Assessment result
Technology	META is not causality according to Granger for the S&P-500	2.E-02	Refuting
	S&P-500 is not causality according to Granger for the META	0.3545	Not Refuting
	GOOG is not causality according to Granger for the S&P-500	3.E-36	Refuting
	S&P-500 is not causality according to Granger for the GOOG	0.0953	Not Refuting
Financial	JPM is not causality according to Granger for the S&P-500	9.E-05	Refuting
	S&P-500 is not causality according to Granger for the JPM	0.0261	Refuting
	BAC is not causality according to Granger for the S&P-500	3.E-13	Refuting
	S&P-500 is not causality according to Granger for the BAC	0.0572	Refuting
Oil and gas	MRO is not causality according to Granger for the S&P-500	0.0043	Refuting
	S&P-500 is not causality according to Granger for the MRO	8.E-05	Refuting
	OXY is not causality according to Granger for the S&P-500	0.0015	Refuting
	S&P-500 is not causality according to Granger for the OXY	1.E-05	Refuting

Source: Author's own calculations.

However, the volatility of the META causes the volatility of the S&P-500. Thus, there is a unidirectional causality between META and the S&P-500 according to the Granger causality test. The same conclusion applies to the causality between GOOG and the S&P-500. It appears to be unidirectional, i.e. GOOG transmits volatility to the S&P-500, but there is no reverse relationship. In fact, Figure 2 reveals that in the case of detecting a causal relationship from META to the S&P-500, as well as from GOOG to the S&P-500, the p-value at all lags is below 0.05. While the direction of causality from the S&P-500 to META and GOOG is detected, the p-value is not below 0.05 at all lags.

Figure 2

P-values found at different lags



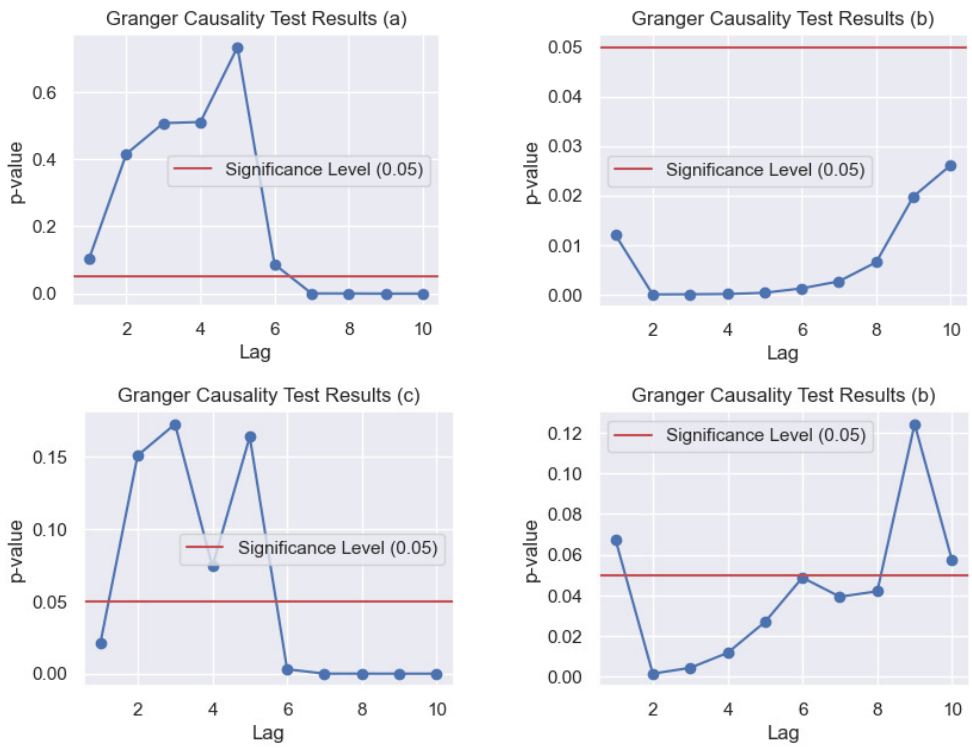
Source: Author's own calculations.

Note: (a) – from META to S&P-500; (b) – from S&P-500 to META; (c) – from GOOG to S&P-500; (d) – from S&P-500 to GOOG.

In terms of the volatility of financial sector stocks, their relationship with the S&P 500 index is bilateral. In Figure 3 graphs (a) and (c) indicate the existence of a peculiarity in the relationship between JPM and the S&P 500, as well as between BAC and the S&P 500, in that there is no transmission of volatility from lag 2 to 5, but starting from lag 6, it stabilises below 0.05. This indicates a delayed yet significant dependence when the volatility of the shares of the largest US and global banks increases and is transmitted to the S&P 500 index. Simultaneously, the S&P 500 transmits volatility to these banks, according to Granger causality.

Figure 3

P-values found at different lags



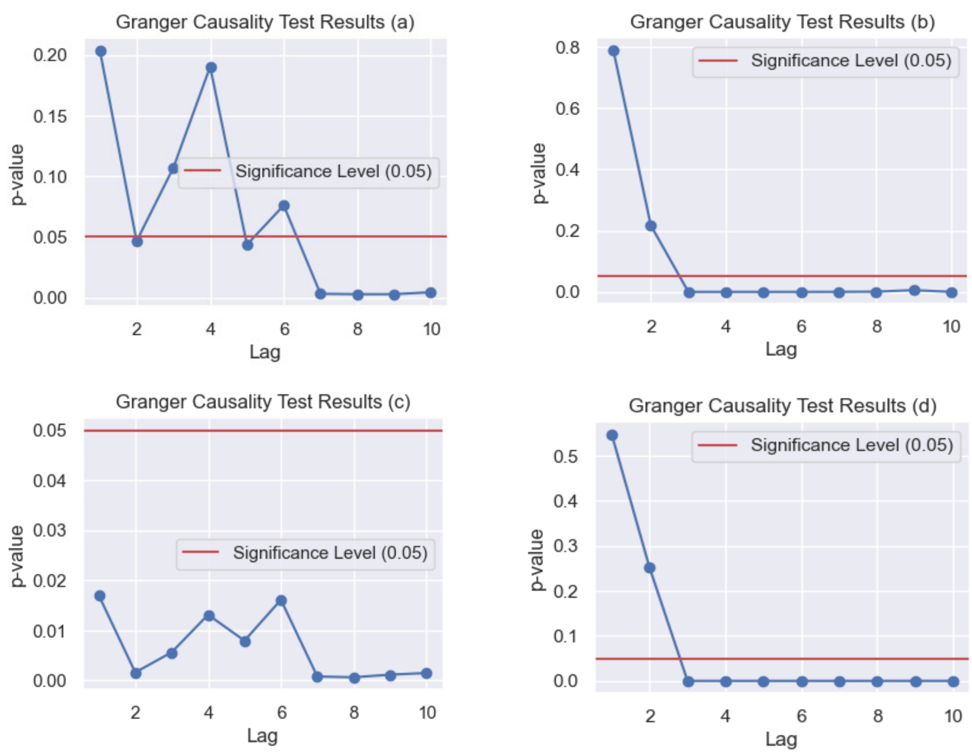
Source: Author's own calculations.

Note: (a) – from JPM to S&P-500; (b) – from S&P-500 to JPM; (c) – from BAC to S&P-500; (d) – from S&P-500 to BAC.

As for the transmission of volatility by oil and gas sector companies, their relationship with the S&P 500 is similarly bilateral. Therefore, the S&P 500 both receives and transmits the volatility of MRO and OXY. In Figure 4, graphs (b) and (d) illustrate the specifics of volatility transmission by the S&P 500 to MRO and OXY stocks. It implies that the p-values at lags 1 and 2 are not statistically significant. This indicates a weak causal relationship, i.e., at the first and second preceding time points, there is no transmission of volatility from the S&P-500 to oil and gas companies. However, starting from lags 3 to 10, the p-value is below 0.05. Thus, MRO and OXY subsequently respond to volatility transmission shocks from the S&P 500.

Figure 4

P-values found at different lags



Source: Author's own calculations.

Note: (a) – from MRO to S&P-500; (b) – from S&P-500 to MRO; (c) – from OXY to S&P-500; (d) – from S&P-500 to OXY.

Conclusions

Granger causality based on the GARCH (1,1) model showed various results for the relationships between the S&P 500 and its constituent stocks. The relationship between the S&P 500 and companies in the technology sector is unilateral. There is no volatility spillover from the S&P 500 to META and GOOG. The volatility spillover estimation allowed us to establish a bilateral volatility between the S&P 500 and oil and gas companies. The transmission of volatility from the S&P 500 is due to the fact that oil and gas companies are unstable, as they often find themselves among the outsiders of the S&P 500 index.

The volatility of the S&P 500 is not transmitted to the leading companies in the technology and financial sectors, which also account for the vast majority of the S&P 500's returns according to Granger causality. The transmission of shocks between the S&P 500 and financial sector companies is two-way. That is, volatility spills over from the financial sector to the real economy and vice versa.

Prospects for further research should focus on analysing the interrelationships and volatility spillovers between stock indices of various national economies and their constituent stocks. This particular relationship is poorly understood, as most recent studies have examined the relationship directly between individual indices. The study of the relationships between the components of an index is a source of valuable information about which stocks actually increase the volatility of the index and which actually transmit volatility to the index. The findings of the study will be useful in diversifying risks and forecasting the return on financial instruments by stock market participants.

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