www.revistageintec.net
ISSN: 2237-0722
revista GEINTEC
Gestão, Inovação e Tecnologias

An Analysis of Inter-Relationship among Commodities, Stock and Economic Indices

Sahil Gupta[1]; Madhvi Sethi[2*]
[1]Symbiosis Institute of Business Management, Bengaluru, Karnataka, India.
[2*]Symbiosis International (Deemed University), Pune, Maharashtra, India.
[2*]madhvi.sethi@sibm.edu.in

Abstract
This research will concentrate primarily on commodity relationships, mainly, prices of oil (OP) and gold (GP), US stock market (S&P500), consumer confidence index (CCI), the US Dollar index (USDX), and the industrial production (IP). The purpose of the analysis is to study the dynamic interconnection between OP, USDX, CCI, GP, IP, and S&P500, by estimating the Vector Auto Regression (VAR) model. OP, CCI, GP, USDX, S&P500, and IP are the different variables used in this paper. Using monthly data from January 1971 to May 2020, this study applies the Granger causality test, Variance Decomposition (VDC) analysis, and Impulse Response Function (IRF). It can be inferred from the results that USDX has a significant relationship with GP and has a causal impact on GP. Industrial Production has also shown a significant relationship with S&P500 and has a causal impact on S&P500. The result also suggested that CCI and S&P500 share a unidirectional relationship; the volatility in CCI in the short run is due to the S&P500. Also, the variables do not have any other significant relationship. The findings also highlighted that USDX directly affected GP negatively. Industrial production directly impacted S&P500 in the short run, while a positive relationship is shared between CCI and S&P 500.

Key-words: Commodity, Economic Indices, Gold Price, Oil Price, Consumer Confidence Index, Industrial Production, S & P500, USDX, Vector Auto Regression, Granger Causality.

1. Introduction

Prices of Gold and Oil have also had a huge effect on the financial system and all aspects of the US economy, seen in both the financial and real sectors of industrial production, consumption, and investment.

The stock market can assess what the economy's financial sentiment is. Much work has been carried out to establish a connection between the OP, GP, and stock S&P 500. It has generally been found that GP and stock markets index (SMI) are highly negatively correlated in times of recession, suggesting gold serves as a hedge when the sentiments are bearish on the economy [1].

Some important metrics like Consumer Confidence Index, US Dollar Index and Industrial Production might also significantly affect GP, OP, stock market, and themselves. If the unemployment rate is high, it might affect the CCI, which in turn has an impact on the demand that may lead to a decrease in Industrial Production, ultimately affecting the S&P 500. As SMI is the clear indicator of market and business sentiment and, as gold is considered a safe-haven investment, eventually it will lead the investors to withdraw and invest money from the stock market to gold, resulting in raising its prices. There can exist many links among these variables these, which will be established in this study [2].

Very few studies have established a relationship between OP, CCI, GP, IP, S&P500, and USDX. These indexes are some of the most frequently used metrics to determine the strength and state of the economy. This paper aims to identify any relationship among these variables. If there exists one, then which factor has the highest impact on that relationship.

2. Review of Literature

A study conducted by Young (2006), to understand the relationship between real activity (Industrial production) and the SMI return, suggested that despite the expectation of breaking down of relationship between the two due to the transformation of the US economy from a manufacturing to establishing itself as a service-oriented economy in the latter part of the 20thcentury, it was observed that the relationship not only continues to exist but also have appeared to strengthen [3].

To understand the dynamics between S&P500 returns, OP, exchange rate, and GP, Sujit & Kumar, in their research, revealed that the exchange rate is highly impacted, as there are shifts in other variables. It also found that S&P500 was impacted far less by the exchange rate.

Another study by Ewing & Thompson focused on the cyclical movement of OP along with industrial production, S & P500, and other variables. They found that after using a variety of significant cyclical relationships and three separate time series, OP is procyclical and is lagged to IP.

The analysis by Junttila et al., studying the hedging of commodities against the stock market during financial crises, highlights that oil futures and US equities share a positive correlation. Simultaneously, it is negative between the futures of oil and gold, which was important because, in times of crisis, market and investor sentiment shifts, and individual risk ability declined significantly [4].

To further explore the interconnection between investor sentiment and S&P500 index and gold returns, a study by Piñeiro-Chousa et al. suggested that there existed a causal relationship between S&P500 and gold prices. The study also observed that gold returns influenced the S&P500 volatility and that the sentiment of experienced users has an impact on S&P500 returns.

Studying the interconnection in the United States between industrial production, interest rate, aggregate S&P500, inflation, and real exchange rate, Kim, in his article, observed that S&P500 is positively linked to IP. However, it is negatively related to the exchange rate [5].

Another study examining the relation between CCI and S&P500 by Hsu et al. discovered that CCI and S&P500 share a bi-directional causality. As SMI triggers CCI shifts, and as S&P500 returns serve as the leading indicator, customers view it as the market feeling directly affecting their sentiments. The variations in the CCI often result in Granger-cause S&P500 returns because of the animal spirits perception of consumers.

While the belief in a causal relationship between GP and S&P500, as suggested by Piñeiro-Chousa et al., holds in most cases, it is important to understand that it might not be necessarily true in every case. In Malaysia, research by Hussin et al. suggested that this hypothesis is not accurate. The study suggested that the GP is not a relevant variable to predict variation in Islamic share prices. At the same time, it also suggested that OP and SMI share a two-way causal relationship. In contrast, the GP, on the other hand, had no effect on the SMI, or vice versa. It can, therefore, be assumed that in the short-term, stock returns in Malaysia were influenced only by the price variables of the OP [6].

The relationship between the S&P500 and the CCI can be further extended by studying the relationship in another developed nation other than the United States to test whether the results differ. It was indicated in the paper by Kloet that CCI is greatly affected by the European Union stock market. It matches the finding of the study by Hsu et al.

The dynamics between financial markets and commodities, revealing the presence of long-term equilibrium among GP, OP volatility, GP volatility, OP, and SMI, was examined by Gokmenoglu & Fazlollah to provide another critical research.

The importance of investment during financial crises remains a challenge. How the investor sentiment changes during crises and what impact it has on the stock markets was shown by Bolaman & Evrim Mandac in their study. Their study indicated that CCI and SMI shared a long-term relationship.

Understanding the market and investor sentiment is a challenge. It remains a very important part of an investment in the developed economies. Low market returns are usually preceded by periods of high consumer confidence, as observed by Ho & Hung in their study to determine the impact of investor sentiment on returns and volatility in the United States, France, and Italy economy. Further, conditional volatility in most countries is significantly caused by a shift in the sentiment [7].

To explain the relationship between OP shocks and SMI and examine the relationship transitions by shifting focus from developed to emerging economies, Maghyereh conducted research, taking into account 22 emerging countries, concluding that OP shocks have no substantial effect on SMI returns.

Cobo-Reyes & Quirós, to examine the impact of OP on IP and SMI, shows that OP impacts IP and SMI returns in a negative and statistically relevant manner. Still, the effect on SMI returns is greater than that on IP.

The purpose of the analysis by Simakova was to examine and assess the character of the price-level co-movement. The study discovered a long-term association between GP and OP [8].

3. Data and Research Methodology

3.1. Source of Data

The study used secondary data to determine the interrelationship between Gold prices, Oil prices, stock market index, Consumer Confidence Index (CCI), Industrial Production, and US dollar index [9]. The data for gold prices was taken from (GoldHub.com) for oil prices from the US. Energy Information Administration, for stock index (S&P500), USDX, the data was taken from yahoo finance. For CCI and Industrial production, data was taken from the OECD website. The data collected is monthly for all the variables for 49 years, starting from 1971-01-01 to 2020-05-01 [10].

3.2. Research Method Used for Analysis

3.2.1. Stationarity Test

The Augmented Dickey-Fuller test is initially performed for all variables. If a unit root is absent, then it is assumed that the data at the level is stationary [11]. If the unit root is present, that implies the non-stationarity of the variables; then, they are made stationary through differencing until there is no root factor in them. The hypotheses for the test are presented below:

H0: Data is not stationary (Unit root is present)

H1: Data is stationary (Unit root is absent)

Suppose ADF statistics exceed the critical value at 95%. In that case, the H0 can be rejected, and the H1 is accepted, which means the data is stationary [12].

3.2.2. Lag-Length Selection

Minimum Akaike information criteria (AIC) are selected to select the optimal lag length. Before selecting the lag length, it is important to consider that if the VAR lag length is too short, it may not capture the dynamic behavior of the variables. If it is too long, then it will distort the data and lead to a decrease in power. Based on the results, the study chose four lags to be appropriate [13].

3.2.3. Vector Auto Regression (VAR) and Granger Causality

Finally, a VAR model is applied to estimate the dynamics in between the variables. A granger causality test is performed to determine the causal effect among them. For each series, the granger causality test is applied. The hypotheses for the test are presented below:

H0: Series1 does not granger cause series 2

H1: Series1 does granger cause series 2.

3.2.4. Variance Decomposition (VDC) Analysis and Impulse Response Function (IRF)

The coefficients that are derived from the VAR model estimate may not be relevant for direct interpretation. Hence, both the VDC and the IRF are used. IRF is used to determine if there are any dynamic relationships between variables [14], which also represent the dynamic response of each variable to all the variables within the system responding to a shock. VDC is used to test and evaluate whether the variables have a causal relationship between them, which also senses that due to a shock in one variable, up to what extent the variation in other variables is explained within the system [15].

4. Results and Analysis

4.1. Stationary Test Results and Discussion

In Table 1, the ADF test findings are presented to determine if the unit root is present and to assess the integration order in variables is presented [14]. The null hypothesis, H_0, the presence of unit root, cannot be rejected when tested on the data. Nonetheless, at the first difference, each variable is evaluated for lack of unit root, signifying that the order I (1) is built into the sequence [15].

Table 1 - ADF Test Statistics

Variables	Level	First Difference
	ADF	ADF
S&P500	-0.5554	-10.370*
GOLD	-0.95003	-7.9856*
OIL	-2.9192	-11.518*
CCI	-2.8097	-8.3954*
INDUSTRIAL PRODUCTION	-1.3573	-4.7500*
USDX	-2.7088	-9.4385*

*Denote significance at 1% respectively

For lag length selection, the one with the minimum AIC is selected. In this study, the optimum lag length is selected to be 4.

4.2. Granger Causality Results and Discussion

Table 2 presents the results of the Granger causality test. The outcome of the Granger causality test indicates that there are ten important causal relationships, namely DFS&P500 causes DFOIL, DFS & P500 causes DFCCI, DFS & P500 causes DFIP, DFGOLD causes DFOIL, DFUSDX causes DFGOLD, DFOIL causes DFCCI, DFOIL causes DFIP, DFS & P500 causes DFCCI. Two causal bidirectional relationships occur between DFS&P500 and DFIP and DFCCI and DFIP [16].

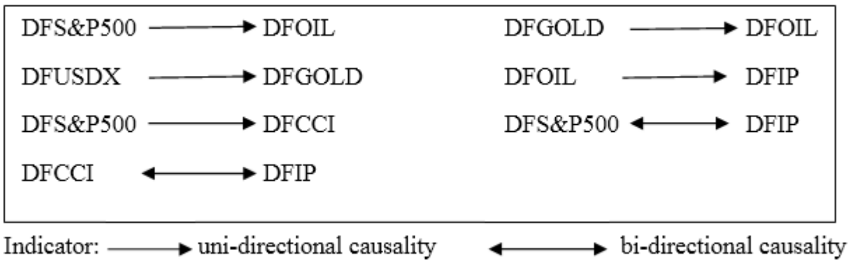
Table 2 - Granger Causality Result

H_0: NULL_HYPOTHESIS	F_STATISTICS	P_VALUE
DFS&P500 do not Granger Cause DFOIL	11.397	6.551e-09 ***
DFOIL do not Granger Cause DFS&P500	1.6902	0.1507
DFS&P500 do not Granger Cause DFGOLD	1.503	0.1998
DFGOLD do not Granger Cause DFS&P500	0.3762	0.8257
DFS&P500 do not Granger Cause DFCCI	11.063	1.185e-08 ***
DFCCI do not Granger Cause DFS&P500	0.5618	0.6905
DFS&P500 do not Granger Cause DFIP	32.814	< 2.2e-16 ***
DFIP do not Granger Cause DFS&P500	3.5267	0.007419 **
DFS&P500 do not Granger Cause DFUSDX	0.876	0.4779
DFUSDX do not Granger Cause DFS&P500	0.0803	0.9884
DFGOLD do not Granger Cause DFOIL	3.9185	0.003782 **
DFOIL do not Granger Cause DFGOLD	2.1933	0.06843
DFGOLD do not Granger Cause DFCCI	1.3936	0.2347
DFCCI do not Granger Cause DFGOLD	1.6926	0.1501
DFGOLD do not Granger Cause DFIP	0.6767	0.6083
DFIP do not Granger Cause DFGOLD	1.2296	0.2971
DFGOLD do not Granger Cause DFUSDX	1.0385	0.3866
DFUSDX do not Granger Cause DFGOLD	11.992	2.279e-09 ***
DFOIL do not Granger Cause DFCCI	5.5008	0.0002371 ***
DFCCI do not Granger Cause DFOIL	1.7341	0.1409
DFOIL do not Granger Cause DFIP	10.73	2.144e-08 ***
DFIP do not Granger Cause DFOIL	2.2821	0.0593
DFOIL do not Granger Cause DFUSDX	1.5211	0.1945
DFUSDX do not Granger Cause DFOIL	1.2419	0.2919
DFCCI do not Granger Cause DFIP	9.1863	3.355e-07 ***
DFIP do not Granger Cause DFCCI	3.9609	0.003515 **
DFCCI do not Granger Cause DFUSDX	0.538	0.7078
DFUSDX do not Granger Cause DFCCI	1.4395	0.2195
DFIP do not Granger Cause DFUSDX	0.3724	0.8283
DFUSDX do not Granger Cause DFIP	0.4533	0.77

***significant at 1%, ** significant at 5%, D/DF- First Difference

Figure 1 - Shows the Likeness of the Connection

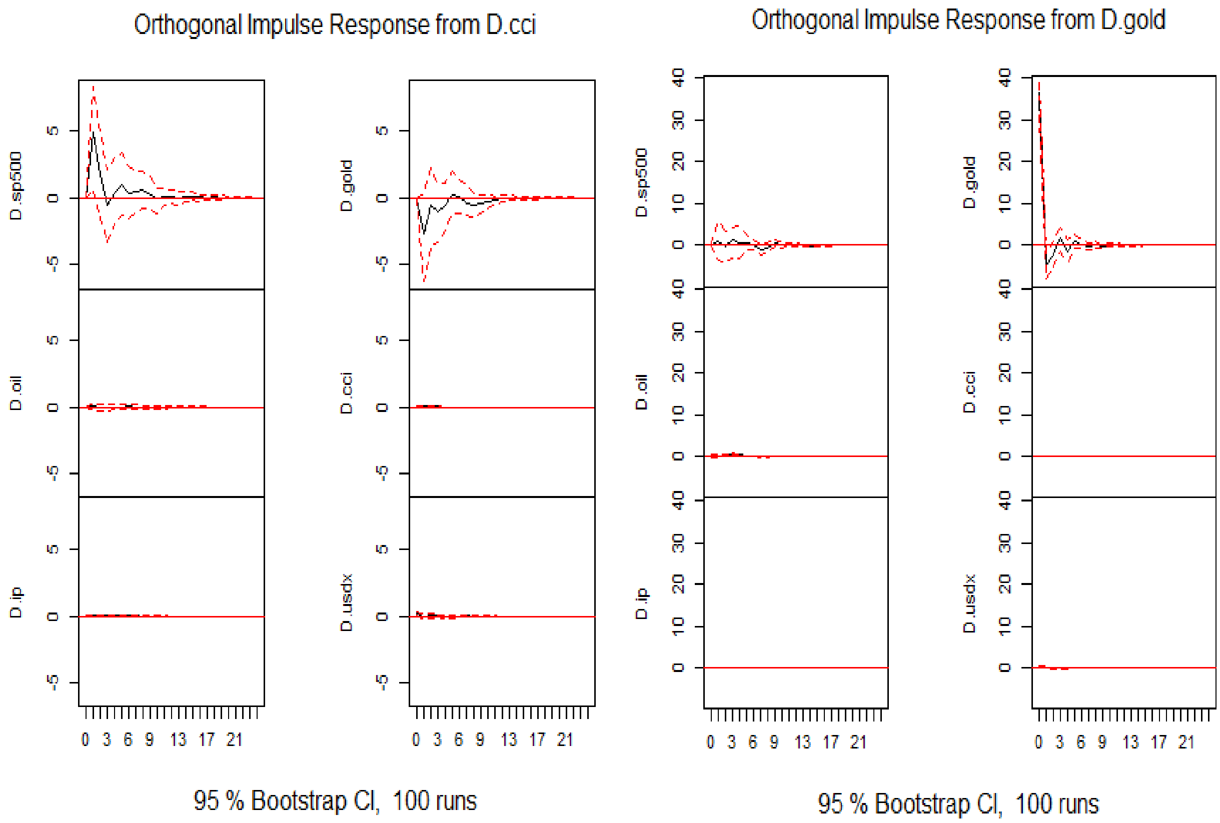
Figure 1 - Granger causal relationship: ANALYSIS



ISSN: 2237-0722
Vol. 11 No. 4 (2021)
Received: 26.07.2021 – Accepted: 30.08.2021

4.3. Impulse Response Function and Variance Decomposition Results and Discussion

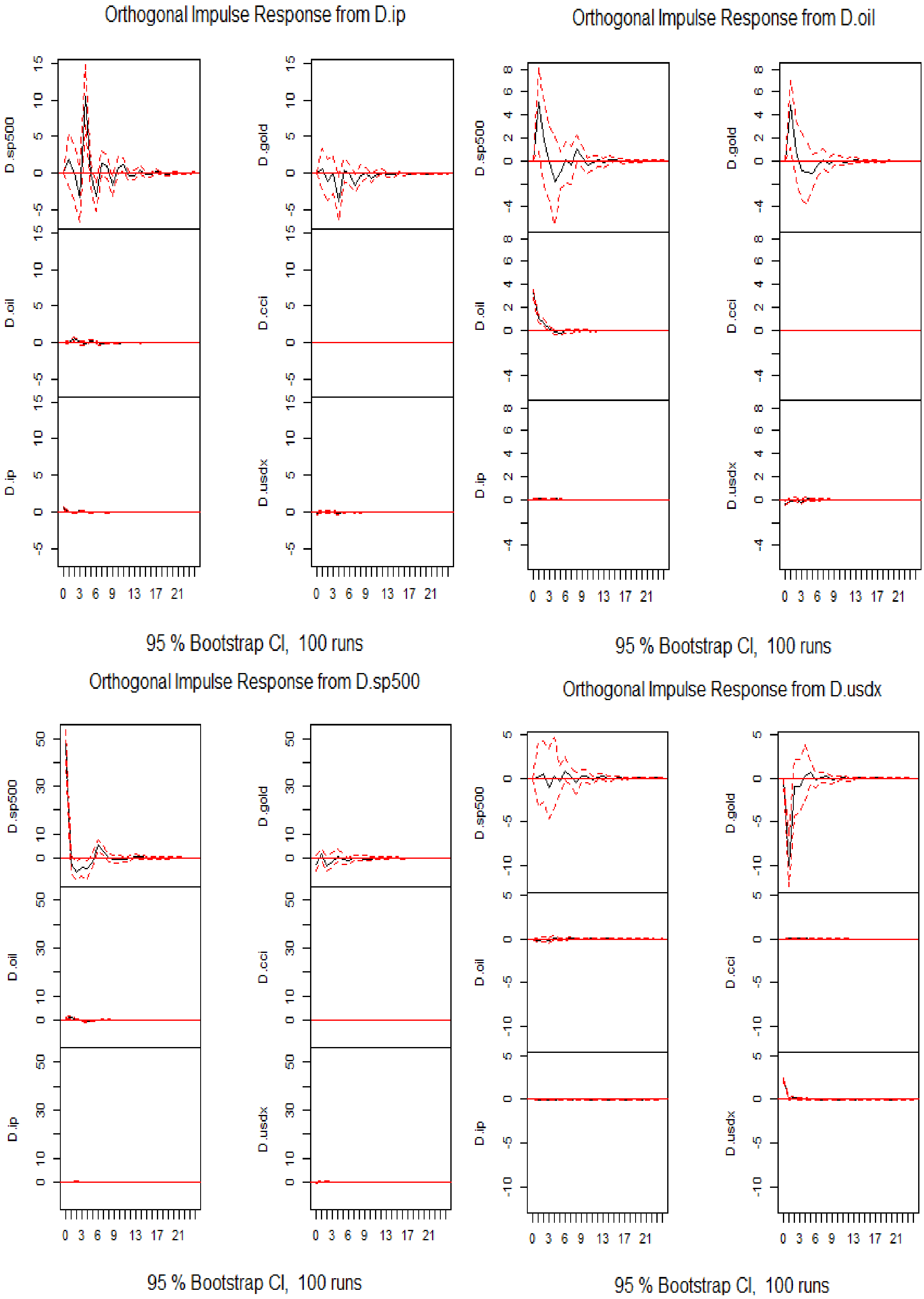
Upon applying the IRF, the results revealed that a shock in the DFS&P500 responds negatively to the DFGP, as seen in Figure 2. In the long run, it becomes stable and has very less impact. DFGP shock impacts positively on DFS&P 500 and is stable in the long term. A surprise in DFOP results in a favorable relationship with DFGP and DFS&P500. For DFS&P500, negative and for DFGP, a shock in CCI reacted positively. The shock in industrial production is positive at the start for both DFS&P500 and DFGP. Still, it is unstable, frequently fluctuating over time, A shock in the DFUSDX results in a positive response for DFS&P500 and strongly negative for DFGP [17].



D/DF denotes the first difference or Integrated of order 1.

ISSN: 2237-0722
Vol. 11 No. 4 (2021)
Received: 26.07.2021 – Accepted: 30.08.2021

Figure 2 - Results from the Impulse Response Function



The VDC analysis results are shown in Figure 3 and Table 3. While performing Variance decomposition, it was found that maximum variation in DFGP was due to DFUSDX of 6.61%. The

ISSN: 2237-0722
Vol. 11 No. 4 (2021)
Received: 26.07.2021 – Accepted: 30.08.2021

majority of the fluctuation in DFOP is due to DFS&P500, i.e., 14.49%, [18]. In comparison, DFS&P500 was also responsible for the maximum variation in DFCCI of about 24.40%. Results of VDC in differenced industrial production led to finding that DFS&P500 was responsible for the majority of the changes, i.e., 17%. [19].

Also, as shown in Figure 4, the model is run for a stability test. The results show that the model is stable [20].

Table 3 - VDC Analysis: Results

VCD OF	DURATION (MONTHS)	CHANGE IN					
		DFS&P500	**DFGOLD**	**DFOIL**	**DFCCI**	**DFIP**	**DFUSDX**
	1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	4	0.9696719	0.0009	0.0119	0.0110	0.0057	5.7723
	8	0.9222	0.0015	0.0128	0.0107	0.0516	8.9086
	12	0.9191	0.0018	0.0132	0.0108	0.0537	0.0010
DFS&P500	**24**	0.9189	0.0018	0.0132	0.0108	0.0539	0.00107
	1	0.0046	0.9953	0.0000	0.0000	0.0000	0.0000
	4	0.0134	0.8966	0.0164	0.0056	0.0009	0.0669
	8	0.0145	0.8838	0.0176	0.0058	0.0119	0.0661
	12	0.0148	0.8828	0.0176	0.0062	0.0122	0.0661
DFGOLD	**24**	0.0148	0.8827	0.0176	0.0062	0.0123	0.0661
	1	0.0507	0.0015	0.9476	0.0000	0.0000	0.0000
	4	0.1191	0.0298	0.8259	0.0011	0.019	0.0047
	8	0.142	0.0367	0.7887	0.0011	0.026	0.0052
	12	0.1447	0.0371	0.7849	0.0012	0.026	0.00531
DFOIL	**24**	0.1449	0.0371	0.7844	0.0012	0.026	0.0053
	1	0.0076	0.00005	0.0158	0.9764	0.000	0.000
	4	0.169	0.0029	0.0286	0.7692	0.0182	0.0117
	8	0.2304	0.0044	0.0396	0.6872	0.0267	0.0114
	12	0.2423	0.0055	0.0416	0.671	0.0271	0.0112
DFCCI	**24**	0.244	0.0059	0.0419	0.6695	0.0272	0.0112
	1	0.0000	0.0041	0.0030	0.0055	0.9872	0.0000
	4	0.1802	0.0056	0.0232	0.0243	0.7634	0.003
	8	0.1692	0.0068	0.0286	0.0393	0.7509	0.0049
	12	0.1699	0.007	0.0288	0.0396	0.7493	0.0051
DFIP	**24**	0.170	0.007	0.0288	0.0397	0.7492	0.0051
	1	0.0101	0.0017	0.0219	0.007	0.0038	0.9552
	4	0.0136	0.0081	0.0320	0.0083	0.0043	0.9332
	8	0.0143	0.0089	0.0323	0.0086	0.0058	0.9298
	12	0.0146	0.0089	0.0323	0.0087	0.0060	0.9292
DFUSDX	**24**	0.0146	0.00897	0.0323	0.0087	0.006	0.9291

Figure 3 - Result of VDC

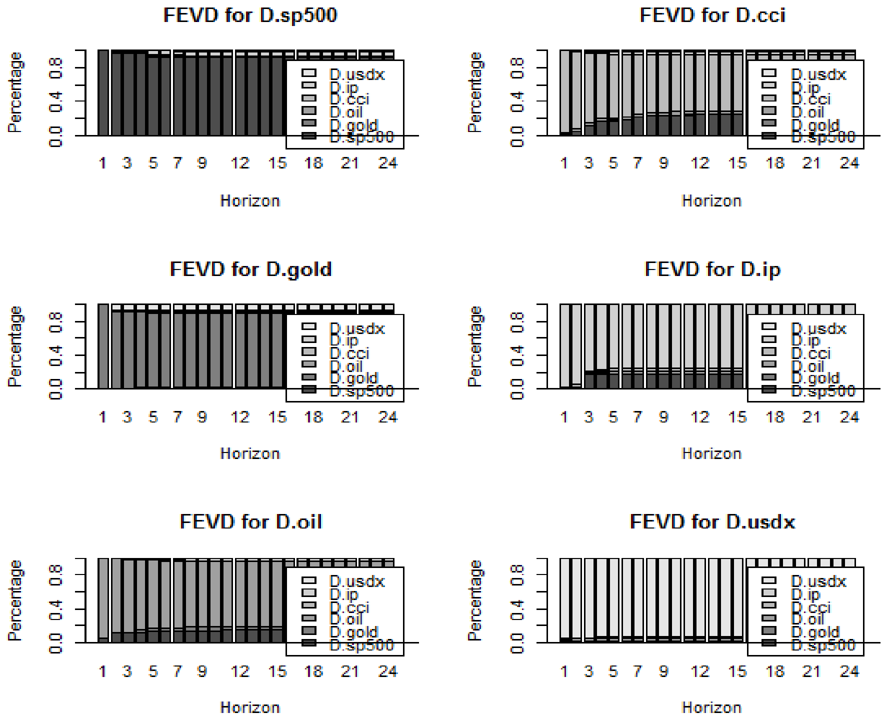
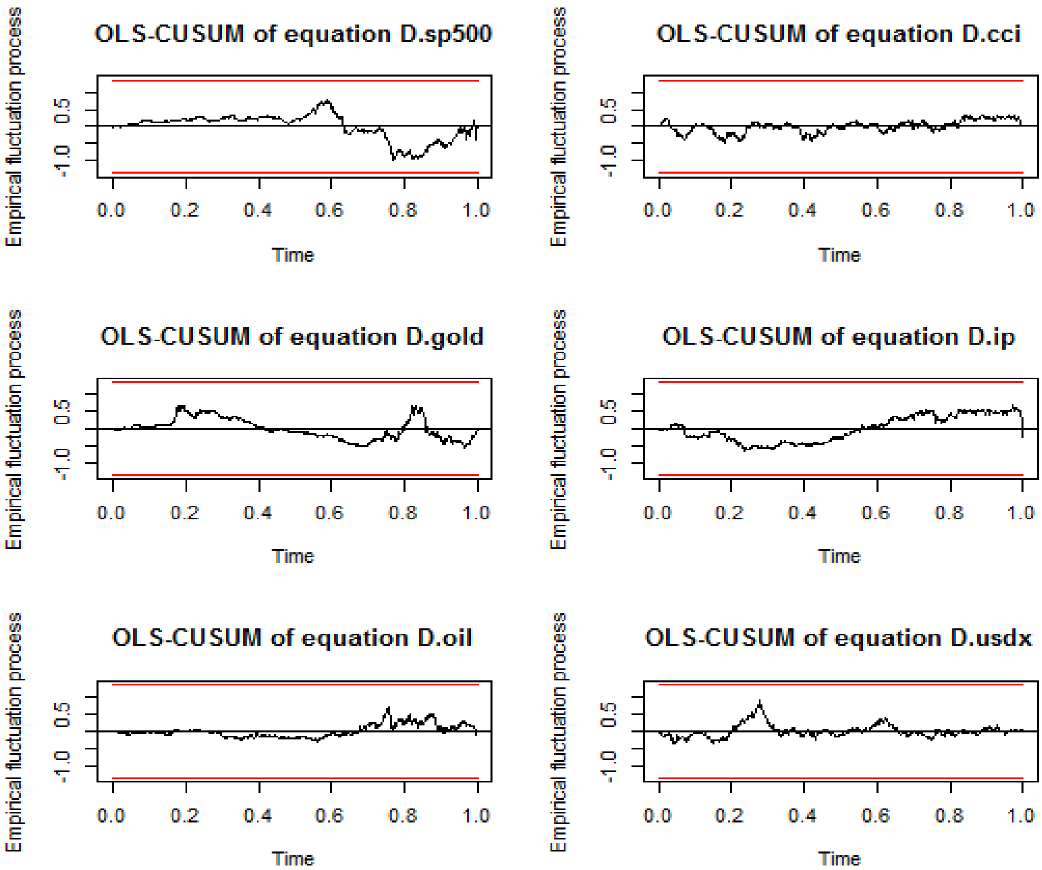


Figure 4 - Results of Stability Test



4. Conclusion

This study's main objective is to investigate the relationship between GP, OP, S&P500, CCI, Industrial production, USDX. From the analysis conducted, it can be concluded that USDX has a significant relationship with GP, having a causal effect on GP. Industrial Production also showed a significant relationship with S&P500, having a causal effect on S&P500. The result also showed that although S&P500 and CCI share a unidirectional relationship between them, the variation in CCI can be due to the S&P500 in the short run. Also, there exists no other significant relationship among the variables listed. The findings also highlighted that USDX directly affected GP negatively; industrial production impacted S&P500 in the short run while CCI and S&P 500 share a positive relationship. The analysis of Crude Oil, Gold, and Silver, in addition to the NIFTY and Sensex, revealed that investing in these assets is more convenient for investors than investing in the increasingly volatile stock market. Since the stock market experiences very large ups and downs, expecting consistent returns is very dangerous. The analysis of returns on Crude Oil, Gold, and Silver helped us realize that the said market does not have as many large swings, as it is commonly assumed and opposed to other commodities, and that investors can select these markets as a safe investment avenue without much concern.

Conflict of Interest: There is no conflict of interest among the authors.

Funding: Self-funded.

Ethical approval: Not applicable.

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