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VOLATILITY SPILLOVER EFFECTS AMONG GOLD, OIL AND STOCK MARKETS: EMPIRICAL EVIDENCE FROM THE G7 COUNTRIES[3]

Economic cooperation of countries across the world has led to the integration of stock and commodities markets. The group of seven countries (G7) represents the world's most industrialised and developed economies. In an integrated market, understanding the price discovery mechanism and volatility spillover across markets is crucial for traders, investors and other stakeholders. This paper investigates the return dynamics and volatility Spillover among the stock markets of G7 countries, oil and gold. We apply VAR and GARCH to examine the relationship between the returns and the transmission of volatility between commodities and stock markets. The research is based on the major stock indices of G7 countries for the years between 2009 and 2018. Oil and gold are taken as a proxy for the commodities market. This study begins by examining the cointegration of the stock and commodities market using the Johansen cointegration test. Stochastic volatility models are used to estimate the volatility and its spillover effect. We estimate the volatility spillover index using variance decomposition. The results indicate the presence of an asymmetric volatility spillover effect between the stock and commodities market. The outcome of the study would facilitate the investors and portfolio managers to understand the return dynamics and volatility spillover effect, which is a prerequisite for an investment decision.
Keyword: Return dynamics; Volatility spillover; Cointegration; Commodities market
JEL: C23; O51; O52; O57; Q02

1. Introduction

The economic integration of various countries influences the nature of commodities and financial markets among the member nations. G7, the group of 7 Nations ambition is to promote prosperity through economic integration and market creation through public and private investment. Integrated markets demonstrate patterns of return and volatility spillover effects between the three key economic drivers, namely the price of oil, gold, and the stock market. Traders, investors, and policymakers have all been interested in learning more about the relationship between the price of oil, gold, and the stock market. The unconventional

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wisdom says, the increase in oil price would increase the price of goods and services, therefore, making the consumer spend less on consumption. Vardar et al. (2018) found evidence of shock transmission and volatility spillover between stock and commodities markets from advanced and emerging markets. Furthermore, the gold and crude oil market are the main representatives of the large commodities market (Zhang, et al., 2010). Pandey (2018) investigated the spillover effect between oil and the stock markets of BRICS countries and found evidence of the spillover effect. Ashfaq et al. (2019) concluded the volatility spillover impact of world oil prices on leading Asian energy exporting and importing economies' stock returns. However, few research studies have found there is no significant correlation between oil price and stock price. For example, Hsiao-FenChang et al. (2013) in their study pronounced that the prices of crude oil, gold price and exchange rate remain considerably independent each other so the policy makers should consider separation of energy and financial policy. Andrea Pescatori (2008) studied the relationship between oil price and S&P 500 in 2008. Government levies taxes on gold and crude oil imports on the exchange rate. This will have a cascading effect on the economy of the country and will directly reflect in the stock market index (Jain, 2016). The results could be inferred in two perspectives. One is the period of study and the nature of economy. An increase in oil prices in the US would benefit the oil and shale gas companies and create more job opportunities in the oil sector. S&P500 stock market index congregates to the long-run level with a speed of daily adjustment by a contribution of oil, and gold price and their volatilities (Gokmenoglu, NegarFazlollahi, 2015). Higher oil prices, on the other hand, would drive up the cost of production and manufacturing across the board. The fast growth of international trade since the 1970s, as well as many industrialised countries' adoption of freely floating exchange rate regimes in 1973, marked a new age of rising exchange rate risk and volatility. The economic vulnerability of enterprises to exchange rate risks has increased, which is unsurprising. The increased volatility and excessive fluctuation of currency rates should induce stock markets to react. Because of the rising integration and deregulation of international financial markets in the 1980s, cross-border cash flows have been easier and faster; currency rates have also become more sensitive to stock market movements and global portfolio investments.

The fundamental theory presumes a direct relationship between oil price and corporate performance. A drop-in oil price means a lesser price of essential items, fuel and transportation costs which leaves more disposable income. According to Patel (2013) the gold price includes a few crucial information to forecast nifty returns. In future, it would be meaningful to develop a model by using econometric modelling techniques which can forecast gold and stock market indices. Priya et al. (2008) examined volatility spillover among gold, silver crude oil futures and spot market in emerging markets and found bidirectional volatility spillover for all commodities except for crude oil in Multi Commodities and Derivatives Exchange in India.

1.1. Gold and exchange rates

The link between gold and currency exchange rates stretches back to the 1870s, when the gold standard was established by the vast majority of countries. The gold standard was considered as a domestic benchmark that slowed the expansion of a country's money supply.

Later on, the gold standard was accepted as an international standard for assessing the value of a country's internal currency with respect to the currencies of other countries. The exchange rate between the currencies related to gold had to be regulated since the market participants to the standard maintained a predetermined price for gold. As a result, a tremor in one country affected domestic money supply and demand, price levels, and real income in another. Although currency exchange rates are no more directly linked to gold, gold is still considered as a safe haven and inflationary hedge. Thus, during high inflation, investors buy gold, and the value of buying currency falls as gold prices rise. Also, when the investors lose confidence in the domestic economy, gold prices rise, and the domestic currency falls in value.

Gold remains a safe haven for centuries and an inflationary hedge, despite the fact that currency exchange rates are no longer tightly tied to gold. As a result, investors buy gold during periods of high inflation, and the purchasing currency's value falls as gold prices rise. Gold prices rise and the value of the domestic currency falls when investors lose faith in the domestic economy. The International Monetary Fund (IMF) estimated in 2008 that the dollar was responsible for 40-50 percent of price movements in gold since 2002. A 1% increase in the effective external value of the US dollar causes a 1% increase in the price of gold. To begin with, a sinking dollar raises demand for commodities such as gold by increasing the value of other local currencies. Second, as the US dollar's value falls in respect to its trade partners, investors seek alternate investment options, such as gold, to protect their capital. Despite the fact that the links and interactions between exchange rates and stock prices have been studied, only a small amount of research has looked into the possibility of volatility transmission or a volatility spillover effect between the stock and currency markets. Understanding how information is transmitted between stock prices and currency rates is aided by studying the volatility spillover mechanism. The current economic globalisation and integration of world financial markets have strengthened the transnational transmission of returns and volatilities among financial markets, thanks to technological advancements.

1.2. Oil and gold

Gold is widely regarded as a safe refuge as well as a monetary replacement. Oil can be used as an inflation hedge for asset portfolios because it is a primary driver of inflation, even if developed countries have improved their energy efficiency and reduced inflation risk. Although both oil and gold are expected to rise in response to a weaker dollar, their relationship is more convoluted because oil is regarded as a hazardous asset, whilst gold is regarded as the inverse. Oil will be acquired at times of trade risk, while gold will be sold, implying that the two should have a negative correlation.

An economically integrated region is prone to spillover effects. The effect could be unidirectional or bidirectional, or with no causality. Examining the dynamics of return and volatility spillover effect facilitates investment decisions. In this paper, we examine the volatility spillover effect of gold, oil and stock markets among G7 countries. This paper is structured as follows. Section 2 highlights the literature review. Section 3 shows the objectives and section 4 explains the methodology. Section 5 deals with analysis and results, and finally, the conclusion in section 6.

2. Literature Review

Qin et al. (2018) used returns of the Chinese RMB exchange rates and the stock markets in China and Japan from 1998 to 2018, empirically examined the volatility spillover effects between the RMB foreign exchange markets and the stock markets. There are co-volatility impacts between the financial markets in China and Japan, according to evidence, and the volatility of RMB exchange rates contributes to co-volatility spillovers across the financial markets. “Return shock from the stock markets, on the other hand, can cause co-volatility spillover to the foreign exchange markets. The estimations also suggest that the Japanese stock market’s spillover effects are stronger than those from foreign exchange markets and Chinese stock markets, implying that the market with the strongest spillover effects is Japan’s stock market. The estimates also reveal that the Japanese stock market has more spillover effects than the foreign exchange markets and Chinese stock markets, implying that markets with greater accessibility have greater spillover effects on other markets. The average co-volatility spillover effects between the RMB exchange markets and the stock markets in Japan and China are generally negative, according to our findings. The ramifications of these findings for risk management and hedging methods are significant.”

While looking at the volatility spillover effects and examining time-varying correlations across four stock indices: CAC, DAX, FTSE100, and S&P 500 from January 5, 2004, to October 1, 2009. They’re also known for displaying numerous elements of volatility and correlation in a time-varying variance-covariance matrix. We first discover that volatility spillover effects between European and US stock markets are pervasive using the BEKK model. The UK stock market is the leading transmitter of volatility in the European stock market, whereas the US stock market is the primary exporter. Second, we use the DCC model to see if there is a time-varying link between global equities markets. Correlations are not only conditional, but also considerably time-varying, according to the author. Furthermore, the results show that in the DCC model, the time-varying conditional correlation follows a mean-reverting process; however, according to this research, this is only true for European stock markets (Xiao & Dhesi, 2010).

Diebold et al. (2009) compared the crises of 2009 to East Asian stock market contagion and dependency outbreaks in the early 1990s. Using the forecast error variance decomposition from a vector autoregression, they produced return and volatility spillover indices over rolling sub-sample windows. They discovered that the East Asian return and volatility spillover indexes function differently over time. While the return spillover index demonstrates that East Asian equity markets are becoming more interconnected, the volatility spillover index demonstrates massive bursts during major market crises such as the East Asian crisis. The severity of the present global financial crisis is evidenced by the fact that both return and volatility spillover indexes hit their respective maximum during the current global financial crisis.

There is an examination of the impact of stock market volatility on the foreign exchange market in Pakistan, India, Sri Lanka, China, Hong Kong, and Japan. From January 4, 1999, through January 1, 2014, data for this study was collected on a daily basis. The EGARCH (Exponential Generalized Auto-Regressive Conditional Heteroskedasticity) model was used to study asymmetric volatility spillover effects between the stock and foreign exchange markets. There is a bidirectional asymmetric volatility spillover between Pakistan's stock market and Hong Kong and Sri Lanka's foreign exchange markets, according to the EGARCH study. Stock market volatility in India is conveyed uni-directionally to the country's foreign exchange markets, according to the statistics. The data show that stock market volatility in India is unidirectionally transferred to the country's foreign currency market. There is no evidence of volatility transmission between the two markets in Japan, according to the research (Jebran & Iqbal, 2016).

To estimate time-varying correlations, multivariate Garch models, which are linear in squares and cross products of the data, are widely utilised. DCC models (dynamic conditional correlation) are a new type of multivariate model. In these correlation models, the flexibility of univariate GARCH models is paired with the simplicity of parametric models. Despite the fact that they aren't linear, they can usually be approximated fast using univariate or two-step processes based on the probability function. They've been shown to work in a variety of scenarios and to produce useful empirical data (Engle, 2002).

X. Diebold et al. (2012) proposed measures of total and directional volatility spillovers using a generalised vector autoregressive framework in which forecast-error variance decompositions are invariant to variable ordering. From January 1999 to January 2010, the researchers used our methodologies to describe daily volatility spillovers across US stock, bond, foreign exchange, and commodities markets. Despite large variations in volatility in each of the four markets across the sample period, cross-market volatility spillovers remained quite minimal until the global financial crisis of 2007. The volatility spillovers grew as the crisis progressed, with the failure of Lehman Brothers in September 2008 triggering particularly large spillovers from the stock market to other markets.

An empirical analysis of volatility spillover from oil prices to stock markets using an asymmetric BEKK model is proposed by Agren & Martin (2006). The study continued with the exception of the Swedish stock market, strong evidence of volatility spillover is found using weekly data on the aggregate stock markets of Japan, Norway, Sweden, the United Kingdom, and the United States. According to news impact surfaces, volatility spillovers are statistically significant but quantitatively insignificant. Oil shocks are less prominent than stock market shocks, which are due to other sources of uncertainty than the price of oil.

Chulia et al. (2008) had two main goals, i.e., to begin, volatility transmission between stocks and bonds in European markets is investigated using the DJ Euro Stoxx 50 index futures contract and the Euro Bund futures contract, two of the most famous financial assets in their respective domains. Second, a trading rule is developed for the major European futures contracts. The economic impact of observed volatility spillovers on a variety of markets and assets can be calculated using this method. Volatility spillovers occur in both directions, according to the statistics, and the stock-bond trading rule provides particularly favourable after-transaction returns. These findings have far-reaching consequences for asset allocation and portfolio management.

Despite the fact that there is now good evidence that sovereign risk premia are driven by a shared mechanism, little is understood about the intricate links between sovereign bond markets. Using daily data on sovereign bond yield spreads and a common component, we use Diebold and Yilmaz's VAR approach to examine the strength and direction of bilateral links between EU sovereign bond markets. The forecast-error variance decomposition of this FAVAR shows that the bilateral spillover communicated and received between bond markets is highly heterogeneous. For all eurozone countries, spillover is more important than internal issues. The CE countries primarily influence one another. Only Denmark, Sweden, and the United Kingdom are relatively free of spillover. Despite starting from a high point, the spillover has expanded significantly since 2007. We use this methodology to analyse the dynamic links between spreads and the ratings of the major credit rating agencies, as well as to quantify the impact of sovereign rating news. Rating news and sovereign risk premia have a two-sided relationship, according to our findings. Rating news has a wide range of effects, with downgrades at lower grades having a far bigger impact. Domestically, the impact is frequently lower than on bond spreads of other sovereigns (Claeys & Vasicek, 2012).

Santis et al. (1998) applied a parsimonious multivariate GARCH process is used to estimate and verify the conditional form of an International Capital Asset Pricing Model. We can extract any quantity that is a function of the first two conditional moments because the approach is fully parametric. The findings back up a model that accounts for both market and foreign exchange risk. These sources of risk, on the other hand, are only discovered when their prices are permitted to fluctuate over time. The analysis also shows that, with the exception of the US equity market, the currency risk premium often accounts for a large portion of the overall premium.

Using a new panel data set for European countries, the relationship between foreign direct ownership of enterprises and firm- and region-level output volatility is studied. At the corporate level, there is a substantial, positive correlation between foreign ownership and value-added volatility. This link holds in cross-sections as well as in panels with fixed effects from companies, capturing change within firms over time. When it comes to domestic enterprises with holdings in other countries, the favourable link is explained by international variety rather than the owner's nationality. The findings are also observable at the aggregate level, where regional volatility is shown to be positively related to foreign investment in the region. The positive association between aggregate volatility and foreign investment can be explained by the granularity of the company size distribution and the fact that foreign ownership is concentrated among the largest firms (Kalemli-Ozcan, Sorensen, & Volosovych, 2014).

Foreign stock markets move in lockstep over time, according to a significant body of research. As a result of this co-movement, returns and volatility spillover effects can be seen in a variety of goods, from equities and bonds to soft commodities. During the recent financial crisis, it was once again demonstrated that no market is immune to the effects of other global markets. Returns and volatility spillover effects from the Hang Seng, London, Paris, Frankfurt, and New York stock markets to the JSE are validated using an aggregate-shock (AS) model. The data also show that the JSE All Share index is influenced directly by the economic sector, where the crisis began as a result of contagion (Heymans & Camara, 2013).

3. Objectives

1. To examine the volatility spillover between Oil, Gold and Stock markets of G7 countries;
2. To examine the cointegration and causal relationship between Gold, Oil and stock markets of G7 countries;
3. To construct a volatility spillover index between commodities and G7 stock.

4. Research Methodology

4.1. Data input

We obtain the major stock market index data for G7 countries from Bloomberg. The following are the indices of the stock market, commodities and oil, used to examine the cointegration and estimate volatility Spillover index.

Index	Country
DAX Index	Germany
CAC 40 Index	France
S&P/TSX Composite Index	Canada
FTSE MIB Index	Italy
TPX Index	Japan
UKX FTSE	United Kingdom
SPX	USA
GOLD	XAU
Crude Oil	WTI

The sample data for the study covers the period between January 2002 and June 2018. The authors have not used the data for the years following 2018 due to the pandemic and disruption in the global supply chain network. In addition, the crude oil prices during 2019 traded within a relatively narrow price range between $55/b and $75/b, the lowest range since 2003. The frequency of data includes weekly high, low, open and closing indexes. The weekly prices indicate the prices from Monday to Friday for all the benchmark indices. The weekly returns are the log returns calculated based on the closing index value on every Friday. The oil price is calculated based on the West Texas Intermediate (WTI), which is a grade of crude ***oil*** used as a benchmark in oil pricing. The nominal values of the oil price are adjusted for inflation using the headline consumer price index for the respective months. Similarly, the historical gold price has also been adjusted for inflation using the consumer price index. Monthly data of Oil, gold and market returns are used for data analysis and interpretation.

Return=ln($COt|COt{-}1$), where COt is the closing price for the current period and COt-1 is the previous period’s closing price.

4.2 Augmented Dickey-Fuller Test (ADF)

The Augmented Dickey-Fuller test is a test of stationarity in time series data. The data is said to be non-stationary if it carries unit root. A non-stationary process is one in which statistical properties vary with the change in time. A stationary process carries constant variance irrespective of time and means reverting to zero. ADF test examines whether the unit root is present in the series for three levels, i.e., only constant, trend & constant, no trend and constant. ADF test equation:

$$\Delta Y_t = \lambda + \gamma Y_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta Y_{t-j} + \beta t + \omega_t \tag{1}$$

Where:

λ is the random walk drift

γ constant for linear trend

P maximum lag length

β constant for time trend

We check for stationarity, applying the ADF test for the time series data of Gold, oil and stock market of G7 countries. Johansen cointegration is applied to examine the nature of cointegration between the stock market and commodities. VAR autoregression and Vector Error Decomposition models are used to model spillover index.

4.3. Granger Causality Test

The Granger Causality test is applied to determine the causal relationship between two variables. The causality may be unidirectional and/or bidirectional. The test was proposed by Granger (1969) and popularised by Sims (1972).

Steps involved in Granger Causality Test

The test begins by converting the time series data to its first order I(1) and runs a regression. Estimate the following unrestricted equation taking an autoregressive lag length *p*

$$x_t = c_1 + \sum_{i=1}^{p} \alpha_i x_{t-i} + \sum_{i=1}^{p} \beta_i y_{t-i} + u_t \tag{2}$$

$$H_0: \beta_1 = \beta_2 = \ldots = \beta_p = 0 \tag{3}$$

Conduct an *F*-test of the null hypothesis by estimating the following restricted equation by OLS.

$$x_t = c_t + \sum_{i=1}^{p} \gamma_i x_{t-i} + e_t \tag{4}$$

Compare their respective sum of squared residuals.

$$RSS_1 = \sum_{t=1}^{T} \hat{u}_t^2 \quad RSS_0 = \sum_{t=1}^{T} \hat{e}_t^2 \tag{5}$$

If the test statistic

$$S_1 = \frac{(RSS_0 - RSS_1)/p}{RSS_1/(T-2p-1)} \sim F_{p,\,T-2p-1} \tag{6}$$

is greater than the specified critical value, then reject the null hypothesis that *Y* does not Granger-cause *X*.

It is worth noting that with lagged dependent variables, as in Granger-causality regressions, the test is valid only asymptotically. An asymptotically equivalent test is given by

$$S_1 = \frac{T(RSS_0 - RSS_1)}{RSS_1} \sim \chi^2(p) \tag{7}$$

5. Analysis and Discussion

5.1. Augmented Dickey-Fuller test of Oil, Gold and Stock Returns

Forecasting requires the data to be stationary and homoscedastic. A stationary data has the properties of mean, variance and autocorrelation invariant of time. The augmented dickey fuller test determines whether the data is stationary or not. We examine whether the series is stationary for three different types of an equation, i.e., random walk without drift and trend, only intercept, trend and intercept. The following are the hypothesis to check for stationarity.

Ho: The time series is non-stationary

H_1: The time series is stationary

The significance of the results is tested at a 5% level. We apply the unit root test at three levels, i.e. Random walk (No drift and trend) $\boldsymbol{\Delta_y = \gamma y_{t-1} + \varepsilon_t}$**,** Drift without linear time trend $\boldsymbol{\Delta_y = a_0 + \gamma y_{t-1} + \varepsilon_t}$**,** drift and linear time trend. $\boldsymbol{\Delta_{y_t} = a_0 + \gamma y_{t-1} + a_2 t + \varepsilon_t}$. The test result indicates the times series data of the stock market, gold and oil are stationary at the first difference for all three equations. The coefficients for drift and trend for all the three variables that indicate the presence of trend, seasonal and irregular variations in the time series data of gold, oil and stock market. The irregular variations indicate the presence of shocks. Converting non-stationary series into stationary would facilitate whether there exists cointegration among the variables. Forecasting accuracy can be improved by applying stationary data in econometric forecasting models.

Table 1

ADF test for the returns of stock and commodities market

ADF stationarity test for the returns of stock and commodities market.			
Market	Intercept	Trend and Intercept	No Intercept and Trend
Crude oil	-0.822895	-0.835255	-0.822884
	(0.0000)*	(0.0000)*	(0.0000)*
Gold	-1.137444	-1.148831	-1.13361
	(0.0000)*	(0.0000)*	(0.0000)*
CAC	-1.092589	-1.092655	-1.090357
	(0.0000)*	(0.0000)*	(0.0000)*
DAX	-0.965641	-0.985646	-0.95112
	(0.0000)*	(0.0000)*	(0.0000)*
FTSE	-1.011393	-1.014319	-1.011322
	(0.0000)*	(0.0000)*	(0.0000)*
SPTX	-1.048481	-1.085481	-1.040593
	(0.0000)*	(0.0000)*	(0.0000)*
SPX	-1.077964	-1.102274	-0.997958
	(0.0000)*	(0.0000)*	(0.0000)*
TPS	-0.970924	-0.979125	-0.954652
	(0.0000)*	(0.0000)*	(0.0000)*
UKX	-1.105171	-1.14348	-1.097165
	(0.0000)*	(0.0000)*	(0.0000)*

5.2. Johansen Co-integration test

We apply the Johansen cointegration test (1988, 1995) to examine whether the stock markets of G7 countries, Gold and Oil are cointegrated. The test examines the long-run relationship between the stock market movements. The results of the ADF test indicate the series of returns of all G7 countries are integrated in the same order I(1). We run unrestricted Vector Auto Regression to estimate the number of cointegrating equations. The assumption made to run the model is no intercept and trend in the Cointegrating equation and Vector Autoregression.

Table 2 and Table 3 show the results of the cointegration test. The test results are interpreted based on two Likelihood ratio (LR) statistics. First is the trace test and second is the Maximum Eigenvalue. To determine the number of the cointegrating equation, the null hypothesis is set as no cointegrating equation against the alternative of k-1 number of equations, where k is the number of variables. The theoretical framework of the Johansen test suggests there may be zero or r number of cointegrating equations, where 0> r < k.

The following are the hypothesis of the cointegration test

H0: r = ro (None – no cointegration)

H1: ro < r < k (There exists r number of cointegrating equations)

The hypothesis is done sequentially, starting from none and proceeding to (k) in steps till the null hypothesis cannot be rejected. The results are interpreted based on the obtained values of Trace and Max Eigen statistic value. The null hypothesis is rejected if the trace or

Eigenvalue is more than the critical value or the probability is less than 5%. Both trace test and Maximum Eigenvalues are statistically significant at a 5% level for all null hypotheses. The trace test and Maximum Eigenvalue indicate 4 cointegrating equations. It is evident that the stock markets of all G7 countries and commodities markets are not cointegrated. The Maximum Eigenvalue indicates 4 cointegrating equations. It shows the price movement of gold, oil and stock market cannot deviate from equilibrium in the long term. Any shock or irregular variations in the price movement will die down with an increase in time, and finally, an equilibrium is established. Forecasting the price movement of one variable using the other is possible when the variables are cointegrated.

Table 2

Johansen cointegration test (Trace test) of stock and commodities market

Johansen cointegration Trace test				
No of cointegrated equations	EV**	F Statistic	Critical value	P – Value
None *	0.504525	315.8219	179.5098	0.0000
At most 1 *	0.399953	235.7666	143.6691	0.0000
At most 2 *	0.364338	177.5414	111.7805	0.0000
At most 3 *	0.281442	125.8894	83.93712	0.0000
At most 4 *	0.208044	88.21143	60.06141	0.0000
At most 5 *	0.197265	61.62102	40.17493	0.0001
At most 6 *	0.128449	36.57179	24.27596	0.0009
At most 7 *	0.107669	20.89898	12.32090	0.0015
At most 8 *	0.067052	7.912258	4.129906	0.0058
Trace test result: 8 cointegrating equations				

*rejection of null hypothesis at 5% significance level.

** Eigenvalue

Table 3

Johansen cointegration test (Maximum Eigenvalue) of stock and commodities market

Johansen cointegration Trace test (Maximum Eigenvalue)				
No of cointegrated equations	EV**	F Statistic	Critical value	P – Value
None *	0.504525	80.05523	54.96577	0.0000
At most 1 *	0.399953	58.22519	48.87720	0.0040
At most 2 *	0.364338	51.65205	42.77219	0.0041
At most 3 *	0.281442	37.67797	36.63019	0.0376
At most 4	0.208044	26.59040	30.43961	0.1401
At most 5 *	0.197265	25.04923	24.15921	0.0378
At most 6	0.128449	15.67281	17.79730	0.1014
At most 7 *	0.107669	12.98672	11.22480	0.0243
At most 8 *	0.067052	7.912258	4.129906	0.0058
Maximum Eigen value test result: There are 4 cointegrating equations				

*Rejection of null hypothesis at 5% significance level

**Eigenvalue

Spillover Index

Spillover is the transmission of volatility induced by one variable into another variable that is supposed to be cointegrated. The spillover effect occurs when one or more markets are interlinked. The spillover index measures the percentage of forecast error variance caused by own and other variables. We construct a spillover index for the return and volatility series of the stock indices of G7 countries.

We follow the stepwise conceptual process to model return and volatility spillover for the G7 countries. The procedural steps involved are as follows

Step 1: Check whether the historical series of returns is stationary using the Augmented Dickey-Fuller test

Step 2: Run unrestricted Vector Auto Regression to estimate the optimum lag structure (p)

Step 3: Conduct the Johansen cointegration test at (p) lags to check the number of cointegrating equations (r)

Step 4: Apply the decision rule to choose between Vector Auto Regression (VAR) and Vector Error Correction Model (VECM). VAR model is used where there is no cointegration among the variables. VECM model is applied when there is at least one cointegrating equation among the variables.

Step 5: Estimate the parameters of the VECM model taking (p-1) lag.

Step 6: Forecast 10 weeks ahead variance decomposition for return and volatility

Step 7: Perform diagnostics test to check for model accuracy.

Step 8: Construct the spillover index separately for the series of returns and volatility of G7 countries.

Using the above-mentioned methodology, we forecasted 3 weeks ahead spillover index and presented the spillover index in Table 4, Table 5 and Table 6. A detailed analysis of the tables is presented after Table 6.

Table 4

One week ahead variance decomposition

	USA	UK	Germany	Japan	France	Canada	Italy	Oil	Gold	Contribution from others
USA	96.08	2.78	0.00	0.03	0.02	0.02	0.08	0.27	0.71	3.92
UK	52.17	46.63	0.02	0.02	0.42	0.08	0.02	0.17	0.48	53.37
Germany	46.72	21.36	30.69	0.13	0.13	0.29	0.33	0.26	0.09	69.31
Japan	22.17	4.76	1.42	70.15	0.00	0.00	0.12	0.01	1.36	29.85
France	53.08	22.92	8.76	0.30	13.66	0.22	0.71	0.27	0.09	86.34
Canada	0.21	0.08	0.21	0.40	0.49	97.97	0.19	0.00	0.45	2.03
Italy	39.53	10.36	2.66	0.00	6.41	0.07	40.81	0.09	0.05	59.19
Oil	8.18	0.46	0.19	0.07	0.02	0.51	0.75	89.68	0.14	10.32
Gold	11.38	2.76	0.24	1.05	0.25	0.04	0.20	0.36	83.70	16.30
Contribution to others	233.45	65.48	13.51	2.00	7.75	1.23	2.41	1.43	3.37	330.63
Contribution including own	329.53	112.11	44.20	72.15	21.40	99.20	43.23	91.11	87.07	900.00
									spillover index	36.74%

Table 5

Two weeks ahead variance decomposition

	USA	UK	Germany	Japan	France	Canada	Italy	Oil	Gold	Contribution from others
USA	95.293	3.086	0.002	0.044	0.178	0.225	0.161	0.354	0.657	4.710
UK	56.078	41.529	0.050	0.620	0.687	0.205	0.086	0.166	0.580	58.470
Germany	49.663	20.511	27.516	0.706	0.187	0.237	0.728	0.346	0.107	72.480
Japan	26.584	4.782	1.274	65.497	0.059	0.004	0.228	0.216	1.355	34.500
France	55.093	22.694	8.047	1.037	11.918	0.185	0.662	0.284	0.080	88.080
Canada	0.290	0.069	0.493	0.356	0.581	97.431	0.243	0.003	0.534	2.570
Italy	40.617	10.141	2.255	0.243	6.195	0.070	40.152	0.092	0.235	59.850
Oil	10.160	0.629	0.351	0.105	0.033	0.554	0.745	87.066	0.356	12.930
Gold	15.604	2.566	0.289	1.336	0.325	0.196	0.187	0.390	79.108	20.890
Contribution to others	254.088	64.477	12.761	4.447	8.246	1.677	3.041	1.851	3.903	354.490
Contribution including own	349.381	106.006	40.277	69.943	20.164	99.108	43.193	88.918	83.011	900.000
									Spillover index	39.39%

Table 6

Three weeks ahead variance decomposition

	USA	UK	Germany	Japan	France	Canada	Italy	Oil	Gold	Contribution from others
USA	93.87	3.92	0.01	0.12	0.23	0.47	0.20	0.32	0.85	6.13
UK	58.07	38.87	0.05	0.89	0.79	0.29	0.15	0.15	0.74	61.13
Germany	51.59	20.58	24.96	1.14	0.25	0.21	0.86	0.31	0.10	75.04
Japan	29.56	5.08	1.22	61.80	0.08	0.05	0.23	0.24	1.74	38.20
France	56.93	22.32	7.35	1.42	10.84	0.17	0.61	0.26	0.11	89.16
Canada	0.34	0.07	0.68	0.34	0.69	96.78	0.31	0.01	0.78	3.22
Italy	41.78	9.75	2.08	0.32	6.04	0.06	39.53	0.09	0.35	60.47
Oil	12.33	0.60	0.36	0.10	0.03	0.71	0.71	84.66	0.51	15.34
Gold	17.65	2.75	0.33	1.27	0.37	0.30	0.21	0.37	76.74	23.26
Contribution to others	268.25	65.07	12.09	5.60	8.47	2.26	3.29	1.74	5.17	371.95
Contribution including own	362.12	103.94	37.05	67.40	19.31	99.04	42.82	86.40	81.91	900.00
									Spillover index	41.33%

Tables 4, Table 5 and Table 6 show the weekly volatility Spillover index of G7 stock market and commodities. We run the Vector Error correction model and forecast the error variance for 10 weeks. The error decomposition quantifies the market variability caused by self (respective index) due to shock and the percentage of volatility coming from other indices. The rows in the table indicate the contribution from others, and the column shows the contribution to others. The spillover tables are to be read as (i x j) matrix. Every ij-th value in the matrix shows the contribution of forecast error variance from country j to i for all j ≠ i. For every country in a row (i), we estimate the contribution of error variance due to shocks or innovations from other countries by simply adding values of (j), for all j ≠ i. The diagonal values in the matrix for every i=j show the contribution from own to the forecast variance. The total values in every row excluding j=j show the contribution of volatility from other countries j_1, j_2 – ---- j_n. The diagonal value shows the contribution from its own. The sum of values in every row (i) excluding i=j or the diagonal element in the row shows the contribution from others. We then add all i=1…..n to get the total contribution from others. The sum of columns (j) for all j ≠ i provides the contribution of every country to the forecast error variance of other countries. In simple terms, the sum of rows for all j ≠ i highlights the contribution from others. Similarly, the sum of columns for all j ≠ i shows the contribution to others.

Spillover index = Contribution from other / Contribution including own

For example, for One week ahead variance decomposition in the above table, the total contribution from others for three weeks ahead variance decomposition is 371.95, and the total contribution, including own, is 900. Thus, the spillover index = 371.95/900 = 41.33%.

6. Conclusion

The economic and financial integration of G7 countries makes the market cointegrated. Price discovery and volatility Spillover is a common phenomenon of cointegrated markets. Gold and Oil price influence the market returns due to oil price affecting inflation. The group of G7 countries contributes nearly 50% of global GDP. The extent of integration among the G7 countries makes the return and volatility getting spillover from one country to another country. For instance, the shock in one country makes the market volatile. When the markets are integrated, the volatility spans from one country to another. We apply the Johansen cointegration test and found the existence of cointegration among gold, oil price and stock markets of G7 countries. During the normal scenario, the price of all three variables would be affected by the economic driving forces. The presence of a cointegrating relationship among the three variables induces the phenomenon of price discovery and volatility spillover effect. If any of the three variables experience shocks, the deviation is temporary and the variables move together in the long run. During economic downturn and high inflation, gold is perceived to be the safer asset and its price is inversely proportional to inflation. Furthermore, during a recession, the stock markets tank, which induces the investors to move to safer investments in gold.

Transmission of volatility is a common phenomenon in an integrated market. We apply Diebold – Yilmax methodology to calculate the spillover index for return and volatility. The spillover index is constructed through a variance decomposition process by running Vector Error Correction Model. We found out the presence of volatility transmission in return and volatility within the G7 countries. The spillover index shows evidence of inward and outward transmission of volatility among the benchmark stock indices of G7 countries and commodities. Traders, investors and speculators can predict the volatility using the spillover index and design appropriate trading strategies.

References

Agren, Martin. (2006). Does Oil Price Uncertainty Transmit to Stock Markets?. – Uppsala University Journal, pp. 1-29.

Ashfaq, S. T. (2019). Volatility spillover impact of world oil prices on leading Asian energy exporting and importing economies' stock returns. – Energy, 188, 116002.

Chulia, H., Torro, H. (2008). The economic value of volatility transmission between the stock and bond markets. – The Journal of Futures Market, pp. 1066-1094.

Claeys, P. G., Vasicek, B. (2012). Measuring Sovereign Bond Spillover in Europe and the Impact of Rating News. Universitat de Barcelona. Institut de Recerca en Economia Aplicada Regional i Pública, pp. 1-37.

Diebold, F. X., Yilmaz, K. (2009). Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. – The Economic Journal, pp. 158-171.

Engle, R. (2002). Dynamic Conditional Correlation A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. – Journal of Business & Economic Statistics, pp. 339-350.

Heymans, A., Camara, R. d. (2013). Measuring spillover effects of foreign markets on the JSE before, during and after international financial crises. – South African Journal of Economic and Management Sciences, pp. 418-434.

Hsiao-FenChang, Liang-ChouHuang, Ming-ChinChin. (2013). Interactive relationships between crude oil prices, gold prices, and the NT–US dollar exchange rate – A Taiwan study. – Energy policy, pp. 441-448.

Jain, A. B. (2016). Dynamic linkages among oil price, gold price, exchange rate, and stock market in India. – Resources Policy, 49, pp. 179-185.

Jebran, K., Iqbal, A. (2016). Dynamics of volatility spillover between stock market and foreign exchange market: evidence from Asian Countries. – Financial Innovation, pp. 1-15.

K.Gokmenoglu, A. l., NegarFazlollahi. (2015). The Interactions among Gold, Oil, and Stock Market: Evidence from S&P500. – Procedia Economics and Finance, pp. 478-488.

Kalemli-Ozcan, S., Sorensen, B., Volosovych, V. (2014). Deep Financial Integration and Volatility. – Journal of the European Economic Association, pp. 1558-1585.

Patel, S. A. (2013). Causal Relationship Between Stock Market Indices and Gold Price: Evidence from India. – IUP journal of applied finance, pp. 99-109.

Qin, F., Zhang, J., Zhang, Z. (2018). RMB Exchange Rates and Volatility Spillover across Financial Markets in China and Japan. – MDPI, pp. 1-26.

Santis, G. D., Gérard, B. (1998). How big is the premium for currency risk?. – Journal of Financial Economics, pp. 375-412.

Thenmozhi, P. S. (2008). Volatility spillover in bullion and energy futures and spot markets. – Journal of Emerging Financial Markets, 1(1), pp. 85-107.

Vardar, G. C. (2018). Shock transmission and volatility spillover in stock and commodity markets: evidence from advanced and emerging markets. – Eurasian Economic Review, 8(2), pp. 231-288.

X.Diebold, F., KamilYilmaz. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. – International Journal of Forecasting, pp. 57-66.

Xiao, L., Dhesi, G. (2010). Volatility spillover and time-varying conditional correlation between the European and US stock markets. – Global Economy and Finance Journal, pp. 148-164.

Zhang, Y. J. (2010). The crude oil market and the gold market: Evidence for cointegration, causality and price discovery. – Resources Policy, 35(3), pp. 168-177.