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Effects of Crude Oil Price Shocks on Stock Markets and Currency Exchange Rates in the Context of Russia-Ukraine Conflict: Evidence from G7 Countries

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Abstract: The present study examines the effects of the steep surge in crude oil prices which has also been considered as an oil price shock on the stock price returns and currency exchange rates of G7 countries, namely Canada, France, Germany, Italy, Japan, the United Kingdom (UK) and the United States (US), in the context of the Russia–Ukraine conflict. Due to the outbreak of the war, the steep surge in Brent crude oil price returns is seen as an exogenous shock to stock price returns and exchange rates during the period from 2 January 2017 to 29 June 2022. The paper applies the Fractionally Integrated GARCH (FIGARCH) model to capture the effect of the crude oil price shock and the Breakpoint unit root test to examine the structural breaks in the dataset. Structural breakpoints in the dataset for the entire stock price returns and exchange rates are observed during the period commencing from the last week of February, 2022, to the last week of March, 2022. Except for TSX, NASDAQ and USD, noteworthy long memory effects running from Brent crude oil price to all the stock price returns along with the currency exchange rates for all G7 countries were also found.

Keywords: G7 countries; crude oil price; stock return; FIGARCH

JEL Classification: C32; C58; F51; Q34; Q43

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1. Introduction

The Russia–Ukraine conflict is having serious consequences, not only for Russia and Ukraine, but as it also potentially threatens to harm the world's advanced G7 economies. Although it is true that Ukraine is the main victim of this conflict and its economy may decline by up to 8% this year, the advanced economies of G7 countries, namely Canada, France, Germany, Italy, Japan, the United Kingdom (UK) and the United States (US) are also in dire straits due to this ongoing conflict (http://hdl.handle.net/10419/204257 accessed on 17 June 2022). In a broader sense, it may be commented that this conflict is causing a significant setback to the global recovery from the COVID-19 pandemic and will likely exacerbate inflation.

According to the experts of the Economic Intelligence Unit (EIU) of The Economists Group, London, the outbreak of the conflict between Russia and Ukraine will affect the global economy via three main channels: financial sanctions, commodities prices and supply chain disruptions (https://onesite.eiu.com/campaigns accessed on 30 June 2022). As a precautionary measure, the United States (US) and the European Union (EU) have previously adopted a cautious approach to sanctioning Russia. Trade ties between Russia and the EU make European policymakers reluctant to impose stringent measures on Russia, although this restraint has disappeared to some extent. However, measures to restrict Russia's energy exports are still off the table, reflecting fears in European capitals that sanctions of such a nature would send EU economies into recession. The US Treasury planned carve-outs from sanctions for Russian energy exports, and Russian banks involved in the energy trade will not be excluded from SWIFT. The economic impact of EU and US sanctions will therefore be small outside of Russia, although Western companies that are highly exposed to Russia will still be affected (https://www.eiu.com/n/global-economic-implications accessed on 2 July 2022).

This conflict is also having a serious economic impact, which may become worsened day by day the longer the war continues. Furthermore, this disaster comes at an extremely fragile time, when the international economy is on the road to recovery from the devastation of the COVID-19 pandemic, and thus may hinder economic revival to some extent. It is also felt that the repercussions of the Russia–Ukraine conflict may hold considerable economic risks, not only in the whole EU region but also throughout the world (https://blogs.imf.org accessed on 2 July 2022).

The recent COVID-19 pandemic has negatively impacted the global economy, especially the oil industry (Bourghelle et al. 2021; Ma et al. 2021). Crude oil prices have been rising ever since the build-up of Russia's special military operation in Ukraine in late 2021.This is because major crude oil-importing countries were apprehensive of the war breaking out between Russia and Ukraine, which would compel Western nations to put sanctions on purchasing crude oil from Russia. During Russia's ongoing invasion of Ukraine, even before the United States (US) and the United Kingdom (UK) barred Russian oil and gas imports, some countries had ceased their purchases whilst others were panic-buying, and as result, prices soared to a 14-year high of USD 140 a barrel on 7 March 2022. Russia supplies 14% of global production or 7–8 million barrels per day of crude oil to markets worldwide. The ban by the US and the UK and the decision of some other pro-Ukraine countries to restrict the purchase of Russian crude oil further aggravated this crisis.

Russia and Ukraine are the major producers of various agricultural commodities such as wheat, corn, sunflower, etc., along with a number of metals and minerals such as cobalt, copper, iron ore, aluminium, crude oil, gasoline, etc. Commodity prices could jump due to three factors: fear of supply shortage, the lack of physical infrastructure and sanctions. As the global impact of sanctions is restricted, the EIU and the global market expect that the major effect of the Russia–Ukraine conflict on the global economy will be observed in the form of higher commodity prices (https://blogs.imf.org accessed on 2 July 2022). On the other hand, it is expected that crude oil prices will remain above USD 100 per barrel due to this crisis. The threats of sanctions on Russian hydrocarbon exports and supply disruptions are to be considered the reasons why the world is losing existing market tightness. Now, it is an issue that little trade is being made with Russian oil out of concern for secondary sanctions from the US on financial transactions with Russian entities. Again, according to some experts, Russia may cut off and halt its gas supply to the European Union countries in the coming winter. It is anticipated that gas prices may increase by at least 50% this year (2022), on top of a five-fold rise in 2021 (https://blogs.imf.org accessed on 2 July 2022). Next, the ongoing war has completely destroyed existing supply chains, which were already severely affected along with international trade because of the financials sanctions imposed by the US and other EU nations. Multinational companies are also struggling to establish alternative means of continuing their trade with Russia. Moreover, this situation is further aggravated with the partial destruction of Ukrainian ports and transport infrastructure due to the ongoing war (https://www.eiu.com/n/global-economic-implications-of-the-russia-ukraine-war accessed on 4 July 2022). The global inflation rate is also soaring high, primarily due to a steep hike in commodity prices. According to the EIU, the current year has experienced a high inflation rate which may still increase during the year 2023. From the producers' end, this sharp rise in commodity prices will dramatically increase the inflation rate which may neutralize the positive effect of higher commodity prices for the producers and suppliers of commodities across the globe (https://www.eiu.com accessed on 5 July 2022).

Brent crude oil price recorded an eight-year high of USD 140 in March 2022, which was exclusively due to the outbreak of the Russia–Ukraine war which disrupted global supply chains. Higher crude oil prices also raised serious concerns amongst the supply chain systems throughout the world which are now more concerned with tackling soaring inflation due to ongoing Russia–Ukraine conflict rather than undertaking a post-COVID-19 pandemic recovery. The negative impact of the war on the economy has been mostly experienced by Russia and Ukraine and both these countries are now passing through the stage of sharp recession. G7 countries are also feeling negative impacts to some extent because of their close trade links with Russia (https://blogs.imf.org accessed on 2 July 2022).

The Russia–Ukraine war has had an imperative impact on all G7 economies. In particular, the prices of all essential commodities including crude oil have soared to record heights, which has also negatively affected the economic growth of all G7 countries. According to the reports published by the IMF, the Russia–Ukraine war will severely hamper the global economic recovery, with the UK being harshly affected than most countries. The conflict is increasing food and fuel prices, which, according to the IMF, will further weaken global economic growth. Moreover, in its latest report, the IMF lowered its global forecast and its outlook for the UK, which implies that the UK will no longer be the fastest growing economy amongst the G7 but may be the slowest by 2023 (https://www.imf.org/en/News/Articles/2022/03/05/pr2261-imf-staff-statement-on-the-economic-impact-of-war-in-ukraine accessed on 5 May 2022).

It was also found that a rapid escalation in the prices of fuel and commodities in Japan signifies an inflationary effect for the last quarter of 2021–2022, and that Japan's economy has been growing at a slower pace due to Russia–Ukraine war. (https://www.reuters.com/markets/asia/more-japan-firms-pass-costs-rising-commodity-prices-weak-yen-2022-07-13 accessed on 13 July 2022). Japanese consumer prices, including fresh food, are expected to rise by 2.6 percent in the current fiscal year through March from a year earlier, mainly due to Russia's invasion of Ukraine (https://www.nippon.com/en/news/kd924238310283051008/ accessed on 2 July 2022).

German banks also heavily on Russia for most of Germany's natural gas imports, as it imports between approximately 60% and 70% of its energy from Russia. However, natural gas makes up less than 20% of Germany's energy mix for power production. Germany is almost completely dependent on Russian crude supplies via pipeline projects such as Nord Stream 1 and Nord Stream 2 (https://www.bbc.com/news/business-44794688 accessed on 12 July 2022). However, in the case of Italy, even as the European Union decided to reduce Russian crude oil imports by up to 90% by the end of the year 2022, Italy stood aside in implementing the sanctions and chose to escalate its crude oil imports from Russia (https://apnews.com/article/russia-ukraine-politics-economy-global-tradeb0c193007210592123112e2db1069461 accessed on 12 July 2022).

An inflationary impact is one of the major consequences of this ongoing war. The rise in inflation has been more pronounced in emerging and developing countries, which severely affects the poorest and most vulnerable in society and contributes to increasing inequalities worldwide. The present war has been accompanied by a sharp rise in inflation under pressure from food, energy and major commodity prices. Inflation has been rising throughout 2021 as the recovery drives demand and continues to disrupt many value chains, however, the war has accelerated it (https://blogs.imf.org/2022/04/27/inflation-to-be-elevated-for-longer-on-war-demand-job-markets/ accessed on 2 July 2022). Therefore, the Russia–Ukraine conflict has caused a double whammy to the global recovery from the COVID-19 pandemic and G7 countries are no exception (https://www.imf.org/en/ accessed on 2 July 2022).

Some recent studies including those by Foroni et al. (2017), Ready (2018), Emrah et al. (2021), Saraswat et al. (2022), Li et al. (2022) and Dai et al. (2022), among others, are of the opinion that all historical oil shocks have been associated with increases in crude oil prices with their subsequent negative effects on the economy. Mensi et al. (2021) indicated that the highest jump in spillovers occurred duringtheCOVID-19outbreakinthestock markets of the Middle East and North Africa (MENA), followed by the global financial crisis and the plunge in crude oil prices during the great lockdown around the world. Again, Roubaud and Arouri (2018) established that oil prices play an active role in the transmission of price shocks to both exchange rates and stock markets.

In this context, the objective of this paper was to examine the effects of surging crude oil prices on the stock price returns and exchange rates of G7 countries, namely Canada, France, Germany, Italy, Japan, the United Kingdom (UK)and the United States (US),due to the outbreak of the war between Russia and Ukraine.

The remainder of this paper is organized as follows: Section 2 deals with previous studies; Section 3 explains the methodology employed in this study; Section 4 reveals the empirical results and discussion and finally, Section 5 concludes the study with some recommendations including the limitations of this study.

2. Previous Studies

Ali et al. (2022) claimed through their study that the bearish trend of stock markets was associated with a downward movement in oil prices during the COVID-19 pandemic. However, on the other hand, studies by Wen et al. (2022) and Hashmi et al. (2022) showed that the oil demand shock and oil risk shock can Granger cause the stock risk–return relation rather than the oil supply shock. A study based on China by Chen et al. (2022) confirmed that the risk of uncertainty fluctuation in stock markets is much more sensitive to that of the oil markets, while the impact of the USD/CNY uncertainty volatility is relatively weak in most cases. Yuan et al. (2022) found that the BRIC's stock markets are more affected by negative oil returns, whereas their oil markets are more affected by positive stock returns. Cai et al. (2022) documented how unplanned oil supplies act as an external cause to decrease industrial production and escalate unemployment rates. Shabir and Bisharat (2022) observed that the impact of oil prices and exchange rates on stock prices vary across bullish and bearish markets. Nusair and Olson (2022) observed that crude oil prices influence not only stock markets but also effective exchange rates, including in a dynamic manner. Again, in a recent study conducted by Zhang and Qin (2022), a clear asymmetric relationship was established between international crude oil prices and the RMB (Renminbi) exchange rate.

Mensi et al. (2021) indicated that the highest jump in spill overs occurred during the COVID-19 outbreak in the stock markets of the Middle East and North Africa (MENA), followed by the global financial crisis and the plunge in crude oil prices during lock downs across the globe. Recently, Jiang and Kong (2021) established the positive one-way spill over effect of international crude oil returns on China's energy stock returns. As observed by authors including Meiyu et al. (2021), Nguyen et al. (2020) and Huang et al. (2017), stock markets and effective exchange rates are vigorously affected by surges in crude oil prices.

Vochozka et al. (2020) proved that the EUR/USD exchange rate is strongly dependent on the international price of oil. Ahmad et al. (2020) showed that the effect of crude oil prices and exchange rates on stock prices varies across bullish and bearish markets, whereas Ahmad et al. (2020) found a positive return spillover from the oil prices to the foreign exchange market, and according to them, high oil prices have a negative impact on exchange rate conditional volatility as the exchange rate responds asymmetrically to disentangled (positive and negative) oil price jumps. More specifically, Wen et al. (2020) observed that the risk spillovers are stronger from exchange rates to crude oil than those from oil to exchange rate markets.

The effects of the Brent crude oil price shocks (due to a steep increase in price) which have arisen due to the Russia–Ukraine conflict on the stock price returns and currency exchange rates of G7 countries are investigated in this study. The present study applies the Fractionally Integrated GARCH (FIGARCH) model. The FIGARCH model is regarded as a more elastic class of method for conditional variance which is able to explain and characterize the identified temporal dependencies of the volatility in an upgraded methodology rather than another GARCH class of models (Davidson 2004). In addition, the long-memory nature of the FIGARCH model makes it superior to other conditional heteroscedastic models, and thus, branding it as a better candidate for modelling volatility in stock market returns and exchange rates (Tayefi and Ramanathan 2012).

The remainder of this paper is organized as follows: Section 3 explains the methodology employed in this study, Section 4 reveals the empirical results and discussion, and finally, Section 5 concludes the study with some recommendations and limitations.

3. Methodology

The data analysis was performed considering the closing daily price returns of stock market indices from G7 countries, namely Toronto stock exchange (TSX—Canada), Cotation Assistéeen Continu (CAC 40—France), Frankfurt Stock Exchange (DAX 30—Germany), BorsaItaliana (FTSE MIB—Italy), Nikkei Stock Average (NIKKEI 225—Japan), Financial Times Stock Exchange 100 Index (FTSE 100—UK) and NASDAQ Composite Index (NASDAQ—USA). Apart from the stock market indices, the currency exchange rates, namely the Canadian Dollar (CAD), Euro (EUR), Japanese Yen (JPY), Pound Sterling (GBP) and US Dollar (USD) were also taken into account in this study. All the currency exchange rates were taken in USD for the purpose of data analysis. The sources of the datasets were the Federal Reserve Economic Data (https://fred.stlouisfed.org/ accessed on 14 July 2022), Trading Economics (https://tradingeconomics.com/ accessed on 14 July 2022) and Investing.com (https://www.investing.com/ accessed on 14 July 2022). Here, in case of Germany, it needs to be mentioned that the Deutsche Mark (DM) was the official currency of Germany until the adoption of the Euro (EUR) in 2002. The Euro banknotes and coins were introduced in Germany on 1 January 2002, after an intermediary phase of three years. During that transitional period of three years, the Euro only existed as 'book money' in Germany. In this analysis, Euro is considered as the currency for Germany, France and Italy.

The study period considered is that during the period from 2 January 2017 to 29 June 2022. However, to examine the economic impact of any war or any other crisis, a period covering five years both before and after the occurrence of the war or crisis in question is more frequently chosen (Chen et al. 2018). However, in our case, the tumultuous conflict between Russia and Ukraine first occurred on 24 February 2022 (reuters.com accessed on 2 June 2022) with the outbreak of the war, and is ongoing. Thus, the authors have no choice but to follow the conventions of the war or crisis literature in selecting a time period, however, we have taken our dataset way back from January2017 to cover a period of five years before the outbreak of the war and continued up until 29 June 2022.

In the beginning, the descriptive statistics of the considered datasets were checked for stock price returns, including currency exchange rates and Brent crude oil price to examine the nature and applicability of the dataset. Thereafter, the cumulative sum (CUSUM) of the recursive residuals test was applied to assess the parameter stability (Pesaran and Pesaran 1997). In order to determine the presence of structural breaks in the dataset, the Break-point unit root test was applied with the innovational outlier model, which was first proposed by Perron (1989, 1997).

Despite the fact that there are several models in the financial literature through which the presence of external shocks and their effects on stock markets can be examined, it was decided to apply the FIGARCH model as proposed by Bordignon et al. (2004), which captures both periodic patterns and long-memory behaviour in conditional variance. Although the model was first introduced by Baillie et al. (1996), it was subsequently developed by Davidson (2004) and Bordignon et al. (2004) to includes a long-memory component that functions at zero and seasonal frequencies. This FIGARCH model has been applied in several studies by authors such as Tayefi and Ramanathan (2012), Rohan and Ramanathan (2012), Li and Xiao (2011), Nasr et al. (2010), Rapach and Strauss (2008) and Conrad and Haag (2006), among others, which make it more reliable. Thus, this model serves as a benchmark model in our study.

3.1. Break-Point Unit Root Test

The stationarity of the individual series was interpreted by directing distinct unit-root tests. A comprehensive augmented Dickey–Fuller test with innovational outlier and additive outlier breakpoints as projected by Perron (1989, 1997) was applied. The models (Equations (1) and (2) below included the variables for a change in the interception of the trend function gradually in a technique that trusts the correlation function and the innovation (i.e., noise) process (Perron 1997).

$$\Delta y_t = \mu + \theta DU_t + \beta_t + \phi D(T_b)_t + \alpha y_{t-1} + \sum_{i=1}^{k} z_i \Delta y_{t-i} + \varepsilon_t \quad (1)$$

$$\Delta y_t = \mu + \theta DU_t + \beta_t + \omega DT_t + \phi D(T_b)_t + \alpha y_{t-1} + \sum_{i=1}^{k} z_i \Delta y_{t-i} + \varepsilon_t \quad (2)$$

Equations (1) and (2) were estimated using the ordinary least squares (OLS). The indicator functions $1(\cdot)$ are expressed as $DU_t = 1\ (t > T_b)$, $D(T_b)_t = 1\ (t = T_b + 1)$, $DT_t = 1\ (t > T_b + 1)$ and $DT^*{}_t = 1\ (t > T_b)(t - T_b)$. As per Perron (1989, 1997), the breakpoint T_b can be selected such that $t_{\hat{\alpha}}(T_b, k)$ is minimized. The minimized t-statistic is stated as:

$$t^*_{\hat{\alpha}} = \min_{T_{b \in (k+1,T)}} t_{\hat{\alpha}}(T_b, k). \quad (3)$$

where k is the truncation lag parameter which is also unknown.

3.2. FIGARCH

Model

Apart from conventional volatility models including the autoregressive conditional heteroscedastic (ARCH) model by Engle (1982), the generalized autoregressive conditional heteroscedastic (GARCH) model by Bollerslev (1986) and Bollerslev and Hans (1996) and integrated GARCH (IGARCH) model by Engle and Bollerslev (1986), there is also another superior model, i.e., the Fractionally Integrated GARCH (FIGARCH) model by Baillie et al. (1996) which has rarely been used in existing studies. This model includes the time dependency of the variance and a leptokurtic unconditional distribution for the returns with long-memory behaviour for the conditional variances and a sluggish hyperbolic frequency of deterioration for the lagged squared (Tayefi and Ramanathan 2012). As per Baillie et al. (1996), the impact of any shock in terms of volatility on a financial series is not limited. It received wide attention from researchers for highlighting the volatility of long-memory persistence and clustering. Long-memory persistence commonly exists in examining the volatility of high-frequency financial time series as observed in a number of studies conducted by authors including (Baillie et al. 1996; Dacorogna et al. 1993; Ding et al. 1993; Granger and Ding 1996). Hence, there is ample opportunity to study such infinite shock using the FIGARCH model.

According to Tayefi and Ramanathan (2012), the volatility equation of the GARCH(p, q) process, as proposed by Bollerslev (1986) and Taylor (1986),can be written as:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon^2{}_{t-I} + \sum_{j=1}^{p} \beta_j h_{t-j} \quad (4)$$

where $p > 0$, $q > 0$, $\alpha_0 > 0$, $\alpha_i \geq 0$, $i = 1, \cdots, q$, $\beta_j \geq 0$, $j = 1, \ldots.., p$ and $\alpha(L)$ and $\beta(L)$ are lag operators such that $\alpha(L) = \alpha_1 L + \alpha_2 L^2 + \cdots + \alpha_q L^q$ and $\beta(L) = \beta_1 L + \beta_2 L^2 + \cdots + \beta_p L^p$.

When $p = 0$, the process reduces to an ARCH(q) and for $p = q = 0$, ϵ_t is simply a white noise process.

The GARCH(p, q) process, as defined above in Equation (4), is widely stationary with $E(\epsilon t) = 0$ and $\mathrm{var}(\epsilon t) = \alpha 0(1 - \alpha(1) - \beta(1))^{-1}$. A similar ARMA type representation of the GARCH(p, q) process is given in Equation (5) below.

ARMA models possess non-random and constant variance that is classically considered to be good to demonstrate homoscedastic data. The GARCH models characterize variable variance which is non-random when conditioning on the past. Therefore, both these models are frequently used to signify heteroscedastic data.

$$\varepsilon_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \varepsilon_{t-j}^2 - \sum_{j=1}^{p} \beta_j v_{t-j} + v_t \tag{5}$$

where $v_t = \varepsilon_t^2 - h_t = (z_t^2 - 1)\, h_t$ and the z_t'S are uncorrelated with $E(z_t) = 0$ and var $(z_t) = 1$. From Equation (5), it can be observed that the GARCH(p, q) procedure can also be articulated as an ARMA(m, p) procedure in ε_t^2,

$$[1 - \alpha\,(L) - \beta\,(L)]\varepsilon_t^2 = \alpha_0 + [1 - \beta\,(L)]v_t \tag{6}$$

where m = max{p, q} and $v_t = \varepsilon_t^2 - h_t$. The v_t procedure can be inferred as the "innovations" for the conditional variance, as it is a zero-mean martingale. Thus, an integrated GARCH(p, q) procedure can be written as:

$$[1 - \alpha\,(L) - \beta\,(L)]\,(1 - L)\varepsilon_t^2 = \alpha_0 + [1 - \beta\,(L)]v_t \tag{7}$$

The fractionally integrated GARCH or FIGARCH group of models is attained by substituting the first difference operator $(1 - L)$ in (6) with the fractional differencing operator $(1 - L)^d$, where d is a fraction $0 < d < 1$. Therefore, the FIGARCH group of models can be acquired by considering:

$$[1 - \alpha\,(L) - \beta\,(L)]\,(1 - L)^d \varepsilon_t^2 = \alpha_0 + [1 - \beta\,(L)]v_t \tag{8}$$

Equation (7) caters to the dominance of elucidating and signifying the observed temporal dependencies of the financial market volatility over other types of GARCH models (Davidson 2004).

Bordignon et al. (2004) applied a FIGARCH model with seasonality, which permits for both periodic patterns and long-memory behaviour in the conditional variance. This combines the two features allowing the model to be both periodic and devise long-memory mechanisms. Such a model is represented by:

$$h_t = \alpha_0 + \alpha(L)\varepsilon_t^2 + \beta(L)h_t + [1 - (1 - L^S)^d]\varepsilon_t^2 \tag{9}$$

In Equation (8) above, the first three terms in the conditional variance duplicate the general GARCH model, the fourth term familiarizes a long-memory component that functions at zero and seasonal incidences. The parameter S denotes the length of the cycle, although d specifies the propensity of the memory.

4. Empirical Results and Discussion

Before moving on to the central theme of this study, it is customary to have the diagnosis of the dataset. For this purpose, a descriptive test and parameter stability test were conducted and the results were exhibited as follows in Sections 4.1 and 4.2. The results of breakpoint unit root test and FIGARCH estimation results are presented in Sections 4.3 and 4.4.

4.1. Descriptive Tests

Here, the descriptive statistics of the considered datasets for stock price returns including currency exchange rates and Brent crude oil price are analysed. The results of this analysis are portrayed below in Tables 1 and 2.

Table 1. Descriptive Statistics Results of Stock Market indices.

	TSX	CAC 40	DAX 30	FTSE MIB	Nikkei 225	FTSE 100	NASDAQ
Mean	0.001	0.001	0.001	0.001	0.002	0.068	0.006
Median	0.001	0.001	0.001	0.001	0.000	0.005	0.002
Maximum	0.113	0.081	0.104	0.085	0.077	0.087	0.096
Minimum	−0.132	−0.131	−0.131	−0.185	−0.063	−0.115	−0.130
Std. Dev.	0.012	0.012	0.012	0.014	0.011	0.011	0.015
Skewness	−2.109	−1.052	−0.964	−2.261	−0.054	−1.262	−0.756
Kurtosis	51.928	19.643	19.668	32.946	7.930	21.587	12.438
Jarque–Bera	133,350	15,559.530	15,567.290	50,715.440	1344.332	19,454.250	5051.605
Probability	0.000 *	0.000 *	0.000 *	0.000 *	0.000 *	0.000 *	0.000 *

(* indicates significance at 1% level).

Table 2. Descriptive Statistics Results of Currency Exchange Rates and Brent Crude Oil Price.

	CAD	Euro	JPY	GBP	USD	Brent Crude Oil
Mean	−0.042	−0.076	0.002	−0.053	0.071	0.001
Median	0.000	0.000	−0.002	0.000	0.000	0.002
Maximum	0.021	0.021	0.334	0.037	0.057	0.329
Minimum	−0.019	−0.016	−0.031	−0.030	−0.021	−0.280
Std. Dev.	0.004	0.004	0.010	0.005	0.004	0.028
Skewness	0.112	0.039	26.688	−0.032	1.467	−0.144
Kurtosis	4.711	4.120	875.569	6.609	22.370	34.292
Jarque–Bera	164.724	69.737	173.345	140.510	121.46	144.47
Probability	0.000 *	0.000 *	0.000 *	0.000 *	0.000 *	0.000 *

(* indicates significance at 1% level).

The above Table 1 represents the results of the descriptive statistics of the select stock price returns. TSX rose to 0.1129 and came down to −0.1317 with an average of 0.0001 during the study period. Similarly, CAC 40 increased to 0.0805 and declined to −0.1309 with a mean of 0.0001. DAX 30 enlarged to 0.1041 and declined to −0.1305 with an average of 0.0001. FTSE MIB enhanced to 0.0854 and came down to −0.1854 with an average of 0.0001. Nikkei 225 experienced the highest value of 0.0773 and a lowest of −0.0627 with an average of 0.0002. Likewise, FTSE 100 also experienced the highest value of 0.0866 and the lowest value of −0.1151 with a mean of 0.0683. NASDAQ rose to 0.0959 and declined to −0.1300 with an average of 0.0006. The value of JB statistics show that all data relating to stock price returns are not normally distributed. Hence, it is to mention that skewed and possess flat tails which very much corroborate the presence of long-memory effect among the variables in this study.

The above Table 2 represents the results of the descriptive statistics of the select currency exchange rates along with Brent crude oil price. CAD rose to 0.0211 and came down to −0.0187 with an average of −0.0420 during the study period. Similarly, EUR increased to 0.0206 and declined to −0.0159 with a mean of −0.0760. JPY increased to 0.3335 and declined to −0.0312 with an average of 0.0002. GBP rose to 0.0371 and came down to −0.0299 with an average of −0.0532. USD experienced the highest value of 0.0568 and the lowest value of −0.0206 with an average of 0.0713. Likewise, the Brent crude oil price experienced the highest value of 0.3292 and the lowest value of −0.2797 with a mean of 0.0005. The value of JB statistics show that all data relating to currency exchange rates and crude oil prices are not normally distributed. Hence, it is also to mention that skewed and possess flat tails which very much corroborate the presence of long-memory effect among the variables in this study.

4.2. Parameter Stability Test

The CUSUM test exhibits systematic changes in the regression coefficients. Figures 1 and 2 below give the results for the CUSUM test. The results indicate the absence of any instability of the coefficients because the plots of all CUSUM statistics fall inside the critical bands of the 5% confidence intervals of parameter stability. In terms of the variables considered in this study, it can be said that the above results indicate the absence of any instability of the coefficients as the plots of the CUSUM statistics of the Brent crude oil price, stock indices and exchange rates fall inside the critical bands of the 5% confidence intervals of parameter stability. Therefore, from Figures 1 and 2, it is evident that stability exists in the coefficients over the sample period for all the selected variables.

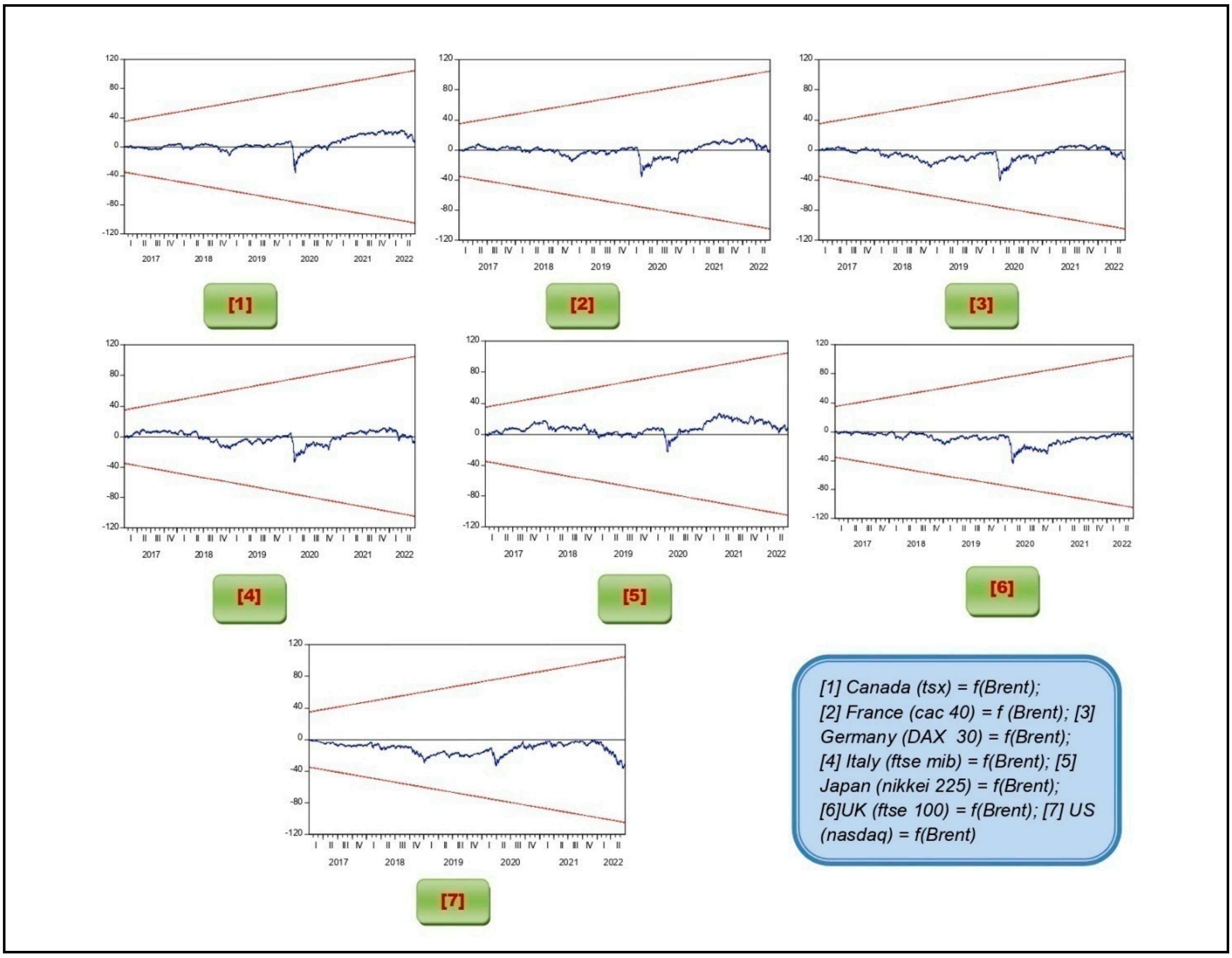


Figure 1. Plots of CUSUM for Parameter Stability between Brent Crude Oil Price and Stock. Indices of G7 countries. Source: Researchers' own representations.

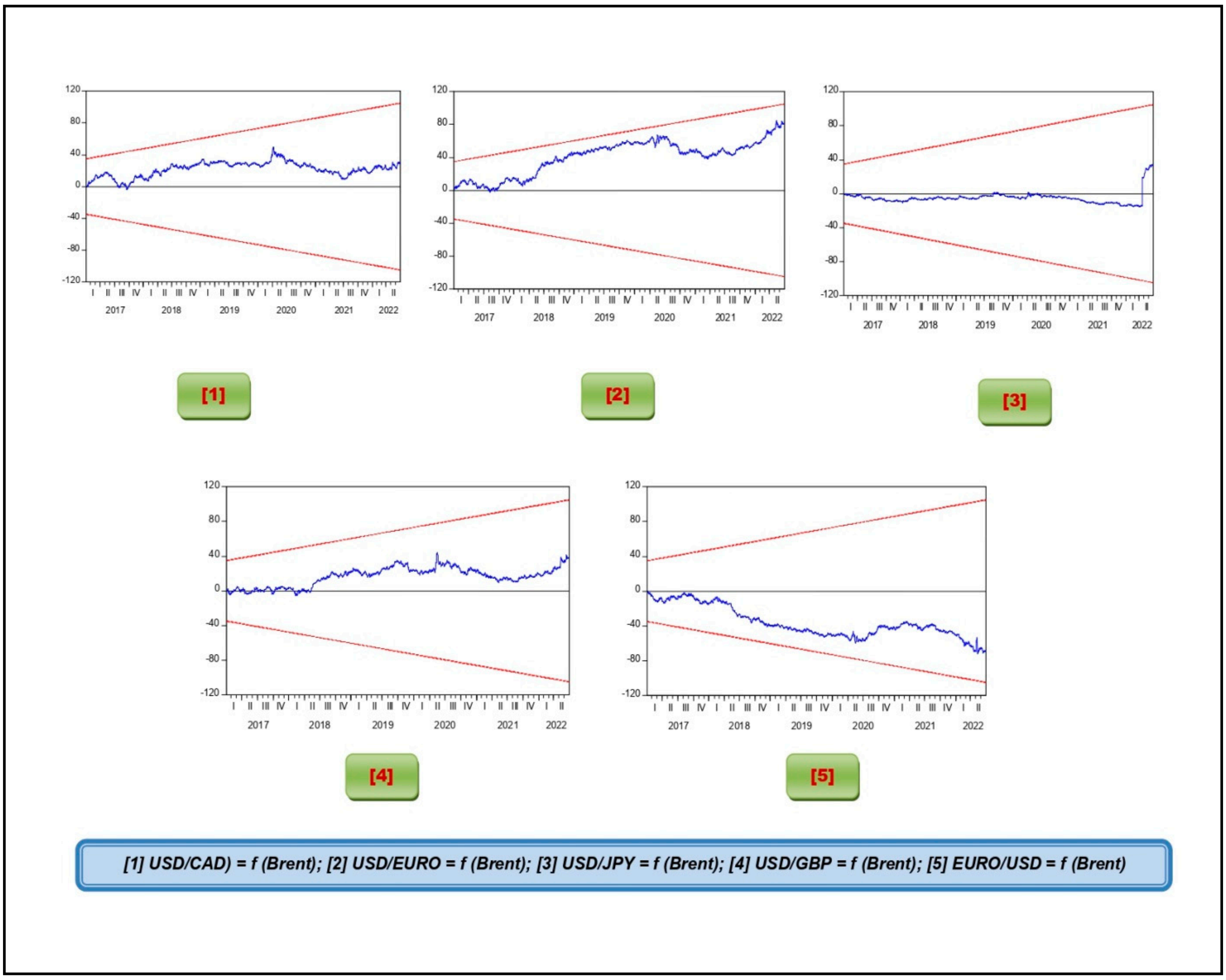


Figure 2. Plots of CUSUM for Parameter Stability between Brent Crude Oil Price and Exchange Rates of the domestic currencies of G7 countries expressed in terms of USD. Source: Researchers' own representations.

4.3. Break-Point Unit Root Test

Table 3 below portrays the results of the unit root test with a structural break. It is observed that all the stock price returns, currency exchange rates and Brent crude oil price are found to be stationary at the level which indicates the non-existence of a unit root. All the variables are significant at a 1% level with a 99% confidence interval, and thus, they are free from a random walk. However, the estimation results of the innovational outlier model also provide us with different break-point dates for all the stock price returns and currency exchange rates of G7 countries including crude oil prices. It is interesting to note that all the stock price returns of these advanced economies had breakeven dates from 24 February 2022 to 1 March 2022. This shows that the stock price returns of advanced economies are more susceptible to soaring crude oil prices as well as uncertainty in production and supply, which may have been hampered by the outbreak of the war. Again, the exchange rates of currencies such as CAD and JPY experienced breakeven dates precisely on 24 February 2022. However, the currency exchange rates of the US (USD), European Union (EUR) and United Kingdom (GBP) demonstrate their hostility due to their strong international presence, and had breakeven dates on 28 March 2022, 16 March 2022 and 15 March 2022, respectively.

Table 3. Break-point Unit root test of Stock Market Indices, Currency Exchange Rates and Brent Crude Oil Price.

Trend and Intercept (Innovative Outlier Model)			
At Level			
Variables	**t-Statistics**	***p*-Value**	**Break Date**
TSX	−12.2611	0.01 *	24 February 2022
CAC 40	−36.2886	0.01 *	28 February 2022
DAX 30	−37.2328	0.01 *	1 March 2022
FTSE MIB	−39.0779	0.01 *	24 February 2022
Nikkei 225	−23.56	0.01 *	1 March 2022
FTSE 100	−13.5555	0.01 *	24 February 2022
NASDAQ	−15.0214	0.01 *	26 February 2022
CAD	−36.8506	0.01 *	24 February 2022
EUR	−36.3835	0.01 *	16 March 2022
JPY	−36.8619	0.01 *	24 February 2022
GBP	−35.3468	0.01 *	15 March 2022
USD	−35.216	0.01 *	26 March 2022
Brent Crude Oil Price	−32.7856	0.01 *	28 March 2022

(* indicates significance at 1% level).

Whilst various political crises across the globe, natural catastrophes, the outbreak of COVID-19 pandemic and war are just a few events that have had profound effects on currency markets, the US dollar has been intensifying its value against other currencies during the Russia–Ukraine conflict. According to Kenneth Rogoff, Professor of Economics at Harvard University and a former chief economist at the International Monetary Fund, this is mainly because the Federal Reserve of the US is on the right track to escalate their interest rates quicker than other major economies. Moreover, investors also rushed in to invest in USD, which is considered a safe haven in times of crisis. The member countries of the European Union and the UK also followed in the footsteps of the US to control the devaluation of their domestic currencies, i.e., EUR and GBP, respectively. Even though the outbreak of war contributed to higher commodity and fuel prices, nevertheless, the Federal Reserve of the US and the central banks of other advanced economies have controlled the devaluation of their domestic currencies to some extent by increasing interest rates (https://www.bbc.com/news/business-61680382 accessed on 17 January 2023).

For a better understanding, a graphical representation of the results is also showcased in Figure 3.

4.4. FIGARCH Estimation Results

Keeping in tune with the central theme of the paper, the FIGARCH model, as given by Bordignon et al. (2004), was applied. The given model was applied where conditional variance h_t denotes select stock indices and exchange rates. Therefore, the conditional variance h_t of y_t (Brent crude oil price in our case) is given by:

$$h_t = \alpha_0 + \alpha(L)\varepsilon_t^2 + \beta(L)h_t + [1 - (1 - L^S)^d]\varepsilon_t^2 \tag{10}$$

where $t = 1, 2, \ldots, 1362$.

After, rearranging the terms of the equation above, y_t can be defined as:

$$y_t = \alpha_0[1 - \beta(1)]^{-1} + \left\{1 - [1 - \beta(L)]^{-1}\phi(L)(1 - L)^d\right\}\varepsilon_t^2 = \alpha_0[1 - \beta(1)]^{-1} + \lambda\,(L)\,\varepsilon_t^2 \tag{11}$$

Table 3 below represents the results of the given FIGARCH model.

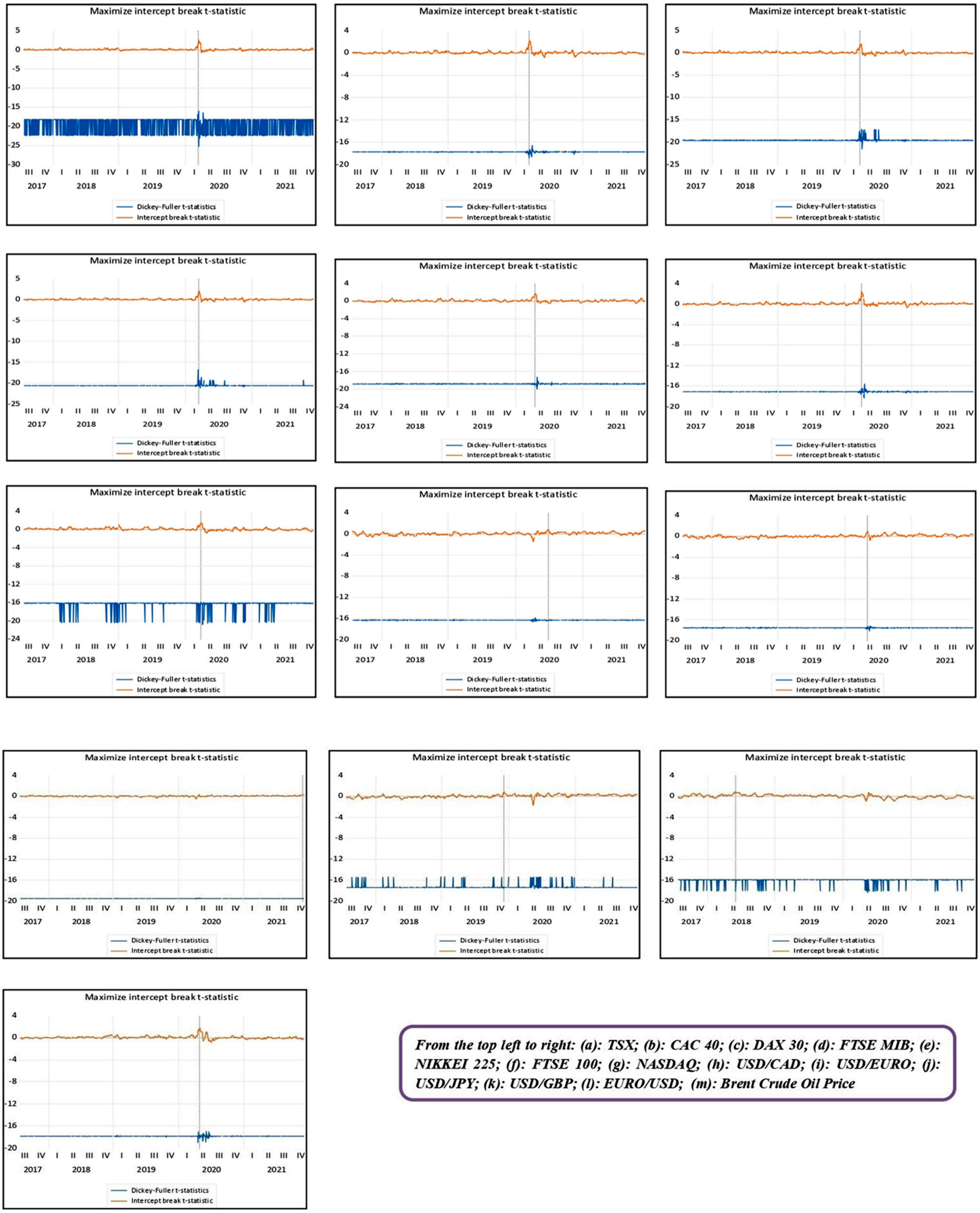


Figure 3. Graphical Representation of Breakeven Unit Root Tests (at level) of the Stock price Returns and Currency Exchange Rates of G7 Countries including Brent Crude Oil Price Returns. Note: X axis measures the time periods as represented by observations to demonstrate the impact of structural breaks in stationarity. The series plotted above shows a structural break in the level and clearly does not revert around the same mean across all of time.

The Table 4 above portrays the constant, ARCH effect and GARCH effect of the select stock price returns, currency exchange rates and Brent crude oil price. The ARCH term explains the volatility clustering, the GARCH term explains the persistency or the variance in volatility and the $\alpha + \beta$ term explains the long memory effect within the variables running from Brent crude oil price. The constant terms are significant for all the variables except EUR and USD. The ARCH term is significant for all variables except NASDAQ and USD. However, the GARCH term is significant for all variables. It is noted that the value of the coefficients of the GARCH term is more than the ARCH term indicating the volatility effects are more persistent due to the existing shocks running from Brent crude oil price. Since the $\alpha + \beta$ term tends towards 1 for CAC 40, DAX 30, FTSE MIB, Nikkei 225, FTSE 100, CAD, EUR, JPY and GBP, it is concluded that these variables portray the presence of the long-memory effect. However, no long-memory effect was observed in TSX, NASDAQ and USD. Long memory is defined as the declining behaviour at a hyperbolic rate in an autocorrelation function of return and impulsiveness that indicates the characteristics of sluggish mean reversion and deterioration in the stock returns.

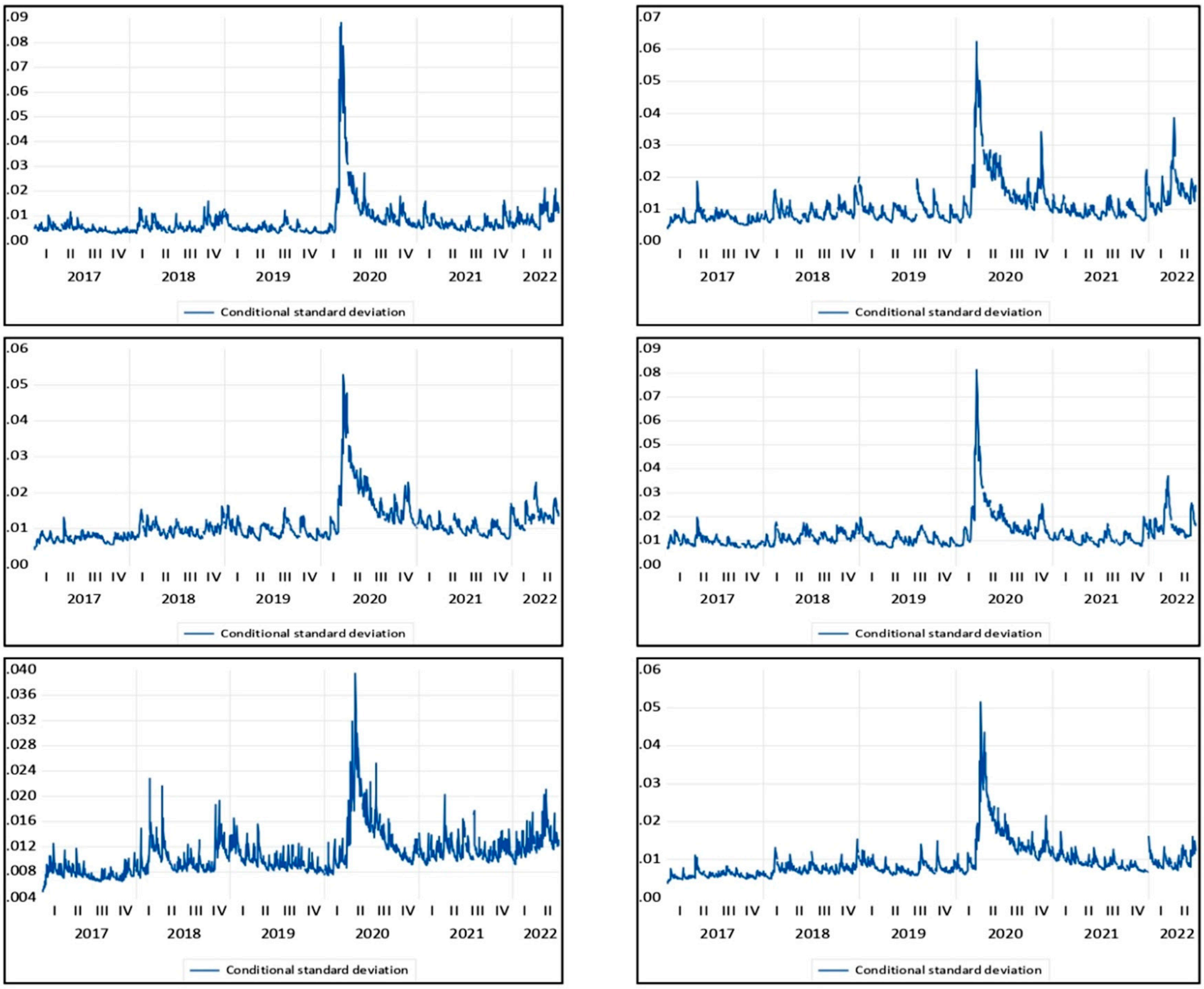
Table 4. FIGARCH test of Stock Market Indices, Currency Exchange Rates and Brent Crude Oil Prices.

Dependent Variable	Constant (ω)	*p*-Value	ARCH Effect (α)	*p*-Value	GARCH Effect (β)	*p*-Value	$\alpha + \beta$
TSX	0.027	0.00 *	0.187	0.10 ***	0.467	0.00 *	0.653
CAC 40	0.011	0.00 *	0.456	0.10 ***	0.499	0.02 **	0.955
DAX 30	0.013	0.00 *	0.461	0.00 *	0.519	0.03 **	0.980
FTSE MIB	0.010	0.00 *	0.472	0.08 ***	0.501	0.00 *	0.973
Nikkei 225	0.064	0.00 *	0.312	0.00 *	0.681	0.00 *	0.992
FTSE 100	0.079	0.01 *	0.401	0.03 **	0.532	0.01 *	0.933
NASDAQ	0.088	0.00 *	0.013	0.84	0.553	0.00 *	0.567
CAD	0.010	0.01 *	0.393	0.00 *	0.603	0.00 *	0.996
EUR	0.062	0.14	0.375	0.00 *	0.565	0.00 *	0.941
JPY	0.202	0.01 *	0.438	0.07 **	0.555	0.04 **	0.993
GBP	0.021	0.00 *	0.080	0.00 *	0.841	0.00 *	0.9215
USD	0.201	0.22	0.151	0.52	0.601	0.05 **	0.750

(* indicates significance at 1% level, ** indicates significance at 5% level and *** indicates significance at 10% level).

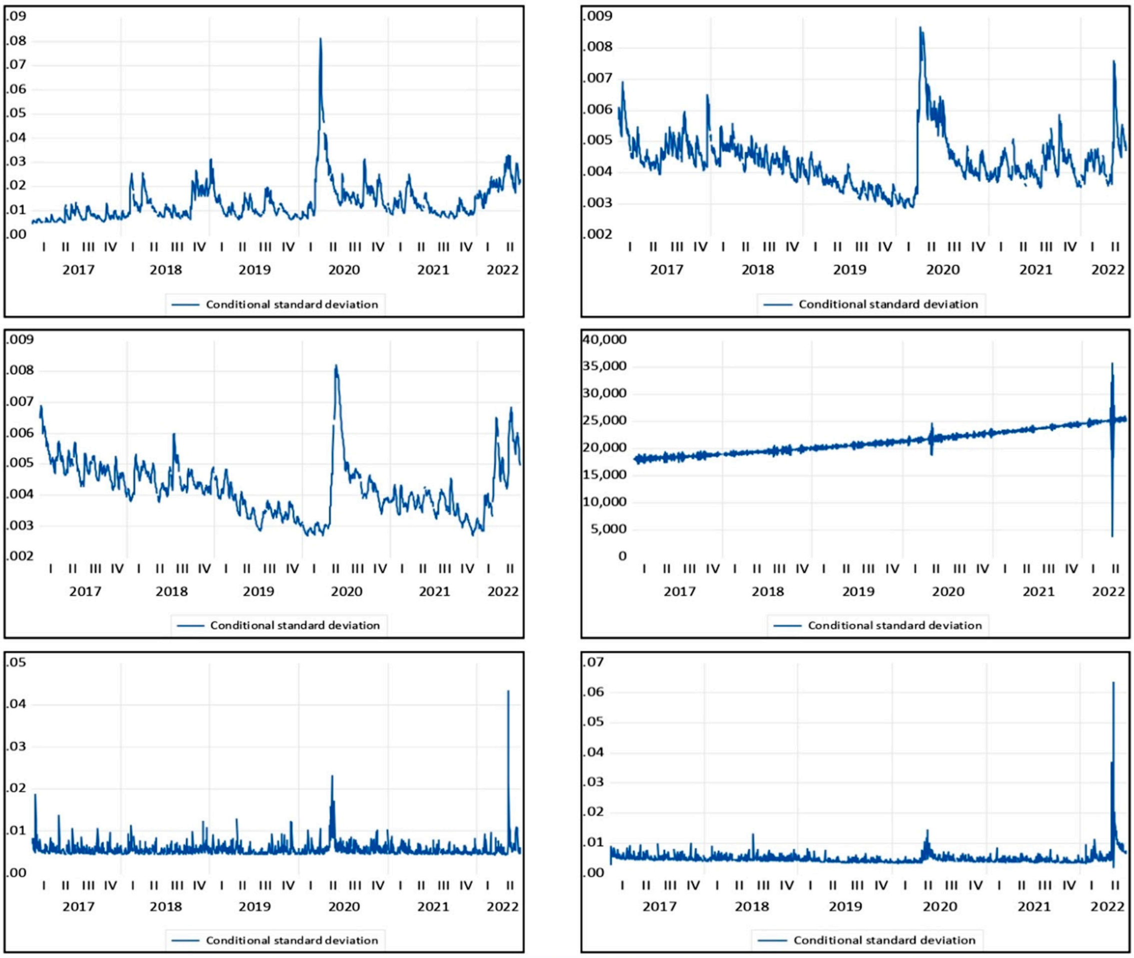
However, it is not implied that the outbreak of the war did not affect TSX, NASDAQ and USD. The ARCH and GARCH values suggested that they have also experienced a negative impact of the war, however, the pessimistic situation did not persist for a long period. When the war broke out between Russia and Ukraine, the Wall Street VIX index, which measures volatility, more than doubled from 16 to 36. The NASDAQ also dipped into the "Bear-Market Zone" and down by more than 22% (https://www.nasdaq.com/articles/ accessed on 30 June 2022). In the last week of February 2022, TSX fell down to its lowest in the last four weeks mainly because of the concerns of the investors over escalating tensions between Russia and Ukraine. However, this situation did not last over a long period (www.reuters.com accessed on 30 June 2022). As discussed earlier, the Federal Reserve of the US acted very quickly to increase the short-term interest rates to tackle inflation, which in turn boosted investors' confidence. According to Federal Reserve officials, they increased the interest rates only because the US economy is strong, and when the country's economy is strong, the stock earnings will also have usual growth (https://www.nasdaq.com/articles/rate-hikes-returns-and-recessions accessed on 30 June 2022).

Figures 4 and 5 showcase the percentage stock price returns and currency exchange rates of G7 countries in a very clear manner to indicate the volatility of the sequences taken under deliberation. A hyperbolic decay of the absolute stock price returns and currency exchange rates is also observed in the figures.



From the top left to right: (a): TSX; (b): CAC 40; (c): DAX 30; (d): FTSE MIB; (e): NIKKEI 225; (f): FTSE 100

Figure 4. Graphical Representation of the variavles (**a**): TSX; (**b**): CAC 40; (**c**): DAX 30; (**d**): FTSE MIB; (**e**): NIKKEI 225; (**f**): FTSE 100 of G7 Countries under FIGARCH Estimation. Note: X axis measures time periods as represented by observations.



From the top left to right: (a): NASDAQ; (b): USD/CAD; (c): USD/EURO; (d): USD/JPY; (e): USD/GBP; (f): EURO/USD

Figure 5. Graphical Representation of the variables (**a**): NASDAQ; (**b**): USD/CAD; (**c**): USD/EURO; (**d**): USD/JPY; (**e**): USD/GBP; (**f**): EURO/USD of G7 Countries under FIGARCH Estimation. Note: X axis measures time periods as represented by observations.

5. Conclusions, Recommendations and Limitations

The present study delved to examine the impacts of the steep surge in crude oil prices on the stock price returns and currency exchange rates of G7 countries using the breakeven unit root test and FIGARCH model. The breakeven unit root test provided an interesting outcome revealing that all the stock price returns of these advanced economies had breakeven dates from 24 February 2022 to 1 March 2022. Again, currency exchange rates including CAD and JPY experienced breakeven dates precisely on 24 February 2022. However, on the contrary, the currency exchange rates of the US (USD), European Union (Euro) and United Kingdom (GBP) demonstrated their hostility due to their strong international presence and had breakeven dates on 28 March 2022, 16 March 2022 and 15 March 2022, respectively. The FIGARCH estimation showed that except for TSX, NASDAQ and USD, noteworthy long-memory effects are running from Brent crude oil price to all stock price returns and currency exchange rates for all G7 countries. It was implied that, during the study period, the persistent increase in ethnic tension between Russia and Ukraine led to the outbreak of conflict which constitutes the underlying shock with a global impact in terms of long-memory effect on the volatility of stock price returns and currency exchange rates.

It is recommended that these European nations belonging to the G7 should shift their purchase of crude oil from Russia to other oil-exporting countries, namely OPEC

(Organisation of Petroleum Exporting Countries), Brazil and others. Moreover, the G7 countries should also adopt necessary policies to make necessary corrections in their domestic currencies by increasing the internal interest rates to check the long-memory effects of increasing crude oil prices on their currency exchange rates.

This study will guide policymakers in making the necessary corrections in order to control the impact of oil price shocks on stock price returns and currency exchange rates during the occurrence of any war-like events. Investors will be assisted in understanding the stock market mechanism and making wise decisions before reacting to actions during a crisis period. This study contributes to the existing literature on event study methodology, providing scope for strengthening the findings with future research. To the best of our knowledge, no study has been conducted to capture the surging crude oil price shocks on the stock price returns and currency exchange rates of the G7 countries during the Russia–Ukraine war using the breakeven unit root test and the FIGARCH model. We examined the long-memory effects of the surging crude oil prices due to the outbreak of war using the FIGARCH model, which makes this study a pioneer in this field.

Regarding the limitations of this study, it can be stated that the present study excluded other macroeconomic variables that could have revealed interesting outcomes. The period of this study was also restricted to only 1362 observations. A more in-depth analytical study covering a longer time period and including important macroeconomic variables may be undertaken in the future to more precisely study the effects of the war. Moreover, the present study only considered G7 countries but other countries could also have been considered.

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