International Review of Financial Analysis 103 (2025) 104218

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Stock market volatility and oil shocks: A study of G7 economies

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ARTICLE INFO

Keywords:
Oil shocks
Oil price volatility
VAR-GARCH model
G7 economies
Stock market volatility

ABSTRACT

Oil shocks have caused economic recessions over the years, affecting various markets, especially the stock market. The objective of this study is to analyze how global oil price index variable and shocks related to supply, economic activity, demand, and inventory affect the volatility and dynamics of G7 countries' stock market indices in the context of the 2014 oil shock. Using monthly data from January 2003 to September 2023, a combined methodology of Vector AutoRegressive (VAR) and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) models was applied to capture mean and conditional volatility dynamics, complemented with exponential GARCH (EGARCH) models to detect asymmetries. The results indicate that oil shocks have a significant impact on stock index volatility, with Canada, Japan and the UK showing high sensitivity, especially during and after the 2014 oil shock. Negative shocks affect volatility more than positive ones. Therefore, economic policies to mitigate extreme volatility and reduce economic uncertainty are necessary. Moreover, for oil-dependent economies, such as Canada, their vulnerability to oil price fluctuations needs to be reduced. This study provides a comprehensive understanding of the influence of oil shocks on the volatility and dynamics of G7 stock markets, offering valuable implications for policymaking and future research.

1. Introduction

Oil shocks can have diverse impacts on stock markets. The occurrence of abrupt changes in the oil market results in significant fluctuations in oil prices, which can have a direct impact on the volatility of stock market indexes in various economies. This has led to an interest in analyzing the effects of oil price variations on the stock market, as evidenced by previous studies, including those of Sadorsky (1999), Malik and Hammoudeh (2007), Park and Ratti (2008), Kilian and Park (2009), Choi and Hammoudeh (2010), Filis et al. (2011), Arouri et al. (2012), Wang et al. (2013), Sukcharoen et al. (2014), Kang et al. (2015), Bastianin et al. (2016), Zhang (2017), Ready (2018), Ferreira et al. (2019), Mokni (2020), Lu et al. (2021), Ben-Salha and Mokni (2022), Al-Fayoumi et al. (2023) and Ziadat et al. (2024).

The growing importance of the interaction between oil and stock markets has turned this relationship into a crucial financial academic field for research (Lin & Su, 2020). Rising oil prices can trigger global recessions, generating economic uncertainty that impacts the productivity of financial markets (Hamilton, 2003). In this context, the effectiveness of stock markets should be even higher in situations of great uncertainty surrounding oil prices (Diaz et al., 2016). This fact underlines the need to understand and effectively manage the influences of oil on financial markets to maintain global economic stability. Moreover, according to Bastianin et al. (2016), economic policies should be designed considering the origin of oil market shocks.

The results of previous research reveal diverse responses in terms of stock market behavior in the face of oil price fluctuations. Arouri et al. (2011) highlights an interrelationship between the oil market and the stock market. In contrast, Anoruo and Mustafa (2007) argue that both markets are integrated and not segmented. The changing nature of the relationship between the stock market and oil prices, noted by Mokni (2020), acts as a risk factor introducing uncertainty. Stock market responses to oil shocks are aligned with aggregate supply and demand, and their impact varies according to the type of economy in each country (Diaz et al., 2016; Hwang & Kim, 2021; Sadeghi & Roudari, 2022; Sarwar et al., 2020; Wang et al., 2013).

The relationship between oil markets and the stock market is intrinsically linked to a country's position as either an oil exporter or importer. Research such as Mohanty et al. (2011) and Wang et al. (2013) show that, for oil exporting countries, oil price shocks have a positive

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https://doi.org/10.1016/j.irfa.2025.104218
Received 22 August 2024; Received in revised form 24 October 2024; Accepted 28 March 2025
Available online 1 April 2025

influence on the stock market, while for oil importing countries, this connection is negative. On the other hand, according to Jones and Kaul (1996), Nandha and Faff (2008) and Miller and Ratti (2009), increasing volatility in oil prices adversely affects stock market movements. Conversely, Sadorsky (1999) argues that there is evidence of asymmetric effects of oil shocks in an economy. Furthermore, oil shocks, whether supply or demand shocks, can generate both positive and negative effects on the stock market according to Ji et al. (2020), Wei et al. (2023), Ready (2018) and Sadorsky (2014).

Filis et al. (2011) note that stock market variability does not always follow the same direction as oil price variability. Moreover, Wang et al. (2013) point out that the impact of oil price shocks on the stock market is conditioned by the relevance of oil in each country's economy. In this context, Guesmi and Fattoum (2014) show that dynamic correlations do not differ significantly between oil importing and exporting countries. Likewise, correlations between oil and stock market volatility vary over time, oscillating between positive and negative values following Boldanov et al. (2016), as these correlation changes respond to economic and geopolitical events. On the other hand, Basher et al. (2018) indicate that oil shocks are crucial for decision making in the construction of investment portfolios. Mokni (2020) highlights that there is a time-varying response of stock market returns to different oil shocks. Finally, oil price volatility has an asymmetric effect relative to stock returns according to Joo and Park (2021) and this variation is subject to oil market conditions.

Variability in oil prices remains a key factor contributing to stock market volatility (Basher et al., 2018; Demirer et al., 2020; Ji et al., 2020; Kilian & Park, 2009). After the 2008 crisis, there is evidence of increased vulnerability of stock markets to oil prices fluctuations, leading to an increase in the risk spread following that financial crisis (Ferreira et al., 2019; Wen et al., 2019). Supply shocks present a more heterogeneous impact, and a significant bidirectional implied volatility effect between oil and equity markets is highlighted (Demirer et al., 2020; Liu et al., 2020). Moreover, demand driven shocks are more noticeable and persistent during recessions (Hwang & Kim, 2021). Mokni (2020) argues that considering the source of oil shocks from a time-varying perspective is essential for designing informed policy decisions.

This study examines the impact of various oil variables, including the global oil price index and different shocks related to supply, economic activity, demand and inventory, on the stock market indices of G7 countries. We use the POILAPSP index to represent the global oil price shock and adopt the categorization of oil shocks proposed by Ready (2018), which offers an innovative methodology to analyze the impact of oil price changes. In line with Baumeister and Hamilton (2019), oil shocks are classified into four categories: supply shocks, economic activity shocks, consumption demand shocks and inventory shocks. The dataset covers the monthly period from January 2003 to September 2023, with a structural break in 2014 due to the oil shock caused by the increase in oil production. For the analysis, three data samples were generated: before 2014, during the oil shock (2014–2018) and after 2018.

The Vector AutoRegressive (VAR) model with Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) was chosen for the residuals. This comprehensive methodology is divided into several key steps. In the first instance, the specification of the VAR model, suitable for the analysis of sets of multiple variables which are interrelated and show mutual influences over time. In the second instance, the elicitation of the residuals of the VAR model and the application of GARCH models to these residuals to capture conditional volatility. As a robustness test, skewness is captured with the EGARCH model, and the Ljung-Box test is applied to the residuals of these models to ensure the validity of the analysis.

The combination of these models allows us to analyze both mean dynamics and conditional heteroskedasticity, providing a comprehensive view of how shocks in oil markets affect volatility and stock market dynamics in different historical periods. Previous studies, such as Al-Fayoumi et al. (2023), Arouri et al. (2011), Bouri (2015), Chang et al. (2013), Diaz et al. (2016), Hammoudeh and Yuan (2008) and Sadorsky (1999) have applied this combination of models in research with similar characteristics. This methodology not only captures the temporal and causal relationships between variables, but also the inferences made are robust and reliable.

The results of the analysis indicated that past shocks have a significant impact on present volatility in all markets analyzed, with high sensitivity to new information in the pre-2014, during the 2014–2018 crisis, and post-2018 periods. EGARCH models revealed an asymmetry in volatility, showing that negative shocks have a greater impact than positive shocks. These findings suggest that implementing economic policies taking into account both positive and negative shocks is crucial to mitigate extreme volatility in stock markets and reduce economic uncertainty. In addition, they highlight the need to diversify oil-dependent economies to reduce their vulnerability to oil price fluctuations and strengthen risk monitoring and management mechanisms.

The analysis showed that the response to oil shocks varies significantly among G7 countries. Canada exhibited high sensitivity to oil shocks due to its economic dependence on the oil industry. During the 2014–2018 oil shock, Canadian stock indices experienced significantly higher volatility compared to other G7 countries. Japan and the United Kingdom also showed prominent responses to oil shocks in the post-2018 period, reflecting greater sensitivity to changes in oil prices post crisis. These results underscore the importance of country specific policies focused on mitigating the impact of oil shocks on their financial markets and fostering long-term economic stability.

This research presents an innovative approach to understanding the relationship between oil and stock markets, which is fundamental to global economic stability. By addressing a gap in the existing literature, this paper goes beyond previous studies that focus on a single benchmark price (Brent, WTI, or Dubai) by employing a weighted average of these three key prices (POILAPSP), which more accurately reflects the global oil market. Additionally, it incorporates four oil shocks related to supply, demand, inventories, and economic activity, and specifically analyzes the 2014 oil shock, an event whose impact on the G7 stock market indices has been little explored.

From a methodological standpoint, the main contribution is the integrated combination of VAR, GARCH, and EGARCH models. The study innovatively applies GARCH and EGARCH to VAR residuals to capture conditional volatility and asymmetry, a methodological approach not previously utilized in this context. This comprehensive method allows for a thorough assessment of how multiple oil variables influence stock markets in both importing and exporting countries, thus filling a significant research gap and providing valuable insights for both scientific understanding and policymaking.

The document is structured as follows: the second section, "Methodology," details the sample, the study variables, and presents the econometric models used. The third section, "Empirical Analysis," presents the results obtained through the application of the different models. The fourth section, "Policy Implications," recommendations and considerations for economic policy formulation based on the results found are presented. Finally, the fifth section, "Conclusions," presents the main findings regarding the impact of oil variables on the stock market indices of the G7 countries.

2. Methodology

The analysis of the influence of oil variables on G7 countries' stock market indices was carried out using a combination of Vector AutoRegressive (VAR) and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) models. This comprehensive methodology is divided into several key steps: the specification of the VAR model, the elicitation of residuals, and the application of GARCH models to these residuals to extract conditional volatility. The combination of these models allows us to analyze both mean dynamics and conditional heteroskedasticity, providing a comprehensive view of how shocks in the oil markets affect volatility and stock market dynamics over different historical periods. This approach is particularly useful for understanding the complex interactions between oil prices and stock market indices, revealing how shocks to oil variables influence financial market volatility (Arouri et al., 2011; Bouri, 2015; Chang et al., 2013; Diaz et al., 2016; Sadorsky, 1999, 2014).

2.1. Data description

The data sample is monthly and covers January 2003 through September 2023. It includes the global oil price and oil shocks indices, as well as the main stock market indices of each G7 member country, which are detailed in Table 1. A structural break is considered in 2014 due to the oil crisis caused by several factors, such as oversupply, the development of fracking in the U.S., increased production in some exporting countries, OPEC decisions and weak demand among oil consuming countries. This crisis had a significant impact on the global economy and financial markets, justifying its consideration as a structural breaking point in the analysis. Therefore, the study sample analyzes three distinct periods: before the oil crisis (pre-2014), during the oil crisis (during 2014–2018) and after the oil crisis (post-2018).

Table 1
Variable description and sources.

Name	Description	Source
POILAPSP	Simple average of three oil spot prices, such as: Dated Brent, West Texas Intermediate and Dubai Fateh, its weight is normalized to 100 at 2016 prices.	Primary Commodity Prices database. International Monetary Fund (International Monetary Fund [IMF], 2023)
Oil Supply Shocks (OSS)	Unexpected changes in oil production, increases or decreases in oil prices can be caused by a variety of exogenous factors.	The oil shocks were taken from the Baumeister and Hamilton (2019) study, which breaks them down into four categories.
Economic Activity Shocks (EAS)	Unexpected events that have drastic effects on an economic system, contradiction in production, employment, and consumption, can be caused by a variety of exogenous factors.	
Oil Consumption Demand Shocks (OCDS)	Unexpected changes in oil demand, impact on supply and demand prices, can be caused by a variety of exogenous factors.	
Oil Inventory Demand Shocks (OIDS)	Unexpected changes in the demand for oil inventories, supply, and demand balance in storage, can be caused by a variety of exogenous factors.	
NYSE (United States)	New York Stock Exchange Index	For the selection of the stock indices of the countries belonging to the G7, the database of the is reviewed World Federation of Exchanges (World Federation of Exchanges [WFE], 2023) and the website of Investing.com (2023)
Dax (Germany)	Frankfurt Stock Exchange Index "Deutscher Aktienindex"	
Euronext Paris (France)	Paris Stock Exchange Index	
TMX Group (Canada)	Toronto Stock Exchange Index	
Borsa Italiana (Italy)	Borsa Italiana Stock Exchange Index	
NIKKEI-225 (Japan)	Tokyo Stock Exchange Index	
LSE Group (United Kingdom)	London Stock Exchange Index	

Note. The database of the four oil shocks is available on Professor Baumeister (2023) website updated to September 2023.

2.2. VAR model

A vector autoregressive model (VAR) is proposed to investigate the effect of the variation of oil prices and oil shocks on the stock market indexes of G7 countries. The VAR model is often used to examine the time-varying regression of lagged variables within a same model. Sims (1980) initially proposed this model, then Darby (1982), and Hamilton (1983), employed it in their studies. In addition, the VAR model has been frequently used to study the relationship between oil prices and the stock market, as in the studies of Sadorsky (1999), Park and Ratti (2008), Arouri et al. (2011), Arouri et al. (2012), Kilian and Murphy (2014), Kang et al. (2015), Du and He (2015), Bouri (2015), Zhu et al. (2016), Bastianin et al. (2016), Diaz et al. (2016), Zhang (2017), Zhu et al. (2019) and Wen et al. (2019).

A VAR model of order p, where p is the number of lags, which includes k variables, can be expressed as:

$$\boldsymbol{y}_t = \boldsymbol{A}_0 + \sum\nolimits_{(i=1)}^{p} \boldsymbol{A}_i \boldsymbol{y}_{t-i} + \boldsymbol{u}_{t,} \tag{1}$$

Where $\boldsymbol{y}_t = [y_{1t} \cdots y_{kt}]'$ is a column vector of all model variables, $\boldsymbol{A}_0$ is a column vector of constant term, $\boldsymbol{A}_i$ is a k x k matrix of unknown coefficients, $\boldsymbol{u}_t$ is a column vector of residuals with the following properties:

$E\,(\boldsymbol{u}_t) = 0\ \forall t,$

$E(u_s u_t') = \Omega \text{ if } s = t,$

$\mathrm{E}(\mathrm{u_s u_t'}) = 0 \text{ if s} \neq \mathrm{t},$

Where Ω is the variance-covariance matrix with non-zero off-diagonal elements, $\boldsymbol{u}_t' s$ is assumed to be serially uncorrelated but may be simultaneously correlated. Within the model all variables $\boldsymbol{y}_t = [y_{1t} \cdots y_{kt}]'$ must have the same order of integration.

2.3. Elicitation of VAR model residuals

Hamilton (1994) and Lütkepohl (2005a) highlight the importance of the elicitation of VAR model residuals, as these can be used as input to model conditional volatility, capturing the dynamics of shocks not explained by the initial VAR model. This approach allows for a deeper understanding of how shocks to oil variables influence stock index volatility. Subsequently, these residuals are used to model volatility using the GARCH model. In this study, the residuals were obtained and analyzed using STATA software, facilitating the application of advanced econometric analysis techniques.

The residuals $\boldsymbol{u}_t$ are obtained as the difference between the observed values and the model fitted values:

$$\boldsymbol{u}_t = \boldsymbol{y}_t - \left(\boldsymbol{A}_0 + \sum\nolimits_{(i=1)}^{p} \boldsymbol{A}_i \boldsymbol{y}_{t-i} \right) \tag{2}$$

Specifically, for each variable $\boldsymbol{y}_{it}$ in the VAR model, the residuals $\boldsymbol{u}_{it}$ are calculated as:

$$\boldsymbol{u}_{it} = \boldsymbol{y}_{it} - \left(\sum\nolimits_{(j=1)}^{p} \boldsymbol{A}_{ij} \boldsymbol{y}_{t-j} \right) \tag{3}$$

Where $\boldsymbol{u}_{it}$ is the residual of variable i at time t, $\boldsymbol{y}_{it}$ is the observed value of variable i at time t, $\boldsymbol{A}_{ij}$ are the coefficients of lag j for variable i, $\boldsymbol{y}_{t-j}$ is the vector of values of the endogenous variables at time $t-j$.

2.4. Applying the GARCH model to the residuals

After determining the residuals of the VAR model, the GARCH model is applied to these residuals to capture conditional heteroskedasticity and analyze volatility, providing a more detailed view of how oil variables influence the volatility of G7 countries' stock indices. Considering the descriptions of Bollerslev (1986) and Hamilton (1994), the GARCH model is specified as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{4}$$

Where $\boldsymbol{\sigma}_t^2$ is the conditional variance at time t, $\boldsymbol{\epsilon}_{t-1}^2$ is the square of the error term at time $t-1$, $\boldsymbol{\alpha}_0$ is a constant, $\boldsymbol{\alpha}_1$ is the coefficient of past innovation (ARCH term), $\boldsymbol{\beta}_1$ is the coefficient of past conditional variance (GARCH term). This model allows capturing the persistence of volatility and its dynamics, providing a robust tool to understand fluctuations in stock markets related to oil price shocks.

The full equation, including the residuals from the VAR model to specify conditional volatility, is expressed as follows:

$$\boldsymbol{u}_t = \sigma_t z_t \tag{5}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \boldsymbol{u}_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{6}$$

Where $\boldsymbol{z}_t$ is a white noise with standard normal distribution. This specification allows us to effectively model how shocks to oil variables impact stock index volatility in different historical periods, providing a comprehensive view of market dynamics.

To capture possible asymmetries in volatility, where positive and negative shocks may have different effects, the EGARCH model described by Nelson (1991) is specified. This model allows volatility to respond differently to shocks of different magnitude and sign, providing a more complete tool for analyzing volatility dynamics in stock markets. The specification of the EGARCH model is as follows:

$$log(\sigma_t^2) = \omega + \beta log(\sigma_{t-1}^2) + \alpha\left(\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right) + \gamma\left(\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| - \mathbb{E}\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right|\right) \tag{7}$$

Where $log(\sigma_t^2)$ is the logarithm of the conditional variance, $\boldsymbol{\omega}, \boldsymbol{\beta}, \boldsymbol{\alpha}$, and $\boldsymbol{\gamma}$ are the model parameters, $\boldsymbol{\epsilon}_{t-1}$ is the error term at time $t-1$, $\boldsymbol{\sigma}_{t-1}$ is the conditional standard deviation at time $t-1$. This EGARCH model allows for greater flexibility by allowing volatility to respond asymmetrically to positive and negative shocks, which is crucial for understanding the complex dynamics of financial markets affected by oil variables.

The Ljung and Box (1980) test was applied to check for autocorrelation in the standardized residuals of the VAR and GARCH models. This test was used to evaluate whether the residuals of a VAR model, after applying a GARCH model, are independent and uncorrelated. Model residuals do not present autocorrelation as ensured by this methodology, which is crucial for the validity of the VAR and GARCH models used in this study. The null hypothesis (H_0) of the test is that there is no autocorrelation in the residuals up to lag h. A p-value greater than the significance level indicates that the null hypothesis is not rejected, suggesting the absence of significant autocorrelation in the residuals. Its specification is as follows:

$$Q = n(n+2)\sum_{k=1}^{h} \frac{\widehat{\rho}_k^2}{n-k} \tag{8}$$

Where $\boldsymbol{Q}$ is the Ljung-Box test statistic, $\boldsymbol{n}$ is the sample size, $\boldsymbol{h}$ is the number of lags considered in the test, $\widehat{\boldsymbol{\rho}}_k$ is the sample autocorrelation coefficient at lag k. This validation is essential to confirm the appropriateness of the estimated models and the robustness of the inferences made about the influence of oil variables on the volatility of stock market indices.

3. Empirical analysis

3.1. Tests of variables

Table 2 shows the values of descriptive statistics of the original data, natural logarithm and first differences of the world oil price index variable and stock index variables of the G7 countries. Three temporal samples are considered: before the oil shock (pre-2014), during the oil shock (during 2014–2018) and after the oil shock (post-2018). This

Table 2
Sample statistic for variables.

Sample	Variable	Obs	Statistic		Natural logarithm		First difference	
			Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Pre - 2014	*Global Oil Price Index*							
	POILAPSP	132	154.2067	55.66928	4.962896	0.4074972	0.8570762	7.90982
	Stock Indices of G7 Countries							
	United States	132	1241.545	215.1197	7.108662	0.1786683	0.5488909	4.533766
	Germany	132	5883.589	1565.023	8.640702	0.2908542	0.951111	5.642504
	France	132	2877.303	592.8774	7.944347	0.2007081	0.3849328	4.856051
	Canada	132	11,330.51	2116.063	9.315611	0.2057892	0.5566539	3.845391
	Italy	132	19,727.66	6017.061	9.845419	0.2966693	−0.0075733	5.601705
	Japan	132	11,832.65	2915.82	9.349945	0.2377029	0.5111265	5.82836
	United Kingdom	132	2956.408	521.1493	7.976476	0.1754862	0.0090599	7.696061
During 2014–2018	*Global Oil Price Index*							
	POILAPSP	54	137.5533	42.11404	4.881158	0.291894	−0.545364	8.961549
	Stock Indices of G7 Countries							
	United States	54	2190.236	268.4569	7.684713	0.118592	0.7684875	3.040954
	Germany	54	11,026.43	1225.541	9.302023	0.1106852	0.4691106	4.40892
	France	54	3713.918	343.6497	8.215694	0.0916677	0.4657427	3.753927
	Canada	54	14,805.42	867.5501	9.601022	0.0596961	0.3298989	2.161602
	Italy	54	18,098.59	1792.337	9.79868	0.1005497	0.3949536	4.818861
	Japan	54	18,508.54	2430.328	9.817477	0.1319907	0.5817731	4.467111
	United Kingdom	54	3739.932	259.0687	8.224491	0.0687724	0.2812085	2.684034
Post - 2018	*Global Oil Price Index*							
	POILAPSP	63	162.0996	48.44652	5.039646	0.3262536	0.4881662	11.71867
	Stock Indices of G7 Countries							
	United States	63	3607.01	661.316	8.173537	0.1879831	0.7140311	5.616613
	Germany	63	13,528.54	1681.964	9.504841	0.125744	0.354617	5.549895
	France	63	4583.44	599.6362	8.421592	0.1331501	0.3740886	5.514114
	Canada	63	18,120.46	2200.124	9.797397	0.1232807	0.2900487	4.636279
	Italy	63	21,216.24	2849.699	9.953532	0.1357069	0.3964333	6.149319
	Japan	63	25,540.52	3637.946	10.13796	0.1433367	0.5658528	4.96615
	United Kingdom	63	3925.765	302.1003	8.272187	0.0812046	−0.0284952	4.197982

disaggregation allows for a detailed analysis of how the statistical characteristics of the variables have changed over these periods, providing a solid basis for understanding the influence of the oil shocks on the G7 stock markets.

Table 3 shows the results of the Dickey and Fuller (1979) test in the three study samples. To estimate the models, we seek to determine the stationarity of the variables, i.e., they have no unit root. This is checked when the values of the statistics are negative with a p-value lower than the desired significance level. It is observed that first log differences have negative test statistics and with *p*-values below 5 %, the usual significance level, which provides sufficient evidence to reject the null hypothesis (H_0) of unit root. Therefore, first log differences of the variables are stationary, which is crucial for the validity of the models estimated in the analysis.

Table 4 shows the statistics and the results of the Dickey and Fuller (1979) test for the four oil shocks in the three study samples. The data –obtained from Professor Baumeister's website (2023)– were already transformed into logarithmic first differences. The series of these variables are verified to be stationary, since the statistical test values are negative, and their p-values are less than 5 % of the significance level. Therefore, the null hypothesis (H_0) of unit root for the four oil shocks is rejected, confirming the stationarity of the series.

Since all variables are stationary, the null hypothesis (H0) of unit root in the series is rejected, we proceed to estimate the VAR model with its order one and order two specifications, to examine the interaction in the lags of the study variables and identify the predictor variables of the model. Generalized impulse-response function analyses were conducted, focusing on the global oil price index and the four oil shocks, in relation to the stock market indices of the G7 countries. The Impulse Response Function (IRF) was used to plot the time path of the current and future values of the model variables when the current value of one of the errors is increased by one unit. In other words, it sought to determine the effect of a one-unit index shock on the model, thus providing detailed insight into how shocks to oil variables influence the volatility and dynamics of the G7 countries' stock markets.

3.2. Post estimation: Stability and autocorrelation

Once the VAR model has been estimated, its stability is verified according to the criteria proposed by Hamilton (1994) and Lütkepohl (2005b). The purpose of this analysis is to confirm that the modulus of each eigenvalue is rigorously less than one. Specifically, the aim is to verify: a) the eigenvalues are less than one; and b) the roots of the characteristic polynomial of the VAR model are located within the unit circle. This will indicate that the model meets the condition of stability over time. Model satisfies the stability condition when looking at the results obtained. All the roots of the characteristic polynomial are located within the unit circle and are less than one. This ensures that the VAR model is suitable and reliable for the analysis of the interactions and dynamics of the variables studied in the stock markets of the G7 countries.

Table 5 examines the residual autocorrelation of the model using the Lagrange-multiplier test, proposed by Breusch and Pagan (1980), discussed by Hosking (1980) and contextualized in the Johansen (1995) model. This test is used to assess whether there is autocorrelation in the order of the residuals of a model. The null hypothesis (H_0) states the absence of autocorrelation in the lag order. The results indicate that the null hypothesis (H_0) cannot be rejected at the second lag order for all three samples. Therefore, the findings point to the absence of autocorrelation in the second order of the model residuals for all three samples.

The variation sensitivity of G7 countries' stock markets to oil shocks can be attributed to several key factors. Firstly, economic structure plays a crucial role. As major oil producers and exporters, Canada and the United States exhibit greater sensitivity because price fluctuations directly impact their energy sectors and related stock market companies (Kilian & Park, 2009). In contrast, Japan and Germany, being net oil importers with economies focused on manufacturing and technology, face increased production costs and inflationary pressures when oil prices rise, negatively affecting their stock markets (Filis et al., 2011). Secondly, the degree of energy dependence varies significantly among these nations. While Canada benefits from high oil prices due to its net exporter status, Japan suffers from higher import costs, illustrating the divergent impacts of oil price changes (Hamilton, 2009). Thirdly, the composition of financial markets is critical. A higher proportion of energy companies in stock market indices implies greater sensitivity to oil price fluctuations (Sadorsky, 2001). Lastly, government policy responses and regulations play a significant role. Energy diversification strategies, management of strategic reserves, and financial regulations can either mitigate or amplify the impact of oil shocks on financial markets (Brown & Yücel, 2002). These structural and policy differences collectively explain the heterogeneous reactions of G7 stock markets to oil shocks, underscoring the complex interplay between oil prices and national economic dynamics.

The various policy responses of G7 countries during the 2014 oil shock significantly contributed to differences in sensitivities of their stock markets. Canada, heavily reliant on energy exports, lowered its benchmark interest rate in, 2015 to counteract the negative impact of falling oil prices on its economy (Bank of Canada, 2015). The United Kingdom implemented targeted tax cuts for its North Sea oil sector to stimulate investment and safeguard jobs in the oil industry (HM Treasury - United Kingdom, 2015). On the other hand, Japan capitalized on reduced energy import costs by intensifying its expansionary monetary policy and accelerating energy diversification towards renewable sources (Bank of Japan, 2014; Ministry of Economy Trade and Industry (METI) - Japan, 2014). These distinct policy actions not only addressed immediate economic concerns but also shaped investor expectations, thereby influencing the reaction of stock markets to oil shocks.

The divergent approaches highlight how each country's unique economic structure and priorities guided their policy responses. These tailored strategies ultimately affected market sentiment and investment patterns, leading to differentiated impacts on their respective stock markets. This underscores the complex interplay between government policy, oil price dynamics, and financial market performance in the context of a major oil shock.

3.3. Impulse response function

Fig. 1 presents the responses of the G7 countries' stock indices to the impulses of oil variables in the three different periods under consideration: Pre-2014, During 2014–2018 and Post-2018. Responses are measured in terms of percentage change over two temporal horizons, 1 month (short term) and 12 months (long term). The Canadian stock index shows a more pronounced response before, during and after the oil shock. This pattern can be attributed to Canada's intrinsic connection to the exploitation and export of oil, which shows how the response of the Canadian stock index to oil shocks is based on the country's considerable economic dependence on the oil industry. Recent research confirms that stock markets of countries with high oil dependence tend to show greater sensitivity to oil shocks (Kilian & Park, 2009; Malik & Hammoudeh, 2007; Sadorsky, 2014). In addition, several studies have shown that oil shocks have a significant impact on market volatility, particularly in oil-dependent economies (Arouri et al., 2011; Mohanty et al., 2011; Y. J. Zhang & Wang, 2015).

In the period leading up to the 2014 oil shock, most G7 countries' stock market indices show a moderate response to oil variable impulses, with more notable increases in the long term. Canada's stock index stands out with the highest sensitivity in both the short and long term, responding to oil variable shocks with an increase of 11.50 % in the short term and 28.26 % in the long term (see Fig. 1). On the contrary, Italy's stock index presents the lowest response to oil variable shocks in both temporal horizons, with an increase of 1.42 % in the short term and 14.32 % in the long term. This behavior can be explained by Canada's

Table 3
Sample Unit Root Test: Global Oil Price Index and Stock Indices of G7 Countries.

Dickey–Fuller							
Sample	Variables	Original		Natural logarithm		First difference	
		Test statistic	*p*-value for Z(t)	Test statistic	*p*-value for Z(t)	Test statistic	*p*-value for Z(t)
Pre - 2014	*Global Oil Price Index*						
	POILAPSP	−1.366	0.5984	−1.508	0.5296	−8.221	0.0000
	Stock Indices of G7 Countries						
	United States	−0.606	0.8696	−1.227	0.6618	−9.613	0.0000
	Germany	−0.848	0.8047	−1.802	0.3793	−10.164	0.0000
	France	−1.677	0.4432	−1.879	0.342	−9.562	0.0000
	Canada	−2.032	0.2729	−2.419	0.1365	−8.797	0.0000
	Italy	−0.940	0.7744	−1.066	0.7285	−9.954	0.0000
	Japan	−1.125	0.7048	−1.350	0.6061	−9.260	0.0000
	United Kingdom	−2.625	0.0879	−2.541	0.1059	−11.9353	0.0000
During 2014–2018	*Global Oil Price Index*						
	POILAPSP	−1.841	0.3601	−1.672	0.4458	−5.271	0.0000
	Stock Indices of G7 Countries						
	United States	−0.249	0.9325	−0.536	0.8848	−8.837	0.0000
	Germany	−1.468	0.5492	−1.524	0.5215	−7.024	0.0000
	France	−1.412	0.5767	−1.482	0.5426	−7.880	0.0000
	Canada	−1.108	0.7120	−1.159	0.6910	−5.606	0.0000
	Italy	−1.798	0.3815	−1.819	0.3712	−7.286	0.0000
	Japan	−0.865	0.7994	−0.945	0.7728	−7.039	0.0000
	United Kingdom	−0.898	0.7886	−0.945	0.7729	−9.162	0.0000
Post - 2018	*Global Oil Price Index*						
	POILAPSP	−0.937	0.7756	−1.208	0.6703	−5.369	0.0000
	Stock Indices of G7 Countries						
	United States	−1.263	0.6460	−1.346	0.6080	−9.011	0.0000
	Germany	−1.553	0.5071	−1.663	0.4502	−8.516	0.0000
	France	−1.393	0.5858	−1.495	0.5361	−8.476	0.0000
	Canada	−1.463	0.5519	−1.523	0.5221	−9.428	0.0000
	Italy	−1.401	0.5820	−1.560	0.5038	−8.473	0.0000
	Japan	−0.882	0.7939	−1.027	0.7434	−8.475	0.0000
	United Kingdom	−2.133	0.2313	−2.129	0.2329	−7.786	0.0000

Table 4
Sample Statistics and unit root test for Oil Shocks.

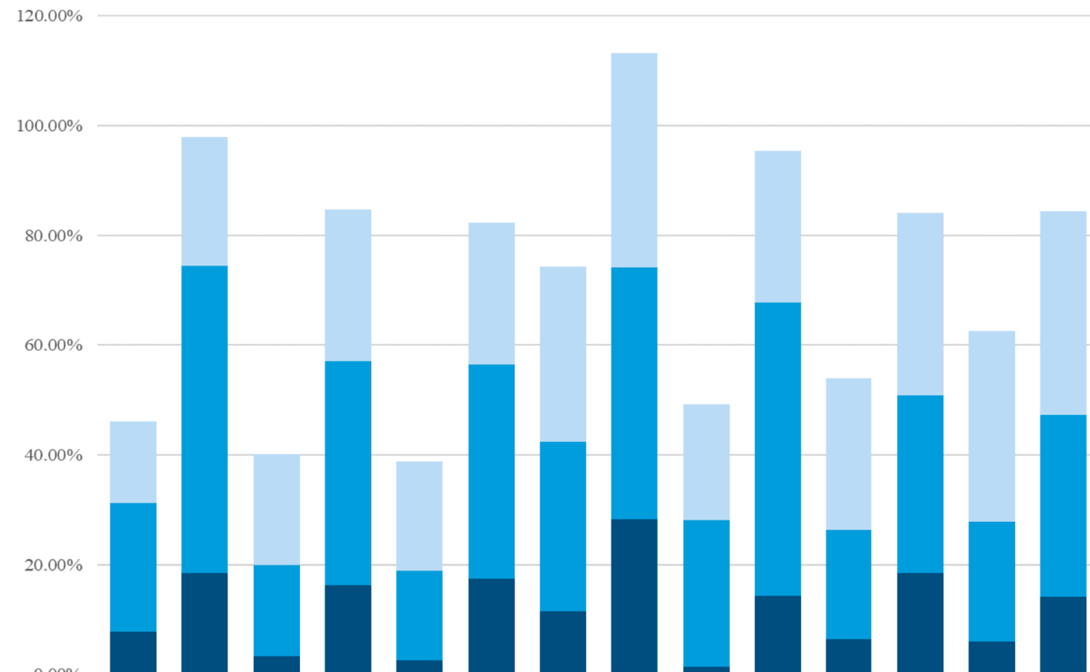
Sample	Variable	Obs	Statistic		Dickey–Fuller	
			Mean	Std. dev.	Test statistic	*p*-value for Z(t)
Pre - 2014	Oil Supply Shocks	132	−0.0860	0.9460	−10.168	0.0000
	Economic Activity Shocks	132	−0.0009	0.5933	−9.975	0.0000
	Oil Consumption Demand Shocks	132	0.1829	3.5622	−11.181	0.0000
	Oil Inventory Demand Shocks	132	0.0165	0.9164	−11.722	0.0000
During 2014–2018	Oil Supply Shocks	54	0.0578	1.0113	−6.024	0.0000
	Economic Activity Shocks	54	−0.0747	0.5175	−9.731	0.0000
	Oil Consumption Demand Shocks	54	−0.0845	3.7393	−6.631	0.0000
	Oil Inventory Demand Shocks	54	−0.1202	1.0096	−6.653	0.0000
Post - 2018	Oil Supply Shocks	63	−0.3705060	1.8560050	−7.725	0.0000
	Economic Activity Shocks	63	−0.0615834	1.4266610	−7.291	0.0000
	Oil Consumption Demand Shocks	63	0.2472024	5.0970440	−6.374	0.0000
	Oil Inventory Demand Shocks	63	−0.3631320	0.9914529	−6.669	0.0000

Table 5
Lagrange-Multiplier test for the VAR model.

Lagrange-multiplier test											
Pre - 2014				During - 2014 - 2018				Post - 2018			
lag	chi2	df	Prob > chi2	lag	chi2	df	Prob > chi2	lag	chi2	df	Prob > chi2
1	184.284	144	0.01317	1	168.233	144	0.08171	1	145.312	144	0.45368
2	151.556	144	0.31676	2	163.754	144	0.12435	2	154.407	144	0.26169

economic dependence on the oil industry, which amplifies the sensitivity of its stock market to fluctuations in oil prices (Chang et al., 2013; Miller & Ratti, 2009). In contrast, the lower sensitivity of the Italian market could be attributed to a lower dependence on oil in its economic structure, which mitigates the impact of oil shocks on its stock market index (Arouri et al., 2011; Cuñado & Pérez de Gracia, 2005).

During the period of the 2014–2018 oil shock, there is a significant increase in the response of all G7 countries' stock indices to oil variable impulses. The United States, Canada and Italy show remarkably high sensitivity in the short term, with 23.47 %, 30.91 % and 26.65 % respectively. In the long term, the responses are even more pronounced, reaching 56.06 % for the United States, 45.95 % for Canada and 53.41 % for Italy. This increase in response may be related to the increased global economic volatility and uncertainty during the oil crisis years. Recent



	1	12	1	12	1	12	1	12	1	12	1	12	1	12
	United States		Germany		France		Canada		Italy		Japan		United Kingdom	
Post - 2018 - 2023	14.86%	23.42%	20.15%	27.52%	19.96%	25.92%	31.90%	39.06%	21.15%	27.61%	27.60%	33.30%	34.72%	37.11%
During 2014-2018	23.47%	56.06%	16.73%	40.91%	16.36%	38.96%	30.91%	45.95%	26.65%	53.41%	19.94%	32.30%	21.90%	33.08%
Pre - 2003 - 2014	7.69%	18.40%	3.26%	16.21%	2.54%	17.48%	11.50%	28.26%	1.42%	14.32%	6.42%	18.49%	5.92%	14.19%

Fig. 1. Impulse response function of oil variables in stock indexes.

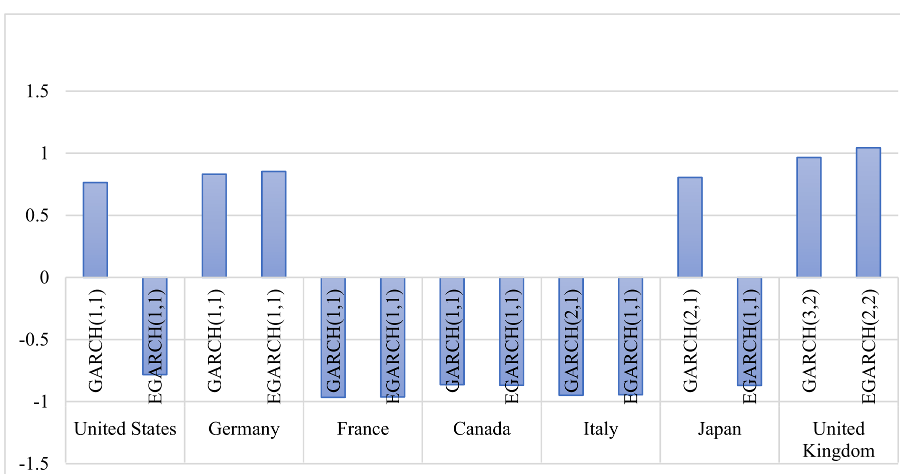


Fig. 2. Volatility dynamics of the GARCH and EGARCH sample Pre-2014 models.

research suggests that the oil crisis and the resulting global economic instability intensified the sensitivity of stock markets to oil shocks during this period (Kang et al., 2015; Park & Ratti, 2008).

In the post-2018 period, although responses decline slightly compared to the period during the oil shock, they remain higher than in the pre-2014 oil shock period. The Canadian stock index continues to show a high response to short- and long-term oil variable impulses. However, in this period, the stock indexes of Japan and the United Kingdom stand out for their high short-term responses, indicating a higher sensitivity to oil impulses after weathering an oil shock. Japan's stock index responds to the impulse of oil variables with an increase of 27.60 % in the short term and 33.30 % in the long term. Similarly, the response of the United Kingdom stock index to the impulse of oil variables is 34.72 % in the short term and 37.11 % in the long term. This behavior can be attributed to the economic recovery and the adaptation of stock markets to changes in the post-crisis global economic environment (Malik & Hammoudeh, 2007; Miller & Ratti, 2009; B. Zhang & Li, 2016).

3.4. GARCH model estimation to the residuals of the VAR model

GARCH and EGARCH model estimations were performed on the residuals of the VAR model for the stock indexes of the G7 countries in the three periods analyzed. The results are presented in Table 6, which includes the estimated coefficients, *p*-values and the results of the Ljung-Box test to accept or reject autocorrelation in the residuals after estimation.

For the three sample periods, the results indicate that past shocks

Table 6
GARCH and EGARCH model to the residuals of the VAR model and the Ljung-Box test.

Sample	Variables	Models	Coefficient	P > |z|	Ljung-Box	
					(Q) Statistic	Prob > chi2(12)
Pre - 2014	United States	GARCH (1,1)	0.7638601	0.000	16.9143	0.1528
		EGARCH (1,1)	−0.7826733	0.000	16.5950	0.1655
	Germany	GARCH (1,1)	0.8311858	0.000	16.4534	0.1713
		EGARCH (1,1)	0.8530775	0.000	17.7780	0.1226
	France	GARCH (1,1)	−0.965699	0.000	18.4493	0.1027
		EGARCH (1,1)	−0.9625426	0.000	17.3806	0.1358
	Canada	GARCH (1,1)	−0.8633979	0.000	14.2386	0.2857
		EGARCH (1,1)	−0.8682797	0.000	14.9567	0.2438
	Italy	GARCH (2,1)	−0.9491340	0.000	20.3269	0.0611
		EGARCH (1,1)	−0.9441514	0.000	19.9120	0.0688
	Japan	GARCH (2,1)	0.8049781	0.000	14.9422	0.2446
		EGARCH (1,1)	−0.869499	0.000	17.2406	0.1408
	United Kingdom	GARCH (3,2)	0.9656473	0.000	8.4169	0.7518
		EGARCH (2,2)	1.04373	0.000	7.8126	0.7996
During 2014–2018	United States	GARCH (5,2)	1.009912	0.000	19.1229	0.0856
		EGARCH (5,1)	1.078848	0.000	16.3121	0.1774
	Germany	GARCH (5,1)	1.120482	0.000	14.9136	0.2462
		EGARCH (5,5)	1.240142	0.000	18.7042	0.0959
	France	GARCH (6,3)	1.16065	0.000	20.3683	0.0604
		EGARCH (5,1)	1.062734	0.000	17.8898	0.1191
	Canada	GARCH (4,7)	−0.9810413	0.000	20.039	0.0664
		EGARCH (4,1)	1.119939	0.000	18.2265	0.1090
	Italy	GARCH (2,2)	0.9855592	0.000	14.4885	0.2706
		EGARCH (2,2)	−1.102762	0.000	17.8016	0.1218
	Japan	GARCH (2,2)	1.054149	0.000	19.3893	0.0796
		EGARCH (2,3)	−1.094179	0.000	20.2697	0.0622
	United Kingdom	GARCH (4,7)	−0.9989553	0.000	19.1103	0.0859
		EGARCH (4,7)	−1.06834	0.000	19.6019	0.0750
Post - 2018	United States	GARCH (3,3)	0.9310562	0.011	19.6604	0.0738
		EGARCH (3,2)	−1.038269	0.000	19.2619	0.0824
	Germany	GARCH (3,1)	−1.083211	0.000	17.0573	0.1475
		EGARCH (3,3)	−1.084847	0.000	19.9541	0.0680
	France	GARCH (2,1)	−0.2787211	0.006	17.7936	0.1221
		EGARCH (3,2)	−1.0415	0.000	16.1203	0.1800
	Canada	GARCH (3,1)	−0.945602	0.000	17.1538	0.1439
		EGARCH (3,2)	0.9387406	0.000	19.0236	0.0880
	Italy	GARCH (3,2)	1.0006420	0.000	14.9834	0.2423
		EGARCH (3,1)	0.8122587	0.000	15.9695	0.1926
	Japan	GARCH (4,4)	−1.007883	0.000	15.7752	0.2017
		EGARCH (3,2)	−1.026367	0.000	16.3458	0.1759
	United Kingdom	GARCH (3,3)	−1.074028	0.000	18.8289	0.0927
		EGARCH (3,3)	−1.05972	0.000	20.0902	0.0654

Note. *Coefficient p-values are less than 0.05, indicating that the coefficients of the models are statistically significant.
Note. **The p-values associated with the Ljung-Box test are greater than 0.05, suggesting there is insufficient evidence to reject the null hypothesis that there is no autocorrelation in the standardized residuals. This indicates the residuals can be considered white noise, which is desirable.

have a significant impact on the present volatility in all markets analyzed. A high sensitivity to new information is observed, reflecting the market dynamics during these periods. The Ljung-Box test applied to the residuals of the models suggests no significant autocorrelation, indicating the models have adequately captured the time structure of volatility.

In the pre-2014 period, before the oil shock, most of the estimated GARCH and EGARCH models present a simple structure of (1,1).[1] This implies market volatility in this period can be adequately captured with a model which considers a single lag for both ARCH and GARCH terms. Economic stability and less complexity in market fluctuations may explain the effectiveness of these simpler models. Furthermore, the estimated coefficients in the models are statistically significant (p-values<0.05), indicating that past shocks have a clear and significant impact on present volatility.

For example, in the United States, the coefficient of the GARCH (1,1) model is 0.7638601, suggesting a high sensitivity of the market to new information. This high significance reinforces the reliability of the estimated models and underlines the sensitivity of the market to past shocks. However, the coefficient of the EGARCH (1,1) model is −0.7826733, indicating that negative shocks affect volatility more than positive shocks. This asymmetry is crucial because it reflects the actual behavior of financial markets, where negative shocks tend to generate more uncertainty and volatility. According to Malik and Hammoudeh (2007), this volatility transmission dynamic is consistent with the response of financial markets to unexpected events, underscoring the importance of considering both positive and negative shocks in volatility analysis. These findings are consistent with the existing literature, which indicates that global financial markets show a greater reaction to negative news due to higher risk perception and associated uncertainty (Kilian, 2009; Sadorsky, 1999).

During the 2014–2018 oil shock, the estimated models present more complex structures, such as (5,1), (6,3) and (4,7) (see Fig. 3). This indicates market volatility required more lags to be considered in order to adequately capture market dynamics The larger number of lags suggests that volatility was more persistent and possibly more affected by past events, reflecting a more uncertain and volatile economic environment with multiple shocks and events influencing volatility. Recent research indicates important contributions of factors such as financial crises,

[1] Figure 2 shows the structure and volatility dynamics of the GARCH and EGARCH models estimated for the stock market indices of the G7 countries before the 2014 oil shock.

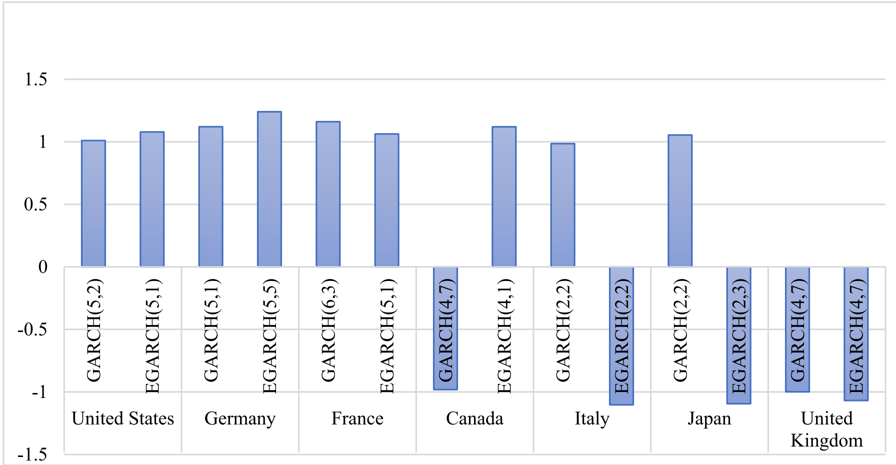


Fig. 3. Volatility dynamics of the GARCH and EGARCH sample during 2014–2018 models.

monetary policy changes and heightened global policy uncertainty to this increased complexity of market volatility. (Kilian & Park, 2009; Malik & Hammoudeh, 2007; Sadorsky, 2014).

For French stock index, the GARCH (6.3) model shows a complex structure capturing highly persistent volatility. This persistence reflects the continuity of economic uncertainty during this period, with significant events continuing to impact markets over time. On the other hand, the EGARCH (5.1) model presents a positive and significant coefficient, indicating positive shocks have a considerable impact on French market volatility, i.e., good news impacts favorably. Mohanty et al. (2011) and B. Zhang and Li (2016) have shown that fluctuations in oil prices and their impact on stock markets can be long-lasting and are influenced by a combination of economic and political factors, which requires more sophisticated models for accurate analysis.

During the post-2018 period, the estimated models present intermediate structures, such as (3,3), (3,1) and (4,4) (see Fig. 4). This shows market volatility requires considering more lags than in the pre-2014 period, but less than during 2014–2018. The moderate complexity suggests some stabilization of financial markets, where past events continue to influence volatility, but do not require as many lags to be adequately captured. In the U.S., the coefficient of the GARCH (3.3) model is 0.9310562, indicating high significance and reinforcing the reliability of the estimated models, highlighting the sensitivity of the market to past shocks. On the other hand, the coefficient of the EGARCH (3,2) model is −1.038269, indicating a higher volatility response to negative shocks. This asymmetry is significant because it reflects how bad news affects market volatility more profoundly during this period, possibly due to higher economic uncertainty. These findings are consistent with recent research highlighting how volatility in financial markets has been influenced by multiple economic and political factors, including changes in oil prices and global financial crises (Al-Fayoumi et al., 2023; Demirer et al., 2020; Lin & Su, 2020; Mokni, 2020; Ziadat et al., 2024).

The differences in the structures of the GARCH and EGARCH models over these periods reflect the evolving dynamics of volatility in response to changes in the global economic and political environment. The ability of the models to adequately capture volatility with different numbers of lags provides valuable insight into how the persistence and complexity of volatility have varied over time. These results underscore the importance of considering both volatility persistence and asymmetry in the response to shocks when analyzing financial markets. Differences in coefficients across countries and periods reflect how specific economic and political events, such as fluctuations in oil prices and economic crises, affect market volatility. Recent studies confirm oil shocks and global financial crises, such as COVID-19, have had a significant impact on market volatility, highlighting the need for models that capture these complex dynamics (Al-Fayoumi et al., 2023; Lu et al., 2021; Managi et al., 2022).

4. Policy implications

Oil shocks have significantly influenced the sensitivity of G7

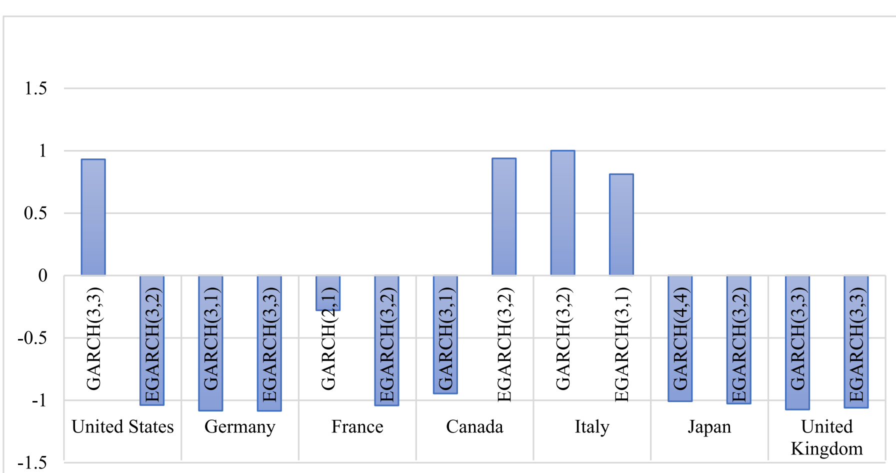


Fig. 4. Volatility Dynamics of the GARCH and EGARCH Sample Post-2018 Models.

countries' stock markets, generating crucial implications for energy policymaking and financial regulation. The variations observed in the structure of GARCH and EGARCH estimated models across different analyzed periods reflect the evolving complexity and persistence of market volatility. These dynamics respond to shifts in the global economic and political landscape, underscoring the necessity for targeted strategies to address such fluctuations.

The findings of this study highlight the intricate relationship between oil price movements and stock market performance, emphasizing the need for nuanced and adaptive policy approaches. For G7 policymakers, these results suggest the importance of developing robust frameworks that can anticipate and mitigate the impacts of oil shocks on their respective financial markets.

Moreover, the heterogeneous responses of G7 stock markets to oil shocks indicate that a one-size-fits-all approach to energy and financial policies may be ineffective. Instead, policymakers should consider tailoring their strategies to their country's specific economic structure, energy dependence, and financial market composition.

This section will delve into the political implications of these findings, offering evidence-based recommendations for policymakers in G7 countries. These insights aim to enhance the resilience of financial markets and promote sustainable economic growth in the face of future oil market volatility.

The results demonstrate that stock markets in Canada, Japan, and the United Kingdom exhibit high sensitivity to oil shocks, primarily due to their significant dependence on oil imports and the substantial role of the energy sector in their economies (Sadorsky, 2014). This vulnerability underscores the urgent need for energy source diversification across these nations.

Germany stands out as a successful exemplar in this regard, having spearheaded energy diversification through substantial investments in solar and wind power as part of its comprehensive Energiewende strategy. This approach has effectively reduced Germany's reliance on fossil fuels and enhanced its energy market stability (Agora Energiewende and Aurora Energy Research, 2019).

The German case illustrates that investment in renewable energy sources serves a dual purpose: it not only diminishes dependence on oil but also contributes to the stabilization of energy prices. This stability, in turn, helps mitigate the financial volatility typically associated with shocks in the hydrocarbon market.

This evidence suggests that policymakers in G7 countries should prioritize comprehensive energy diversification strategies, balancing short-term economic considerations with long-term sustainability and market stability goals.

The creation and strategic management of oil reserves emerges as a crucial strategy to mitigate the effects of high volatility periods in the oil market (Kilian & Murphy, 2014). Expanding these reserves during periods of low prices can enable countries to stabilize their financial markets more effectively during energy crises. This approach not only provides a buffer against short-term supply disruptions but also offers a tool for price stabilization in times of market turbulence. Furthermore, promoting investments in green energy infrastructure, such as wind farms and solar parks, serves a dual purpose. It not only reduces dependence on oil but also presents investment opportunities with lower exposure to external shocks. This diversification can enhance the resilience of national economies and their financial markets to oil-related volatilities.

The observed sensitivity in GARCH and EGARCH estimated models, particularly in response to negative shocks, underscores the necessity for more robust financial regulations capable of effectively managing market volatility. The implementation of Basel III stands out as a successful regulatory example, strengthening capital and liquidity requirements to bolster the stability of the financial system in the face of crises (Bank for International Settlements, 2011).

Financial regulators should prioritize the implementation of macroprudential policies that enhance the resilience of the financial system to external shocks (Demirer et al., 2020). A particularly effective policy in this regard is the establishment of countercyclical capital buffers. These buffers enable financial institutions to accumulate capital during periods of stability and utilize it during times of crisis. Acting as an additional reserve, these buffers can be deployed in adverse situations, allowing institutions to absorb losses without compromising the overall stability of the financial system. Moreover, they play a crucial role in moderating the business cycle by encouraging capital accumulation during growth periods, while permitting its use to mitigate negative impacts during recessions.

Complementing countercyclical capital buffers, it is imperative to establish more stringent capital requirements for financial institutions, such as elevated minimum capital ratios. This approach ensures that institutions maintain adequate financial resources to weather periods of crisis effectively. Additionally, promoting transparency in the use of hedging instruments, particularly financial derivatives, is crucial, especially in sectors vulnerable to oil shocks. These measures will empower investors to manage risk more effectively and reduce the impact of market volatility.

Furthermore, regulators should consider implementing stress tests specifically designed to assess the resilience of financial institutions to oil price shocks. These tests would help identify vulnerabilities in the financial system and guide the development of targeted regulatory responses. Encouraging the diversification of investment portfolios, particularly in oil-dependent economies, can also help mitigate the impact of oil price volatility on the broader financial market.

By adopting this comprehensive approach to financial regulation, policymakers can enhance the stability of their financial systems, better protecting them against the ripple effects of oil shocks and other external economic pressures. This strategy not only safeguards individual institutions but also contributes to the overall resilience of national economies in an increasingly interconnected global financial landscape.

The utilization of oil futures contracts has proven to be an effective tool for managing risks associated with oil price volatility. The persistent nature of this volatility underscores the need for continuous monitoring of financial markets. Clear and effective communication by monetary and fiscal authorities can significantly reduce uncertainty and prevent market overreactions (Lu et al., 2021). Transparent communication allows investors and market participants to develop a more accurate understanding of policy expectations, thereby minimizing uncertainty and, consequently, volatility.

To bolster the analysis and provide actionable recommendations to policymakers, it is valuable to examine concrete examples of successful measures implemented in response to oil market volatility. Canada, for instance, has implemented policies that encourage economic diversification, including incentives for clean energy development (Government of Canada, 2022). These policies have helped mitigate the sensitivity of its stock market to oil shocks, demonstrating how economic diversification can effectively reduce volatility. Similarly, the UK has strengthened its regulatory framework for banks and insurers, enhancing the resilience of its financial sector to global volatility events (Bank of England, 2024).

Japan has adopted a strategy of diversification and promotion of energy efficiency following the oil crises. This approach includes implementing policies such as the promotion of renewable energies, the development of nuclear technology, and improvements in energy infrastructure efficiency (Bank of Japan, 2014; Ministry of Economy Trade and Industry (METI) - Japan, 2014). These measures have reduced dependence on imported oil and improved the country's energy security (International Energy Agency, 2019). This regulatory approach can serve as a benchmark for other countries seeking to reduce the vulnerability of their financial markets to oil shocks.

Coordinating energy and financial policies among G7 countries is crucial, as the results of this research highlight the interconnectedness of their financial markets and how this interdependence makes such coordination essential.

In light of these findings, the development of joint frameworks for energy crisis management, including the coordinated release of strategic reserves, is recommended. A prime example of successful cooperation is the joint action of the International Energy Agency (IEA) during the 2011 oil crisis, when strategic reserves were released to stabilize global energy supply. This coordinated release helped counter supply shortages, reducing pressures on oil prices and providing temporary relief that allowed for an orderly recovery of the energy market.

Furthermore, policymakers should promote innovation in financial products that facilitate the management of market volatility. This includes the development of specialized derivatives products in the energy sector or investment funds focused on renewable energy. These financial innovations can provide market participants with more sophisticated tools to hedge against oil price fluctuations and invest in alternative energy sources.

These recommendations aim to reduce market volatility caused by oil shocks, promote greater financial stability, and guide the formulation of energy and financial policies that strengthen the resilience of G7 countries in the face of global uncertainty. By implementing a combination of diversification strategies, regulatory improvements, international coordination, and financial innovation, G7 countries can enhance their ability to withstand and adapt to the challenges posed by oil market volatility and broader economic uncertainties.

5. Conclusion

In this study, the impact of various oil variables, including the global oil price index and different shocks related to supply, economic activity, demand and inventory, on the stock market indices of the G7 countries was analyzed. A monthly data set was used from January 2003 to September 2023, with a structural break in 2014 due to the oil crisis. The methodology applied, which combined Vector Autoregressive (VAR) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, allowed to comprehensively capture the dynamics of the means and conditional volatility of the study variables. It highlights the complexity of the interaction between oil and stock markets and the need for sophisticated approaches to their analysis and management. The findings underline the importance of considering both mean dynamics and conditional volatility to fully understand the impact of oil variables on G7 financial markets.

Analysis results indicate significant influence of past shocks on current volatility in all markets analyzed. In particular, high sensitivity to new information was observed in all analyzed periods: pre-2014, during the 2014–2018 crisis and post-2018. The significance of the coefficients of the GARCH and EGARCH models reinforces the reliability of the estimated models and underlines the sensitivity of the market to past shocks. During the 2014–2018 oil crisis, the volatility of stock indices increased significantly, reflecting the increased uncertainty and volatility in the global market during this period.

In addition, the EGARCH models captured the asymmetry in volatility, showing that negative shocks have a greater impact on volatility than positive shocks. This asymmetry is crucial for understanding how bad news generates more uncertainty and volatility in financial markets. The temporal structure of volatility also varied significantly across different periods. Prior to 2014, most models presented a simple structure, while during the crisis the models showed more complex structures. In the post-2018 period, the models presented intermediate structures, suggesting a partial stabilization of the financial markets.

The study's specific findings reveal certain G7 countries show more pronounced responses to oil shocks. In particular, Canada stands out for its high sensitivity in the GARCH and EGARCH models, reflecting its economic dependence on the oil industry. Impulse response function analyses also indicate that Canadian stock indices exhibit higher volatility to oil shocks. Japan and the UK, in the post-2018 period, show significant responses in both GARCH models and the impulse response function, highlighting their vulnerability to fluctuations in oil prices. These results emphasize the need for economic policies tailored to country-specific characteristics to mitigate the impact of oil shocks and promote stability in stock markets.

These findings have important policy implications. First, they underscore the need to design economic policies to take into account both positive and negative shocks in oil markets. The implementation of stabilization policies could mitigate extreme volatility in stock markets and reduce economic uncertainty. Second, for highly oil-dependent countries, such as Canada, it is crucial to diversify their economies to reduce the sensitivity of their financial markets to fluctuations in oil prices. This may include the promotion of alternative sectors and investment in green technologies. Third, there is a need to strengthen risk monitoring and management mechanisms by regulators and investors, using advanced econometric analysis tools to anticipate and react appropriately to oil shocks.

Finally, this study provides a solid foundation for future research. Extending the temporal horizon to include data beyond 2023 will allow us to analyze the impact of recent events such as the COVID-19 pandemic and current fluctuations in oil prices. In addition, comparing the response of other economic sectors to oil shocks could provide a more complete picture of the interrelationship between oil and different segments of the financial market. Integrating geopolitical factors into econometric models will also improve the understanding of how global political events affect market volatility and the relationship between oil prices and stock market indices.

Author statement

During the preparation of this paper, the authors used [ChatGpt4o] to [IMPROVE WRITING]. After using this tool/service, the authors reviewed and edited the content as necessary and take full responsibility for the content of the publication.

Data availability

No

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