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Economies

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Suggested Citation: Aladwani, Jassim (2024) : Oil volatility uncertainty: Impact on fundamental macroeconomics and the stock index, *Economies*, ISSN 2227-7099, MDPI, Basel, Vol. 12, Iss. 6, pp. 1-23,
<https://doi.org/10.3390/economies12060140>

This Version is available at:

<https://hdl.handle.net/10419/329066>

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Article

Oil Volatility Uncertainty: Impact on Fundamental Macroeconomics and the Stock Index

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Abstract: This study utilized both single-regime GARCH and double-regime GARCH models to investigate oil price volatility, Spanish macroeconomic factors, and stock prices during major crises such as geopolitical conflicts, the global financial crisis (GFC), and COVID-19, covering the period from Q2-1995 to Q4-2023. Additionally, the impact of crude oil price volatility on these factors was examined. The empirical results confirmed the presence of the leverage effect and identified multiple volatility switches associated with remarkable events like the GFC, the European debt crisis, the COVID-19 pandemic, and the Russian war. ARDL model analysis revealed a statistically significant positive relationship between oil prices and both unemployment and inflation rates in the long term, while other factors showed a negative correlation.

Keywords: GARCH-type models; MS-GARCH models; macroeconomic factors; oil price fluctuation; ADRL model

JEL Classification: D53; E31; E32; G15; C32

1. Introduction

In the contemporary global economy, oil plays a fundamental role as a primary energy source. Despite the notable rise in alternative and renewable sources such as wind, water, nuclear, and solar energy, oil is predominant in the worldwide energy landscape. According to the International Energy Agency (IEA 2020), oil has remained the most essential form of energy consumption from the mid-20th century to now. Given the significant role oil plays in the global economy, its price level holds considerable importance as a benchmark for all countries. In theory, low global oil prices prove advantageous for oil-importing nations: lower oil prices lead to reduced production costs, increased consumer activity, and accelerated economic growth (Hamilton 1983; Kilian 2009; Baumeister and Kilian 2016; IMF 2016). Conversely, high global oil prices benefit oil-exporting countries; elevated oil prices result in increased export income, greater investments in infrastructure, and improved welfare for the populations of these countries (Tiwari et al. 2013; Babatunde 2019; Ordóñez et al. 2019; Braun et al. 2019).

The dynamics of oil prices have witnessed substantial transformations over the years. While the pricing mechanism in the oil market used to be oligopolistic for an extended period, since 1986, crude oil prices have been determined by a stock exchange market. In this market, oil prices undergo daily fluctuations and are shaped by a diverse array of geopolitical and natural crises, weather, transportation, and other factors. Minor price fluctuations may not exert a significant impact on the economies of oil-exporting countries, but abrupt shifts in global oil prices have the potential to destabilize national economies. To analyze how alterations in oil prices affect the economy of Spain, it is fundamental to recognize that this country is evolving within distinct economic circumstances.

In today's interconnected world economy, numerous factors exert an influence on the worldwide prices of energy resources, particularly oil. These include local and global economic crises, the economic growth rates of major countries, revolutionary shifts in



Citation: Aladwani, Jassim. 2024. Oil Volatility Uncertainty: Impact on Fundamental Macroeconomics and the Stock Index. *Economies* 12: 140. <https://doi.org/10.3390/economies12060140>

Received: 31 March 2024

Revised: 23 May 2024

Accepted: 28 May 2024

Published: 4 June 2024



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oil production technology, and the substantial impact on global prices stemming from decisions made by IEA and OPEC. Furthermore, embargoes, military events, geopolitical events, and other related factors play a significant role in shaping world prices. Given these circumstances, it is impossible to predict global oil prices solely based on statistical data, as the fluctuations and sudden surges in the energy market are mostly influenced by qualitative factors. Hence, in a dynamic environment where indicators frequently and sometimes unexpectedly shift, preparedness for change is crucial, along with understanding the potential effects on national economies. This underscores the significance and relevance of the study. The focus of this study is on the economy of Spain, examining key macroeconomic indicators and the repercussions of global crude oil price fluctuations.

Striving for precision in assessing macroeconomic variable uncertainties, including the crude oil price and stock price for Spain, our approach involves the careful consideration of the Markov Switching Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model, commonly referred to as the MS-GARCH model, and its variant, MS-GARCH. This model is employed to estimate regime-switching conditional volatility, serving as a proxy for macroeconomic variables uncertainty. The choice of the MS-GARCH model is deliberate, driven by a valid concern that macroeconomic time series may exhibit structural breaks. It is well established in the literature that estimates from GARCH-type models can be biased when structural breaks in volatility dynamics are present (Baillie and Bollerslev 2003; Bauwens et al. 2006; Aloui et al. 2015; Chkili and Nguyen 2017).

From 1995 to 2023, Spain experienced a tumultuous economic journey with periods of stability and crises. This included major events such as the GFC in 2007–2008, the Eurozone debt crisis in 2009–2010, the COVID-19 pandemic in 2020–2021, and geopolitical conflicts like the Russian war in 2022–2023. These events had a lasting impact on Spain's economy, leading to fluctuations in financial markets, disruptions in global trade, and overall economic uncertainty. Remarkably, previous research has not extensively examined the specific temporal dynamics between crude oil prices and the macroeconomy factors during this period. Therefore, the aim of this study is to bridge this gap by investigating the effects of crude oil price shocks on various macroeconomic factors in Spain.

The novelty and contribution of the paper studying the impact of oil price volatility on Spain's macroeconomic variables using the MS-GARCH model from 1995 to 2023 lie in several key aspects: first, the methodological innovation; introducing the MRS-GARCH model to analyze the relationship between oil price volatility and Spain's macroeconomic variables represents a methodological innovation. This model allows for a more nuanced understanding of how changes in oil prices affect various economic indicators, considering the dynamic nature of volatility. Second, the temporal scope that covers the period from 1995 to 2023 provides a comprehensive analysis of how oil price volatility has influenced Spain's economy over more than two decades. This extensive temporal scope allows for the identification of long-term trends, cyclical patterns, and potential structural shifts in the relationship between oil prices and macroeconomic variables. Third, a regional context that focuses specifically on Spain adds value by examining the impact of oil price volatility within a distinct economic and geopolitical context. This approach enables researchers to uncover Spain-specific dynamics that may not be captured in broader, global analyses. Fourth, there are policy implications; by elucidating the effects of oil price volatility on various macroeconomic variables in Spain, the paper offers valuable insights for policymakers. Understanding these dynamics can inform the development of more effective economic policies aimed at mitigating the adverse effects of oil price fluctuations and promoting stability and resilience in the face of external shocks. Finally, there is a contribution to the academic literature; the paper contributes to the academic literature by advancing our understanding of the complex relationship between oil prices and macroeconomic variables, particularly within the context of Spain. By employing the MRS-GARCH model and providing empirical evidence from a considerable timespan, the study enriches the theoretical framework and empirical basis for future research in this area. Overall, the paper's novelty and contribution lie in its methodological innovation, extensive temporal scope, focus on

the regional context of Spain, implications for policy formulation, and advancement of academic knowledge in the fields of oil price volatility and macroeconomics.

The results uncovered notable and consistent volatility persistence in macroeconomic variables across both regimes. Both single-regime GJR-GARCH and double-regime MS-GJR-GARCH models confirmed the presence of the leverage effect. MS-GARCH-type models, especially, allowed for the identification of multiple volatility switches, notably associated with events like the GFC, the European debt crisis, the COVID-19 pandemic, and the Russian war. Notably intriguing results emerged for the unemployment rate and inflation rate, where a pronounced leverage effect suggested distinct specifications of volatility regimes, as indicated by the double-regime MS-GJR-GARCH model. Consequently, the influence of crude oil price fluctuations on these macroeconomic factor's uncertainty measures was assessed using the ARDL model. The findings indicate a statistically significant positive relationship between the crude oil price and the unemployment rate, as well as the inflation rate, in the long term, while the remaining factors exhibit a negative correlation.

The rest of the paper is structured as follows: Section 2 delves into a comprehensive literature review of the Spanish economy. Section 3 is dedicated to presenting the MS-GARCH method. Section 4 provides details on the data sources and empirical results. Finally, Section 5 outlines the main conclusions derived from the study.

2. Literature Review

The literature review is divided into two main sections. The first section will concentrate on examining the impact of crude oil price changes on macroeconomic variables, while the second section will focus on exploring the applications of GARCH models.

2.1. The Relationship between Crude Oil Price Changes and Macroeconomic Variables

Previous studies on the relationship between crude oil prices and macroeconomic activity have primarily investigated two distinct facets: the effects of crude oil price shocks and volatility on the macroeconomy. These two approaches vary in their methods of integrating crude oil prices into their models.

The first approach considers crude oil prices at their current levels, whereas the second approach utilizes various volatility measures to grasp the uncertainty surrounding crude oil prices. Considering two consecutive crude oil shocks experienced during the early and late 1980s, numerous studies have investigated the effects of these shocks on macroeconomic activities. This extensive array of studies was pioneered by [Hamilton \(1983\)](#) and further expanded upon by [Burbidge and Harrison \(1984\)](#), [Gisser and Goodwin \(1986\)](#), [Mork and Olsen \(1994\)](#), [Ferderer \(1996\)](#), [Brown and Yücel \(2002\)](#), [Cunado and de Gracia \(2003, 2005\)](#), [Huang et al. \(2005\)](#), [Lardic and Mignon \(2006\)](#), [Huntington \(2007\)](#), [Chen and Chen \(2007\)](#), [Hamilton \(2008\)](#), [Cologni and Manera \(2008\)](#), [Jimenez-Rodriguez \(2009\)](#), and, more recently, by [van Eyden et al. \(2019\)](#), [Katsampoxakis et al. \(2022\)](#), [Mohd et al. \(2022\)](#), and several authors yet to be named.

Within the extensive literature concerning the relationship between commodity prices and the economy, works such as those by [Jimenez-Rodriguez and Sanchez \(2005\)](#) and [Katsampoxakis et al. \(2022\)](#) suggest that, for certain economies, this influence of crude oil prices on macroeconomic activities is asymmetric. Specifically, the negative effect of increases in crude oil prices outweighs the positive impact of decreases in crude oil prices.

Unlike the above studies that examine the effects of crude oil price shocks, investigations into the influence of crude oil price volatility on macroeconomies are scarce and trace their origins to the rise in crude oil price volatility starting from the 1980s. [Lee et al. \(1995\)](#) argued that fluctuations in crude oil prices exert a significant influence on the economic activities of the United States, particularly affecting unemployment and GNP, but notably, this impact is more pronounced during periods of price stability rather than high volatility or unpredictability. [Ferderer \(1996\)](#) analyzed data from the United States spanning from January 1970 to December 1990 to investigate the significance of the relationship between crude oil price volatility and macroeconomic performance.

The author utilizes the simple standard deviation to measure crude oil price volatility, and it suggests that uncertainty channels and sectoral shocks provide a partial explanation for the asymmetry observed between output and crude oil prices. Utilizing the measure volatility calculated from daily crude and WTI oil futures prices traded on the New York Mercantile Exchange, [Guo and Kliesen \(2005\)](#) ascertain that during the period from 1984 to 2005, crude and WTI oil price volatility significantly impacted several crucial economic indicators in the United States, including the unemployment rate, employment rate, fixed investment, and consumption. The results indicate that fluctuations in crude and WTI oil prices have a greater significance compared to uncertainties surrounding future prices. It is noteworthy that all the studies mentioned above, which aim to identify the influence of crude oil price volatility, focus on the United States economy. A recent paper exploring the effects of crude oil price volatility within the context of Spain is authored by [Cantavella-Jordá \(2020\)](#).

[Cantavella-Jordá \(2020\)](#) examines the influence of crude oil price volatility on macroeconomic indicators in Spain, employing an autoregressive distributed lag (NARDL) model. The variables considered include crude oil price volatility, GDP growth, capita GDP, inflation, and the budget deficit of Spain, spanning from 1945 and 2018. The impacts of such fluctuations on per capita GDP are enduring, with long-term decreases in crude oil prices having a greater effect on per capita GDP than increases in crude oil prices. Despite these asymmetric effects, the energy policy agenda should tackle issues related not only to tax management but also to market competition and efficient wage mechanisms. The findings suggest that changes in oil prices are less significant than the uncertainty about future prices.

There are fewer references to studies on the relationship between crude oil prices and the macroeconomy for Spain, the focus of our analysis. [Cunado and de Gracia \(2003\)](#) examined the influence of crude oil price shocks on industrial production and inflation across several European countries from 1960 to 1999. The authors observed short-term and asymmetric effects on production growth rates for Spain, although such effects were not apparent in the long term. Recently, [van Eyden et al. \(2019\)](#) conducted a study examining the connection between crude oil price volatility and economic growth across OECD countries over an extended period from 1870 to 2013 using a panel cointegration approach for its analysis. For Spain specifically, the authors found a consistently negative and significant elasticity throughout the entire period. [Katsampoxakis et al. \(2022\)](#) investigated the connections between crude oil price shocks and stock price returns among European countries that either export or import crude oil. The study employed an A vector autoregression (VAR) model to estimate the significance of stock market responses to fluctuations in crude oil prices during the COVID pandemic period from 2019 to 2021. A Granger causality test is utilized to ascertain both the direction and strength of the relationship between crude oil price shocks and indices within the European stock markets. The authors argued that the results of this study remain consistent regardless of the presence of the COVID-19 pandemic episode, demonstrating a clear interaction between the crude oil price shocks and European stock markets. The findings indicate that during stable periods—both prior to the COVID-19 outbreak crisis and following the introduction of vaccinations—there is no correlation between stock price returns and crude oil prices. However, during periods of high volatility, the causality from stock price returns to crude oil prices increases, affecting both oil-importing and oil-exporting countries equally.

Finally, [Mohd et al. \(2022\)](#) investigated the crucial relationship between crude oil price fluctuations and stock price returns, considering oil-importing and oil-exporting countries separately. The authors provide evidence utilizing Granger causality, error variance decomposition, and impulse response analysis through panel vector autoregression. The findings from the panel Granger causality analysis indicated that following the crude oil price crash during the COVID-19 pandemic, the correlation between stock price and crude oil price changes increased. This trend was also corroborated by the findings from both forecast error variance decomposition and impulse response graphs. During the period character-

ized by the sudden onset of the COVID-19 pandemic, the causality from crude oil to stock price returns increased. While both oil-importing and oil-exporting countries experienced similar effects, crude oil price fluctuations had a greater impact on oil-exporting countries.

2.2. Applications of GARCH Models

The conclusive importance of crude oil prices regarding macroeconomy factors is evident. Serving as a critical upstream product in the supply chain, the abrupt and substantial volatility of crude oil often triggers shocks in productive capacity, leading to economic fluctuations. Moreover, oil-exporting and oil-importing countries experience economic instability due to changes in purchasing power. Furthermore, crude oil, being a unique commodity with political and financial characteristics, is influenced by non-fundamental factors such as the US dollar exchange rate, financial crisis, geopolitics, global health crisis, and speculation. Therefore, modeling and forecasting volatility in the oil market represent vital and intricate challenges within both financial and commodity markets (Fan et al. 2008; Kilian and Vigfusson 2011; Serletis and Elder 2011; Wang and Wu 2012; Güntner 2014; Zhang et al. 2015; Van Robays 2016; Cantavella-Jordá 2020; Živkov and Đurašković 2021; Aladwani 2023; Szczygielski and Chipeta 2023; Zhang and Wong 2023).

Forecasts of oil price volatilities commonly rely on time-varying high-frequency data, where samples with high volatility frequently exhibit clustering features. Therefore, the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model, introduced by Bollerslev (1986), is widely employed for predicting oil market volatility. This model is favored for its effectiveness in capturing the time-varying characteristics of high-frequency data, as demonstrated by studies such as Hung et al. (2008), Agnolucci (2009), Kang et al. (2009), Mohammadi and Su (2010), Zagaglia (2010), Hou and Suardi (2012), and Liu et al. (2013). Recent contributions to this field, including those of Sekati et al. (2020) and Wacuka Ng'ang'a and Oleche (2022), further underscore the ongoing relevance and applicability of the GARCH model in forecasting oil market volatility.

Nevertheless, the conventional GARCH model inherently possesses symmetry, and when dealing with skewed time series, forecast outcomes using this standard model may be biased (Engle 1982; Franses and Dijk 1996). In response to this issue, various nonlinear and asymmetric GARCH models have been introduced for forecasting macroeconomic variables volatility. Examples include the EGARCH model proposed by Nelson (1991), TGARCH suggested by Zakoian (1994), and the GJR-GARCH model developed by Glosten et al. (1993). It is important to highlight that the GARCH-type models mentioned primarily concentrate on a single regime of macroeconomic factors, stock prices, and oil price changes. However, experts argue that structural breaks in the variance process of single-regime GARCH-type models frequently result in high volatility persistence. This is because these models typically fit both in-sample and out-of-sample time series data with the same pattern, neglecting potential structural changes (Hamilton 1983; Lamoureux and Lastrapes 1990; Litzenberger and Rabinowitz 1995; Pérez-Quiros and Timmermann 2000; Robays 2012).

To address this issue, Hamilton (1994) and Cai (1994) incorporate the regime-switching process (Hamilton 1988) into the GARCH model to account for potential structural breaks. Specifically, the Markov Switching-based GARCH (MS-GJR-GARCH) model allows the regimes in the Markov chain to exhibit different GARCH behaviors, implying distinct volatility structures. This extension of the GARCH model to dynamic forms aims to achieve improved estimation and forecasting performance (Cai 1994; Klaassen 2002; Linne 2002; Haas et al. 2004; Marcucci 2005; Zhang and Zhang 2015; Zhang and Wang 2015; Ardia et al. 2019; Muşetescu et al. 2022). However, in the context of forecasting macroeconomic factors, oil price volatility, and stock price volatility using GARCH-type models, there are still intriguing challenges to investigate. For example, while Markov Switching models are adept at capturing potential changes in state transitions and non-linearities in macroeconomic factor volatility, it remains uncertain whether the MS-GARCH-type model consistently

outperforms single-regime GARCH-type models in forecasting macroeconomic factors (including the oil prices and stock prices) volatility across all samples.

In the meantime, considering that the precision of forecasts by GARCH-type models is frequently influenced by the data frequency and time horizon employed for volatility measurement (Moore and Wang 2007; Manera et al. 2007; Frommel 2010; Zhang et al. 2015), it becomes intriguing to examine how the outcomes vary when calculating macroeconomic variables volatility (including oil prices and stock prices) at distinct data frequencies—specifically, quarterly. Furthermore, within the empirical literature comparing the forecast performance of linear and nonlinear GARCH-type models, there is no unanimous consensus.

3. Methodology

Analyzing the individual returns of the time series data allows for the determination of the continuous compounded returns. These returns are represented as R_t , with the subscript t denoting time.

$$R_t = \text{Log} \left(\frac{x_t}{x_{t-1}} \right) \quad (1)$$

where x is a time series variable.

3.1. The GARCH(1,1) Models

As per Bollerslev (1986) and Sadorsky (1999), the conventional linear GARCH (1,1) model for macroeconomic factors, encompassing crude oil price and stock price returns, can be expressed as follows:

$$\begin{aligned} r_t &= \theta + \varepsilon_t \\ \varepsilon_t &= \eta_t \sqrt{h_t} \\ h_t &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma h_{t-1} \end{aligned} \quad (2)$$

where the coefficients α_0 , α_1 , and γ must be greater than zero to guarantee a positive conditional variance and $\alpha_1 + \gamma < 1$ represents the persistence of shocks to volatility. The unconditional volatility for GARCH, represented by μ , can be computed as follows:

$$\mu = \sqrt{\frac{\alpha_0}{(1 - \alpha_1 - \gamma)}} \quad (3)$$

Sollowing the Klaassen (2002) and Haas et al. (2004) studies, we employ the student's t – distribution. As suggested by Gelman (2004), Fahrmeir et al. (2010), and Westfall (2014), the student's t – distribution is preferred due to its thicker tails, allowing for a higher probability of encountering outliers or extreme values. This characteristic is advantageous when working with real-economic and financial data, which frequently deviates from the idealized bell-shaped curve of the normal distribution.

To account for the asymmetric leverage effect in macroeconomic factors volatility, including the crude oil price and stock price, Glosten et al. (1993) introduced the non-linear GJR-GARCH model. The variance equation for this model is specified as follows:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 (1 - I_{\varepsilon_{t-1} > 0}) + \vartheta \varepsilon_{t-1}^2 I_{\varepsilon_{t-1} > 0} + \gamma h_{t-1} \quad (4)$$

The indicator function, indicated as $I_{\varepsilon_{t-1} > 0}$, is utilized to assign values 1 if $\varepsilon_{t-1} > 0$ and 0 if $\varepsilon_{t-1} \leq 0$, and $\alpha_1 + 0.5 \vartheta + \gamma < 1$ represents the persistence of shocks to volatility. The unconditional volatility for the GJR-GARCH model can be computed as follows:

$$\mu = \sqrt{\frac{\alpha_0}{(1 - \alpha_1 - 0.5\vartheta - \gamma)}} \quad (5)$$

3.2. MS-GARCH Model

The primary distinction between the multi-regime MS-GARCH-type models and the conventional single-regime GARCH-type models lies in the ability of the parameters in the MS-GARCH model to transition between different regimes based on the Markov process. To elaborate, the regime variable has the potential to switch in accordance with a Markov process, and the probability of transitioning from regime i at time $t - 1$ to regime j at time t is denoted as $P_{ij} = P(s_t = j | s_{t-1} = i)$. In the context of this study, it is assumed, as per [Klaassen \(2002\)](#), [Bialkowski \(2004\)](#), and [Haas et al. \(2004\)](#), that the innovation ε_t of MS-GARCH adheres to a student's t -distributions depending on the degree of freedom ($d.f.$). The conditional variance, the conditional mean following the GARCH process, and the expectation of squared innovations are specified as the equations below:

$$r_t = \mu_t^{(i)} + \varepsilon_t = \theta^{(i)} + \varepsilon_t \quad (6)$$

$$\varepsilon_t = \mathfrak{N}_t \sqrt{h_t} \quad (7)$$

$$h_t^{(i)} = \alpha_0^{(i)} + \alpha_1^{(i)} \varepsilon_{t-1}^2 + \delta_i^{(i)} E_{t-1} \left(h_{t-1}^{(i)} | s_t \right) \quad (8)$$

The conditional expectation is written as follows:

$$E_{t-1} \left(h_{t-1}^{(i)} | s_t \right) = p_{ii,t-1} \left[\left(\mu_{t-1}^{(i)} \right)^2 + h_{t-1}^{(i)} \right] + p_{ji,t-1} \left[\left(h_{t-1}^{(i)} \right)^2 + h_{t-1}^{(i)} \right] - \left[p_{ii,t-1} \mu_{t-1}^{(i)} + p_{ji,t-1} \mu_{t-1}^{(i)} \right] \quad (9)$$

In the MS-GARCH-type models, the symbols $i, j = 1, 2$ represent the two regimes.

$$p_{ji,t} = Pr(s_t = j | s_{t-1} = i, \Pi_{t-1}) = \frac{p_{ji} Pr(s_t = j | \Pi_{t-1})}{Pr(s_{t+1} = i | \Pi_{t-1})} = \frac{p_{ji} p_{j,t}}{p_{i,t+1}} \quad (10)$$

where the term Π_{t-1} denotes the information set at time $t - 1$.

The anticipated duration in each regime (denoted as $E(D_i)$ for $i \in \{1, 2, \dots, K\}$), signifying the average length of staying in a specific regime, can be computed as outlined in previous studies ([Rotta and Pereira 2016](#)).

$$E(D_i) = \frac{1}{1 - P_{ii}} \quad (11)$$

The stable probabilities (also known as the unconditional probabilities), denoted as τ_i , of being in a particular regime ($i = 1, 2$) can be determined using the following formula:

$$\tau_i = \frac{(1 - P_{ii})}{(2 - P_{ii} - P_{jj})} \quad (12)$$

3.3. ARDL Model

After quantifying the uncertainty in macroeconomic factors and the stock prices, we proceed to evaluate the impact of oil price fluctuations on the uncertainty of macroeconomic factors and stock prices through the ARDL model. The specification of the ARDL model is outlined as follows:

$$R(N, p)y_t = \theta + D(N, q)x_t + \mu_t \quad (13)$$

where, y_t represents the time series data of uncertainty and x_t denotes the crude oil price return. The term μ_t stands for the vector of other parameters, including both the time term and intercept trends.

$$R(N, p) = 1 - b_1 N - b_2 N^2 - \dots - b_p N^p \quad (14)$$

and

$$D(N, q) = a_0 - a_1N - a_2N^2 - \dots - a_qN^q \quad (15)$$

where N represents a lag operator. From Equations (11) and (12), the long-term effect in the ARDL model is expressed as follows:

$$\frac{D(N, q)}{R(N, p)} = \frac{\sum_{j=0}^q a_j}{1 - \sum_{j=1}^p b_j} \quad (16)$$

The short-term effect in the ARDL model is computed using the following equation:

$$\Delta y_t = b_0 \Delta x_t + \omega \varepsilon_{t-1} + \mu_t \quad (17)$$

where b_0 denotes the short-term effect in the ARDL model.

μ_t is calculated using the following equation:

$$\mu_{t-1} = y_{t-1} - \frac{\delta}{1 - (b_1 + \dots + b_p)} - \frac{(a_0 + a_1 + \dots + a_q)}{1 - (b_1 + \dots + b_p)} x_{t-1} \quad (18)$$

SIC (Schwarz Information Criterion) is employed to choose the optimal lags (p and q) for the ARDL model relationship involving macroeconomic factors, stock price uncertainty, and oil price fluctuation.

3.4. The Evaluation Criteria

In this stage, the optimal model is selected from the chosen models in each variable (conventional linear GARCH and MS-GARCH) based on two methods, namely, information criteria and forecast accuracy measures. The criteria include the Schwarz Information Criterion (SIC) and Akaike Information Criterion (AIC), providing a relative measure of information loss. Additionally, two forecast accuracy measures, the root mean squared error (RMSE) and mean absolute percentage error (MAPE), are employed for evaluation.

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (\hat{y}_t - y_t)^2} \quad (19)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{\hat{y}_t - y_t}{y_t} \right| \quad (20)$$

where \hat{y}_t indicates forecasted values and y_t indicates actual values.

4. Data Description

The dataset being examined consists of quarterly data on four major macroeconomic factors for Spain: the economic growth (GDPS), inflation rate (INFS), unemployment rate (UES), and interest rate (IRS). Additionally, two more factors, namely, stock prices (IBEX) and crude oil prices (COP), are included in the dataset. All data were obtained from the Federal Reserve Bank of St. Louis (FRED), except for the stock market (IBEX 35), which was obtained from Yahoo Finance. For commodity indicators, the data reflect a combination of both spot prices and futures prices. The IBEX 35 data reflect a total return (including dividends).

Incorporating a combination of both spot prices and futures prices for commodity indicators can provide a more comprehensive view of market dynamics, capturing both current market conditions and future price expectations. This approach allows for a deeper analysis of commodity markets, including assessments of supply–demand dynamics, speculation, and hedging activities. By considering both spot and futures prices, the analysis can better reflect the complexities and uncertainties inherent in commodity markets, potentially leading to more robust and nuanced results. Regarding the IBEX 35 data reflecting a

total return (including dividends), this choice provides a more accurate representation of investors' actual returns from holding the index, as it accounts for dividends distributed by the component stocks. Total return indices offer a more complete assessment of investment performance compared to price indices, which only reflect changes in stock prices.

The data cover the period from Q2-1995 to Q4-2023, resulting in 112 observations. Analyzing this period of over 28 years provides comprehensive insights into the examined time series' behavior during periods of stability and various crises and turmoil. These include events such as the Dot-com Bubble Burst in 2000, the Iraq war and oil price shock in 2003, Spain's accession to the EU in 2004, the GFC in 2007–2008, the European debt crisis in 2011, the shale oil boom and price slump in 2014, the Russia–Saudi Arabia oil price war in 2020, the COVID-19 pandemic in 2020–2021, and the Russian war in 2022–2023.

5. Empirical Results

Utilizing the models outlined in Section 3, estimation is performed for two single-regime GARCH-type models: the linear GARCH model and the non-linear GJR-GARCH model. Concurrently, estimation is also carried out for the two double-regime GARCH-type models: the MS-GARCH model and MS-GJR-GARCH model. The results are presented in Tables 1–3, revealing various findings.

Table 1 shows that all estimated parameters were statistically significant, except for the α_0 parameter in the linear GARCH model for the stock price and inflation rate returns, and the parameter γ was not statistically significant for crude oil price returns, interest rate returns, and inflation rate returns. The estimates of the parameter θ in the non-linear GJR-GARCH model for all macroeconomic factors, crude oil price, and the stock price returns were positive, indicating the presence of an asymmetric effect of past returns on conditional volatility. The economic growth (GDP) exhibited the strongest volatility reaction to past negative returns, followed by the crude oil prices, while the inflation rate showed a significantly weaker leverage effect. Regarding log-likelihood (*L.L.*) values, the non-linear GJR-GARCH model demonstrated higher values than the GARCH model for all analyzed time series returns. The “covariance stationarity” assumption for both the linear GARCH and non-linear GJR-GARCH models was met for all time series returns. Additionally, these totals suggested a high volatility persistence, ranging between 0.76 and 0.99 for the non-linear GJR-GARCH model and between the slightly lower values of 0.74 and 0.98 for the linear GARCH model. The crude oil price and interest rate returns, when compared to other factors under consideration, exhibited the lowest estimate for the degree of freedom (*d.f.*), suggesting a significantly fat-tailed distribution. The choice of the student's *t* – distribution was thus validated as appropriate, given the small degrees-of-freedom parameters *d.f.*, suggesting a significant departure from normality (Nelson 1991; Klaassen 2002; Haas and Paolella 2012; Ahsanullah et al. 2014; Raihan 2017; Ardia et al. 2019). The computed unconditional volatilities μ closely aligned with their sample counterparts in Table 1. Specifically, for both the linear GARCH and non-linear GJR-GARCH models, the highest values of unconditional volatilities μ were observed for the inflation rate returns, while lower values were noted for the economic growth (GDP) returns.

The results of the estimations for the double-regime MS-GARCH and MS-GJR-GARCH models were formulated assuming student's *t* – distributed innovations and double regimes, regime 1 signifying low volatility and regime 2 representing high volatility, as shown in Table 2. The degrees-of-freedom parameters (*d.f.*) for the student's *t* – distribution were consistently applied across both regimes, following the approach of Haas and Paolella (2012). The estimated *d.f.* values, ranging from 4.3 to 19.5, affirm that the modeled distributions exhibit finite variance (given *d.f.* > 2) and possess tails that are heavier than those of a normal distribution.

Table 1. Estimation results of GARCH and GJR-GARCH models.

Coeff.	$rCOP_t$	$rGDPS_t$	$rUES_t$	$rIRS_t$	$rIBEX_t$	$rINFS_t$
Linear GARCH model						
α_0	0.0008 *	0.0003 ***	0.0001 ***	0.0029 *	0.0010	0.0041
α_1	0.2980 *	0.4600 ***	0.2239 *	0.1712 ***	0.0157	0.1063
γ	0.4400	0.3340 ***	0.7516 ***	0.7560	0.8440 *	0.7760
$d.f.$	4.5001 **	5.6134 **	7.8480 **	3.7255 **	5.7716 **	11.6300 **
$\alpha_1 + \gamma$	0.7380	0.7940	0.9755	0.9272	0.8597	0.8823
$L.L.$	53.6581	143.5620	119.083	81.8467	114.7021	86.0331
μ	0.0534	0.0357	0.0765	0.0730	0.0840	0.1059
Non-linear GJR-GARCH model						
α_0	0.0013 *	0.0004 ***	0.0003 ***	0.0026 ***	0.0029 **	0.0045 *
α_1	0.1316 *	0.1887 **	0.1778 ***	0.1950 ***	0.2380 *	0.1334 ***
θ	0.7646 *	0.8323 ***	0.6120 *	0.2591 ***	0.4213 *	0.1407 **
γ	0.2433 ***	0.3878 ***	0.5017 ***	0.6071 ***	0.5199 ***	0.7221 ***
$d.f.$	4.7010 ***	5.8810 *	5.5539 **	3.9280 **	6.6822 **	10.4376 **
$\alpha_1 + \alpha_2 + \frac{1}{2}\gamma$	0.7585	0.9931	0.9858	0.9343	0.9715	0.9304
$L.L.$	61.2484	230.0170	192.8820	86.5688	124.9110	94.8700
μ	0.0554	0.0340	0.0535	0.0587	0.0663	0.1103

Note: ***, **, and * suggest statistical significance at 1%, 5%, and 10% levels, respectively. $L.L.$ denotes log-likelihood, $d.f.$ signifies degrees of freedom of the student t – distribution, and the term μ represents unconditional volatility of the single-regime GARCH-type models.

Table 2. Estimation results of the MS-GARCH model.

Coeff	$rCOP_t$	$rGDPS_t$	$rUES_t$	$rIRS_t$	$rIBEX_t$	$rINFS_t$
Regime 1—low-volatility regime						
α_{01}	0.0264 **	0.0916 ***	0.0451	0.0143	0.0120 **	1.3900 ***
α_{11}	0.2526 **	0.7640 ***	0.8282 **	0.1451 ***	0.2744 **	0.1846 ***
γ	0.2321 ***	0.3730 ***	0.3020 ***	0.6282 ***	0.3050 **	0.7305 ***
$\alpha_{11} + \gamma$	0.4840	0.7369	0.9201	0.7729	0.0304	0.5461
Regime 2—high-volatility regime						
α_{01}	0.0061	0.0121 ***	0.0107 **	0.0125 **	0.0253 **	0.0040 ***
α_{11}	0.0538 ***	0.1336 ***	0.1994 **	0.4106 ***	0.1474 ***	0.1933 ***
γ	0.3970 ***	0.3781 ***	0.3211 ***	0.2670 ***	0.2390 ***	0.6620 ***
$\alpha_{11} + \alpha_1$	0.4507	0.2446	0.5205	0.6767	0.3864	0.8550
$d.f.$	18.1892 ***	17.937 ***	14.7865 ***	18.7617 ***	13.5570 ***	12.4000 ***
p_{11}	0.9213 ***	0.9464 ***	0.7780 ***	0.9031 ***	0.6610 ***	0.9850 ***
p_{21}	0.0788 ***	0.1879 **	0.0164 **	0.0244 ***	0.4720 **	0.0307
$L.L.$	64.8973	249.1149	194.0167	75.3913	127.2704	90.4500
μ_1	0.0510	0.0743	0.0214	0.0628	0.02050	0.0560
μ_2	0.0110	0.0248	0.0223	0.0385	0.0412	0.0867
τ_1	0.0788	0.0621	0.1847	0.0904	0.3911	0.0154
τ_2	0.9212	0.9380	0.8154	0.9101	0.6101	0.9847
$E(D_1)$	3.5823	1.2312	4.4890	10.3117	1.8786	31.5954
$E(D_2)$	12.7035	17.6253	61.3103	41.1651	2.9471	66.3019

Note: *** and ** suggest statistical significance at 1% and 5%, levels, respectively. $L.L.$ denotes log-likelihood, $d.f.$ represents degrees of freedom of the t – distribution, and μ represents the double-regime of MS-GARCH-type models.

In regime 1, all estimated parameters revealed statistical significance in both models. However, in regime 2, this significance was observed in all parameters except for α_{01} for the interest rate and stock price returns in the MS-GJR-GARCH specification. The asymmetry parameters varied across individual regimes. Specifically, in both regimes, the crude oil price and inflation rate returns demonstrated a more pronounced impact of negative news in the case of MS-GJR-GARCH. Conversely, during the turbulent regime 1 and regime 2,

both the unemployment rate and interest rate returns exhibited a significantly stronger reaction to adverse news in the MS-GARCH model.

Table 3. Estimation results of the MS-GJR-GARCH model.

Coeff	$rCOP_t$	$rGDPS_t$	$rUES_t$	$rIRS_t$	$rIBEX_t$	$rINFS_t$
Regime 1—low-volatility regime						
α_{01}	0.0019 ***	0.0016 ***	0.0020 ***	0.0021 **	0.0028 *	0.0016 ***
α_{11}	0.0061 ***	0.2544 ***	0.2967 ***	0.2160 **	0.2770 *	0.1315 ***
θ	0.9653 ***	0.1830 ***	0.2538 **	0.2918 **	0.5871 *	0.8983 **
γ	0.4515 ***	0.4034 ***	0.3861 **	0.4624 **	0.3310 ***	0.3595 **
$\alpha_{01} + \alpha_{11} + \frac{1}{2}\gamma$	0.9412	0.7494	0.8096	0.8239	0.8967	0.9401
Regime 2—high-volatility regime						
α_{01}	0.0034 ***	0.0011 ***	0.0015 ***	0.0010	0.0008	0.0002 ***
α_{11}	0.020 ***	0.0874 ***	0.1110 ***	0.2576 ***	0.2826 *	0.1670 ***
θ	0.8940 ***	0.7604 ***	0.8378 ***	0.6164 ***	0.7041 **	0.8842 ***
γ	0.5031 ***	0.3732 ***	0.2701 ***	0.2667 ***	0.2427 ***	0.3610 ***
$\alpha_{01} + \alpha_{11} + \frac{1}{2}\gamma$	0.9700	0.8409	0.8003	0.8324	0.8784	0.9701
$d.f.$	19.4941 ***	18.9141 ***	4.3156 ***	6.6687 ***	15.2694 ***	15.5394 ***
p_{11}	0.9252 ***	0.9889 ***	0.8932 ***	0.8961 ***	0.9057 ***	0.980 ***
p_{21}	0.4531 ***	0.2970 ***	0.2012	0.0266	0.4323 ***	0.1021 **
$L.L.$	397.3161	252.8515	137.6488	76.0090	132.0958	249.7012
μ_1	0.0751	0.0795	0.0519	0.0660	0.0634	0.0619
μ_2	0.0347	0.0826	0.0861	0.0753	0.0826	0.0819
τ_1	0.1205	0.0156	0.1180	0.9035	0.1425	0.9781
τ_2	0.8801	0.9843	0.8812	0.0965	0.8756	0.0211
$E(D_1)$	2.2074	3.3674	4.9720	9.6160	1.1012	48.6046
$E(D_2)$	14.5468	9.7710	9.3715	7.6871	1.6715	10.8039

Note: ***, **, and * suggest statistical significance at 1%, 5%, and 10% levels, respectively. $L.L.$ represents log-likelihood, $d.f.$ denotes degrees of freedom of the t -distribution, μ represents the double-regime of MS-GJR-GARCH models.

The estimated parameters affirmed that the volatility process displayed a heterogeneous nature between the two regimes. The within-regime volatility persistence in the double-regime MS-GARCH-type models is equal to that of the single-regime GARCH-type models. The findings indicated that the within-regime volatility persistence differed across both regimes. In regime 1 (low volatility), there was a notably higher within-regime volatility persistence compared to that of regime 2 (high volatility) for both model specifications. However, for both the crude oil price and inflation rate returns, the immediate impact of a shock on conditional volatility was greater in the high-volatility regime than in regime 1. This suggests that a significant source of volatility clustering in regime 2 could be regime persistence rather than the persistence of a particular shock (Aktan et al. 2010; Raihan 2017).

The second factor contributing to the enduring nature of volatility is the persistence of regimes, as indicated by transition probabilities P_{11} and P_{22} . These probabilities represent the likelihood of remaining in regime 1 and regime 2, respectively. Particularly, the probabilities associated with staying in the low-volatility regime P_{11} for all-time series returns in double-regime MS-GARCH-type models ranged from 0.89 to 0.98 and were found to be statistically significant. In contrast, the probabilities of remaining in the high-volatility regime ($P_{22} = 1 - P_{21}$) were lower and, in certain instances, even statistically insignificant. Consequently, regime 1 demonstrated a greater persistence compared to regime 2, with the exception being the unemployment rate and interest rate returns in the MS-GJR GARCH model.

Concerning the expected durations and stability probabilities outlined in Equations (11) and (12), respectively, in Section 3, the stable probabilities for being in the high volatility (regime 2) and the expected durations of regime 2 (high volatility) were found to be higher for the crude oil price, economic growth (GDP), unemployment rate, and stock price returns when compared to the corresponding values for the low-volatility regime 1.

For the inflation rate and the interest rate returns, both the MS-GARCH and MS-GJR-GARCH models produced divergent outcomes. According to the MS-GARCH model, the stable probabilities distinctly revealed a significantly higher-volatility regime 2. Also, the expected durations of regime 2 were higher than the values associated with the lower-volatility regime 1. However, the results of the MS-GJR-GARCH estimation, considering the substantial leverage effect, demonstrated an increased stable probability for the low-volatility regime 1. Furthermore, the expected durations of regime 1 were found to be higher compared to the values associated with the high-volatility regime 2. The log-likelihood values (*L.L.*) provide an initial perspective for evaluating the significance of regime persistence in volatility (Klaassen 2002). Specifically, for the macroeconomics factors, stock price and crude oil price, the log-likelihoods associated with double-regime MS-GARCH-type models (refer to Tables 2 and 3) were higher than their single-regime GARCH-type model counterparts (refer to Table 1). The comparison of log-likelihoods indicates that accounting for regimes can enhance the ability to capture volatility persistence.

The smoothed probabilities for the low-volatility regime 2 from the MS-GARCH and MS-GJR-GARCH models are represented in Figure 1. These probabilities offer valuable insights into the behavior of specific time series returns. The results demonstrate unique characteristics among the variables that were analyzed. When examining the inflation rate, interest rate, and unemployment rate returns, both double-regime models consistently yielded the same results. This suggests that the market experienced stable periods with occasional abrupt shifts to high-volatility regimes. Notably, these transitions coincided with well-known periods of turmoil, such as the GFC in 2007–2008 and the emergence of the COVID-19 pandemic in 2020–2021 for the unemployment rate returns. However, for interest rate returns, shifts to the high-volatility regime were observed during the COVID-19 pandemic and the Russian war in 2022. This detailed analysis provides a deeper understanding of market dynamics during remarkable events, highlighting the double-regime MS-GARCH-type models' ability to capture subtle variations in volatility regimes. Moreover, when analyzing the returns of crude oil prices, economic growth (GDP), and stock prices from 1995 to 2023, both double-regime models consistently produced similar results.

These results suggest that the market experienced periods of calm, with occasional sudden shifts to high volatility. These shifts coincided with well-known periods of turmoil, including various crises and global events. The identified turmoil periods, characterized by changes in volatility, align with significant global influences. The analysis considers the impact of events such as the GFC in 2007–2008, speculative bubbles from 2000 to 2004, the European debt crisis in the summer of 2011, the onset of the COVID-19 pandemic in 2020–2021, and the Russian war in 2022, which led to economic sanctions on Russia. Each of these events had a significant impact on international financial markets, causing fluctuations and uncertainties that also affected the crude oil market and the Spanish stock market.

By conducting double-regime MS-GARCH-type models, which distinguish between periods of increased volatility and tranquility, we gain valuable insights into how the market reacts to various GFCs, health global crises, and geopolitical conflicts. This in-depth analysis not only helps us comprehend the market's behavior but also enables us to identify and assess crucial factors that drive market trends during specific periods. Consequently, this comprehensive understanding of Spain's financial markets enhances our knowledge of how significant international and domestic events have influenced market conditions over the years.

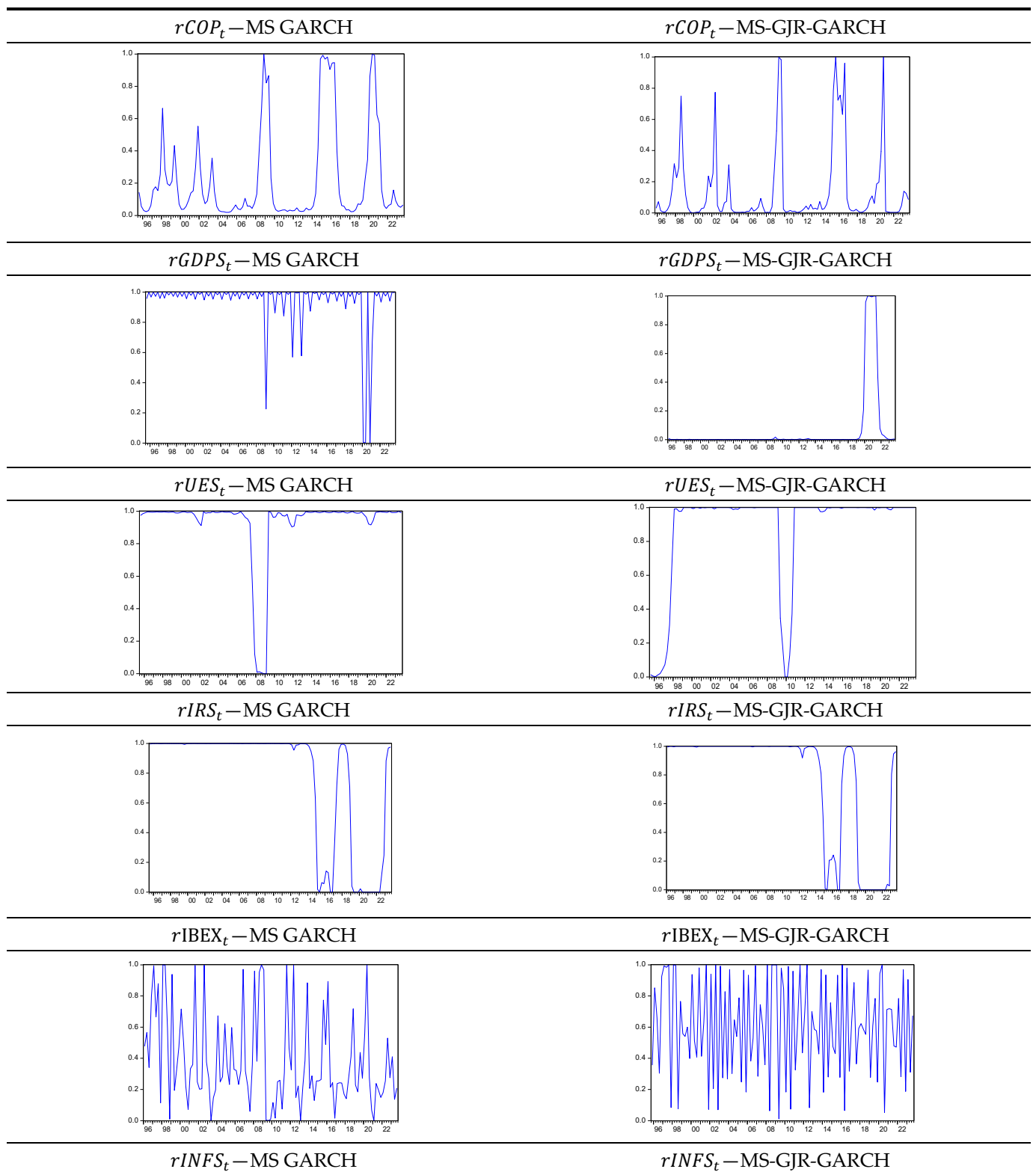


Figure 1. Cont.



Figure 1. Smoothed probabilities for the high volatility (regime 2).

Another surprising finding concerning interest rate returns is the significant volatility observed during two distinct periods: the Eurozone sovereign debt crisis in 2009–2010 and the economic recovery of Spain spanning from 2014 to 2015. During the Eurozone sovereign debt crisis, Spain, like other Eurozone countries, faced severe economic challenges. The crisis was marked by concerns over the sustainability of sovereign debt, leading to increased market uncertainty and financial instability. The impact on interest rates can be attributed to market reactions, government debt dynamics, and efforts to address fiscal imbalances. In the subsequent crisis from 2014 to 2015, labeled as the economic recovery Spain crisis, it becomes crucial to delve into specific economic events and policy measures undertaken during this period. Identifying the factors contributing to interest rate volatilities during this period could involve examining economic recovery strategies, external influences, or changes in monetary policy that might have influenced market sentiments and interest rate dynamics.

Table 4 shows the dynamics of conditional volatilities in individual markets for the next four quarters, with a particular emphasis on the period coinciding with the COVID-19 pandemic, the Russian war, and the imposition of restrictions on Russia by the United States and European countries. The estimated double-regime GARCH-type models were utilized to calculate the five-step-ahead conditional volatilities. Notably, the forecasted values from both model specifications indicated that the crude oil price, stock prices, and economic growth (GDP) demonstrated the highest conditional volatility, followed by inflation rates, unemployment rate, and interest rates.

Table 4. Five-step-ahead conditional volatilities of double-regime MS-GARCH models.

	$rCOP_t$	$rGDPS_t$	$rUES_t$	$rIRS_t$	$rIBEX_t$	$rINFS_t$
MS-GARCH Model						
2024Q1	0.0346	0.0254	0.0041	0.0159	0.0255	0.0247
2024Q2	0.0366	0.0190	0.0039	0.0145	0.0265	0.0387
2024Q3	0.0323	0.0148	0.0022	0.0041	0.0286	0.0341
2024Q4	0.0321	0.0151	0.0016	0.0052	0.0308	0.0376
2025Q1	0.0316	0.0159	0.0013	0.0069	0.0372	0.0421
MS-GJR-GARCH Model						
2024Q1	0.0368	0.0113	0.0069	0.0304	0.0234	0.0335
2024Q2	0.0318	0.0217	0.0057	0.0412	0.0217	0.0424
2024Q3	0.0331	0.0180	0.0095	0.0303	0.0249	0.0461
2024Q4	0.0315	0.0152	0.0064	0.0241	0.0250	0.0411
2025Q1	0.0286	0.0136	0.0049	0.0135	0.0254	0.0335

Increased volatility in inflation rate forecasts may signal heightened uncertainty about the future purchasing power of consumers (price levels) in Spain. This could result from several factors, including supply chain disruptions, shifts in consumer behavior, or monetary policy adjustments. Higher volatility may indicate potential risks of inflationary pressures or deflationary trends, impacting consumers' purchasing power and businesses' pricing strategies.

Elevated volatility in unemployment rate forecasts could indicate greater uncertainty in labor market conditions. This uncertainty may stem from factors such as the changing demand for labor, technological disruptions, or policy interventions. Higher volatility may reflect challenges in predicting future job market trends, making it difficult for policymakers and businesses to plan effectively.

Higher volatility in forecasted interest rates suggests increased uncertainty regarding future monetary policy decisions by the European Central Bank (ECB) or the Bank of Spain. This uncertainty can stem from ambiguous economic signals, fluctuating inflation expectations, or external economic shocks. Elevated interest rate volatility can lead to unpredictable borrowing costs for businesses and consumers, potentially delaying or scaling back capital expenditures due to uncertain financing conditions. For consumers, such volatility can influence saving and spending behaviors, as unpredictable interest rate movements may encourage saving overspending, potentially slowing economic growth. In financial markets, higher volatility in interest rates can destabilize the bond market, leading to higher risk premiums and yield fluctuations, thereby affecting bond prices and returns. Additionally, increased interest rate volatility can impact the exchange rate of the euro against other currencies, as international investors adjust their portfolios based on varying expected returns across different markets. This can lead to heightened exchange rate volatility, further complicating the economic landscape.

This information provides insights into the expected volatility patterns in Spain macroeconomic factors including the oil price and stock markets, underscoring the heightened volatility anticipated during the specified period, as captured by the models.

Table 5 illustrates the optimal model selection for variables displaying the ARCH effect, determined through a comprehensive evaluation of information criteria such as SIC and AIC and forecast accuracy measures. Based on the results of SIC and AIC, the double-regime MS-GARCH-type models emerge as the most suitable choice for all variables under scrutiny. This decision is grounded in the meticulous scrutiny of information criteria and forecast accuracy, with the double-regime MS-GARCH-type models identified as the preferred option for capturing the volatility characteristics of the variables in question. The SIC and AIC values in double-regime MS-GARCH-type models are remarkably lower than those in single-regime GARCH-type models, a trend clearly depicted in Table 5. Across all variables examined, the double-regime MS-GARCH-type models exhibit smaller RMSE and MAPE values compared to their single-regime GARCH-type counterparts. The reduced prediction errors in the chosen double-regime MS-GARCH-type models, as indicated by these evaluation criteria, affirm its efficacy in providing accurate predictions for various variables. This compelling evidence underscores the superior performance of the double-regime MS-GARCH-type models over single-regime GARCH-type models, emphasizing its robustness in capturing the inherent dynamics of the time series returns under investigation.

Table 6 displays the conclusive ADRL model, encompassing both the short-term and long-term effects of crude oil price fluctuations on the macroeconomic factor's uncertainty within the optimal model that encompasses single- and double-regimes.

In the short term, the statistical analysis reveals a notable negative correlation between the crude oil price and stock price, signifying that higher crude oil prices coincide with a downturn in stock prices. This adverse association can be attributed to the heightened operational costs for businesses, potentially leading to diminished profit margins and constraints on consumer spending. Simultaneously, a statistically significant positive correlation is evident between crude oil price fluctuations and inflation rate uncertainty. Increased crude oil price activity contributes to cost-push effects on the inflation rate, resulting in elevated production costs that may be transferred to consumers, thereby intensifying uncertainty regarding the inflation rate.

Table 5. The optimal model of variables.

	$rCOP_t$	$rGDPS_t$	$rUES_t$	$rIRS_t$	$rIBEX_t$	$rINFS_t$
Single-regime GARCH-type Models						
Model	GARCH	GARCH	GJR-GARCH	GARCH	GARCH	GJR-GARCH
SIC	−0.7476	−3.9610	−3.1664	−1.1975	−1.8901	1.9498
AIC	−0.8689	−4.0822	−3.2525	−1.3423	−2.0128	1.8042
RMSE	0.1556	0.0445	0.0550	0.2652	0.0850	1.2730
MAPE	0.1124	0.0380	0.0396	0.1455	0.0637	1.1208
Double-regime GARCH-type Models						
Model	MS-GARCH	MS-GARCH	MS-GJR-GARCH	MS-GARCH	MS-GARCH	MS-GJR-GARCH
SIC	−0.7970	−4.0325	−3.7340	−1.2990	−1.9774	1.7028
AIC	−0.8952	−4.1773	−3.8871	−1.4441	−2.1221	1.6319
RMSE	0.1506	0.0411	0.0528	0.2556	0.0812	1.2545
MAPE	0.1102	0.0340	0.0350	0.1436	0.0613	1.1131

Table 6. Short-term and long-term effect of the crude oil prices on the macroeconomic factors including stock prices uncertainty.

Variables	Short-Term		Long-Term	
	Regime 1	Regime 2	Regime 1	Regime 2
$rGDPS_t$	−0.4414	−0.6423	−2.1203 *	−1.3302 **
$rUES_t$	0.0821	0.3439	0.8214 **	0.7955 **
$rIRS_t$	−0.1160	−0.3442	−1.0810 **	−1.2271 **
$rIBEX_t$	−0.0562 *	−0.2764 **	−0.5438 *	−0.6101 *
$rINFS_t$	0.0504 **	0.0614 **	1.6423 *	2.0034 *

Note: *** indicates significance at the 1% level; **, at the 5% level; and * at the 10% level.

The findings are consistent with several research studies, including those conducted by [Hooker \(1996\)](#), [Camarero et al. \(2006\)](#), [Ewing and Thompson \(2007\)](#), [Lescaroux and Mignon \(2008\)](#), [Wang et al. \(2012\)](#), [Carrion-i-Silvestre and Kim \(2000\)](#), [Gormus and Soytaş \(2020\)](#), and [Tuna et al. \(2021\)](#). These studies collectively support the notion of a negative correlation between the crude oil price and stock price, along with a positive correlation between the crude oil price and inflation rate. Moreover, the lack of statistical significance in the correlation between crude oil price fluctuations and other macroeconomic factors under investigation, such as the interest rate, economic growth (GDP), and unemployment rate, is consistent in both regimes. This observation aligns with the findings of previous research studies, such as those conducted by [Kilian \(2009\)](#), [Álvarez and Urtasun \(2013\)](#), [Kitous et al. \(2016\)](#), [Kanjilal and Ghosh \(2017\)](#), and [Cheratian et al. \(2019\)](#), which similarly highlighted the absence of a significant relationship between crude oil price fluctuations and these economic metrics in the short-term context. This reinforces the understanding that, within the specified period, the dynamics of the crude oil price may not distinctly impact variables like the interest rate, economic growth (GDP), and unemployment rate. These findings can be interpreted to support two plausible explanations. First, it is conceivable that the European Central Bank (ECB) has implemented adept monetary policies to counteract the adverse impacts of crude oil price shocks. Such policies could involve strategic adjustments to interest rate adjustments or well-timed liquidity injections, aimed at supporting economic growth and mitigating the effects on the unemployment rate. Second, it is possible that Spain has successfully implemented robust energy policies and technologies, thereby reducing their reliance on crude oil as a primary energy source. This strategic move could serve to minimize the economy's susceptibility to the negative impacts of crude oil price shocks, highlighting the effectiveness of their energy diversification efforts.

Over the long term, every estimated parameter exhibited statistical significance in the correlation between crude oil price fluctuations and the macroeconomic factors uncertainty. Similarly, a significant negative relationship was observed between crude oil price fluctuations and the uncertainties associated with economic growth (GDP), stock prices, and the interest rate in both regimes. The considerable magnitude of these parameters underscores their substantial impact on the economic dynamics in Spain. The negative correlation identified can be ascribed to many factors.

First, an upsurge in the crude oil price has a cascading effect on production across various industries, such as transportation and manufacturing. This surge, in turn, contributes to an increase in price for both services and goods, resulting in a potential reduction in consumer demand and a slowdown in overall economic growth. Additionally, the uncertainty associated with the crude oil price can instill caution in business trading activities, as companies grapple with uncertainty regarding future costs and profitability. This cautious approach by businesses can further impact economic dynamics as companies navigate uncertainties and make strategic decisions amidst fluctuating crude oil price conditions. The second explanation is that the repercussions of soaring crude oil price extend to adversely affect the uncertainty of the stock price. Crude oil plays a pivotal role as an essential input cost for numerous companies, and when prices experience an upward surge, it tends to impede their cash flow and overall profitability. The subsequent decline in earnings, coupled with the inherent uncertainty linked to the crude oil price, can contribute to a reduction in the stock price. This interplay between crude oil price dynamics and broader economic indicators emphasizes the interconnectedness of financial markets and the potential cross-border impact on monetary conditions.

Finally, a surge in the crude oil price tends to contribute to an upswing in the interest rate. The rise in the crude oil price triggers heightened inflationary pressures, prompting the European Central Bank (ECB) in European countries (including Spain) to elevate the interest rate level as a measure to mitigate economic growth. However, this subsequent increase in the interest rate can pose challenges for the respective countries, as it results in a scenario where the cost of borrowing becomes more expensive for both individuals and businesses.

Overall, the negative correlation identified between crude oil price fluctuations and uncertainties related to the stock price, economic growth (GDP), and interest rate indicates that a thriving crude oil price can potentially have adverse effects on Spain's economy over the long term. These empirical findings are consistent with prior research conducted by researchers such as [de Miguel et al. \(2003\)](#), [De Blas and Russ \(2015\)](#), [Del Rio and Rodríguez-López \(2016\)](#), [Castro et al. \(2017\)](#), [Ordóñez et al. \(2019\)](#), [Rodríguez-Zúñiga et al. \(2019\)](#), and [Topan et al. \(2020\)](#), reinforcing the agreement and further contributing to an expanding body of literature that emphasizes the intricate interplay between the crude oil price and various elements of economic indicators within the context of Spain.

Regarding the realms of the unemployment rate and inflation rate, the empirical findings reveal a robust positive statistical significance at the 5% level concerning the interdependence between crude oil price fluctuations and uncertainty in the unemployment rate. Simultaneously, a notably stronger positive statistical significance is evident at the 1% level for the interdependence between crude oil price fluctuations and uncertainty in the inflation rate.

This finding can be clarified through the consideration of three key factors. First, the significant reliance of Spain on imported crude oil plays a crucial role in its economy. Spain heavily depends on imports of crude oil to meet their energy needs, resulting in any fluctuations in the global crude oil price directly influencing their domestic economies. An increased crude oil price contributes to elevated transportation, consumption, and production costs, thereby exerting inflationary pressures on the economy. The second explanation is that Spain is characterized by a significant presence of energy-intensive industries encompassing the transportation, manufacturing, chemical, and automotive industries. These industries heavily rely on crude oil and petroleum products as essential inputs for

their operations. Consequently, any upswing in the crude oil price directly influences the cost dynamics of these industries, potentially leading to job losses and layoffs, thereby contributing to an increase in the unemployment rate. Third, a plausible explanation lies in the fact that Spain stands as one of the world's premier tourist destinations, with its economy shaped by the tourism industry. An increase in the price of crude oil contributes to heightened transportation costs, encompassing airfares and fuel expenses for tourist vehicles, thereby directly impacting the affordability of travel for both international and domestic tourists. Therefore, a decrease in tourist arrivals carries adverse implications for the hospitality industry, leading to reduced employment opportunities within this industry. The results align with the outcomes of earlier research conducted by Gómez-Loscos et al. (2011), Becken and Lennox (2012), Barrios and Rodríguez-Palenzuela (2015), Bergareche (2019), and Koirala and Ma (2020).

6. Conclusions

In this study, the volatilities of macroeconomic factors, the crude oil price, and the stock price in Spain is assessed through the application of two single-regime GARCH-type models, namely, the linear GARCH model and the non-linear GJR-GARCH model, alongside the two double-regime MS-GARCH-type models. Subsequently, their performances are contrasted with those of the single-regime GARCH-type models under Student's t – distributions. To conclude, the study delves into estimating the influence of crude oil price fluctuations on macroeconomic factors uncertainty and stock price uncertainty within a regime-switching environment. The study results unequivocally validate that the double-regime MS-GARCH-type models extend the generality of the single-regime GARCH-type models by offering enhanced flexibility in the volatility process. Beyond the specific results associated with each macroeconomic factor, several overarching conclusions can be inferred. The estimated double-regime MS-GARCH-type models effectively identify breakpoints in inflation rate volatilities, notably during the GFC, the European debt crisis, and the COVID-19 pandemic. Meanwhile, interest rate returns exhibited heightened volatilities in two periods, COVID-19 and the Russian war, and unemployment rate returns displayed notable volatility transitions during the GFC and small volatilities during the COVID-19 pandemic period. Analyzing crude oil price returns, economic growth (GDP) returns, and stock price returns in Spain (2000–2023) using double-regime models revealed consistent outcomes. Periods of stability were interrupted by occasional shifts to high volatility, aligning with global upheavals like the 2007–2008 GFC, speculative bubbles, the European debt crisis, the COVID-19 pandemic, the oil price war between OPEC and Russia, and the Russian war, inducing economic sanctions. These events impacted international financial markets, causing fluctuations in both the crude oil and Spanish stock market. Another primary objective of the study is to assess and compare the performance of single-regime GARCH-type models and double-regime MS-GARCH-type models in characterizing and predicting the volatility of the macroeconomic factors, crude oil price, and stock price. Overall, the empirical findings indicate that double-regime MS-GARCH-type models exhibit a significantly superior performance compared to single-regime GARCH-type models when forecasting volatility over quarterly horizons. Additionally, the impact of the crude oil price fluctuations on macroeconomic factors and stock price uncertainties is estimated in a regime-switching environment. Short-term outcomes reveal both negative and positive effects of the crude oil price fluctuations on the stock price and inflation rate, respectively, under both regimes. In the long term, a positive relationship is observed between the crude oil price fluctuations and unemployment rate and inflation rate, while a negative relationship is identified between the crude oil price fluctuations and other the macroeconomic factors such as the economic growth, interest rate, and stock price in both regimes.

The instability of crude oil price fluctuations during financial crises, global health crises, and geopolitical conflicts holds substantial practical implications for policymakers and investors, particularly in oil-import-dependent countries like Spain. The financial crises and geopolitical conflicts, especially in oil-rich regions like the GCC countries, often

trigger an increase in oil prices due to concerns about supply disruptions. This surge in oil prices directly impacts industries reliant on oil, such as agriculture, manufacturing, and transportation. Investors may witness increased costs for companies in these sectors, leading to potential decreases in profitability and subsequent decreases in stock prices. Policymakers face the challenge of mitigating these negative effects on the economy. Striking a balance between crude oil price stability and economic growth becomes crucial. In response to higher oil prices, policymakers may implement measures like interest rate adjustments or fuel subsidies to address inflation and support consumers. These policy decisions directly influence stock prices as investors react to their potential implications for businesses in various industries. Macroeconomic factors in Spain are significantly affected by high oil prices due to the country's heavy reliance on oil imports. Increased oil prices result in a higher cost of living as transportation expenses rise, potentially reducing consumer spending and slowing economic growth. Consequently, macroeconomic indicators such as GDP growth rates and inflation may experience negative effects. The impact of oil price fluctuations on Spain's stock market depends on specific industries. Sectors heavily dependent on oil may witness decreases in stock prices due to increased costs, while companies in renewable energy and alternative fuels may benefit, leading to stock price increases. These nuanced effects contribute to the broader landscape of Spain's stock market. The practical implications of crude oil price fluctuations during financial crises and geopolitical conflicts reverberate across various aspects of Spain's economy. From industries reliant on crude oil to macroeconomic indicators and specific sectors within the stock market, these implications underscore the importance of monitoring and understanding these dynamics for informed decision-making by policymakers and investors.

Even more notable are the empirical results regarding the relationships between crude oil price changes and macroeconomic variables in Spain, offering valuable insights for investors, portfolio managers, and policymakers. However, there are potential limitations in the methodology due to the sample size. Nonetheless, this presents an opportunity for future research to expand the dataset and time periods and to apply additional techniques such as Copula transformation to the selected variables.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: Upon request.

Conflicts of Interest: The authors declare no conflict of interest.

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