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# THE IMPACT OF CRUDE OIL PRICE SHOCKS ON SPAIN'S MACROECONOMIC AND STOCK MARKET PERFORMANCE: A LONG-TERM PERSPECTIVE

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## ABSTRACT

Using standard GARCH-type, Markov Switching GARCH-type, and autoregressive distributed lag (ARDL) models, this study employs quarterly dataset from 1995 to 2023 to investigate the volatility shifts of macroeconomic variables, incorporating crude oil prices in Spain. The empirical results of the study clearly confirm that MS-GARCH-type models extend beyond the capabilities of standard GARCH-type models, providing enhanced flexibility in modeling the volatility process. The estimated MS-GARCH-type models effectively identify breakpoints in all macroeconomic variables volatilities, specifically during significant events such as the global financial crisis (GFC) in 2008, the European debt crisis in 2011, and the Covid-19 pandemic of 2020, Russia-Ukraine War in 2022. In addition, our results indicate that high crude oil price shocks during the global events are important drivers of uncertainty. There is strong evidence that the effects of crude oil price shocks on macroeconomic uncertainty are highly dependent on the prevailing regime. These impacts vary based on investor sentiment and the level of perceived volatility within financial markets. The responses of economic uncertainty to crude oil shocks appear to experience a dramatic change in the major global events, such as the post-global financial crisis (GFC), COVID-19 pandemic, and the Russia-Ukrainian war

## 1. INTRODUCTION

The macroeconomic impacts and influence of stock prices due to crude oil price shocks have been extensively examined in academic literature, especially following the groundbreaking research conducted by Hamilton (1983). It is widely recognized that crude oil shocks are strongly linked to various macroeconomic and financial market indicators, such as exchange rates, employment, stock market returns, interest rate, consumer spending, inflation, government budgets, and gross domestic product (GDP) (see, e.g., Peersmann & Van-Robays, 2009; Van-Robays, 2012; Kang et al., 2015; Leduc et al., 2016; Mohaddes & Pesaran, 2016; Obstfeld et al., 2016; Antonakakis et al., 2017; Castro et al., 2017; Hollander et al., 2019; Huiming et al., 2020; Sheng et al., 2020; Gupta & Pierdzioch, 2022; Aladwani, 2023; Aladwani, 2024a; Zhang et al., 2024). In recent studies, Hailemariam et al. (2019) and Zhang et al. (2022) emphasize that much of the existing literature has predominantly concentrated on the negative effects of crude oil price shocks on macroeconomic performance, particularly in relation to business cycles. However, it could be highly valuable for policymakers to explore how macroeconomic uncertainty functions as a channel through which crude oil market shocks impact the economy. Additionally, gaining a deeper understanding of the mechanisms of information transmission between crude oil price fluctuations and macroeconomic uncertainty could provide critical insights into managing energy-related risks and formulating more resilient economic policies. The authors propose that fluctuations in crude oil prices can serve as a significant catalyst for both macroeconomic uncertainty and instability in financial markets.

This is a crucial question, as the impact of uncertainty on macroeconomic variables has garnered substantial attention from both financial practitioners and policymakers, particularly during periods of crisis such as the Global Financial Crisis (GFC), COVID-19 pandemic, trading war between biggest oil exporters, and wars such as Russia-Ukrainian war. Building on the influential work of Bloom's (2009), a growing body of research has emerged, highlighting the significant effects that uncertainty has on both overall economic performance and financial activity (see, e.g., Ajmi et al., 2015; Charles & Darné, 2017; Lin & Bai, 2021; Gkillas et al, 2022; Aladwani, 2025a). Understanding the factors that drive economic uncertainty is a key concern for policymakers, as it holds significant relevance for shaping effective fiscal and monetary policies aimed at preventing recessions. Simultaneously, uncertainty plays a critical role in influencing investment decisions, making it a key factor in determining optimal portfolio allocations for investors. The unpredictability of market conditions can lead to shifts in risk tolerance and investment strategies, as investors seek to minimize potential losses while maximizing returns.

Theoretically, various channels exist through which shocks in crude oil prices influence the uncertainty of economic (Cheng et al., 2019; Anand & Paul, 2021). For instance, unanticipated shifts in the prices of crude oil price can significantly impact the volatility of both macroeconomic variables and financial market dynamics especially in oil importer countries (Park & Ratti, 2008; Aladwani, 2024b). Changes in crude oil prices impact relative price levels and influence expectations surrounding real interest rate, industrial production, and the inflation. Unexpected fluctuations in crude oil prices can amplify volatility in a firm's projected cash flows, contributing to heightened uncertainty regarding future stock price returns and overall economic performance. These unexpected price shifts may also affect inflationary pressures, trade balances, and currency valuations, potentially disrupting broader economic stability and influencing policy decisions related to fiscal and monetary management. Aye et al. (2014) concluded that crude oil price shocks significantly influence the investment and consumption decisions of economic agents, primarily due to uncertainties surrounding future prices movements and growth prospects. These shocks can increase economic uncertainty, affecting overall economic activity. The unpredictability of crude oil prices may lead to shifts in investment strategies, consumer spending, and policy adjustments, thereby impacting employment, inflation, and long-term economic growth trajectories.

In light of these theoretical connections, there has been increasing interest in the energy economics literature regarding the effects of crude oil market shocks on economic uncertainty. Several studies, including those by Robays (2012), Kang and Ratti (2015), Chen et al. (2020), and Xin et al. (2020), present empirical evidence demonstrating that demand shocks in the crude oil market have significant medium- and long-term impacts on uncertainty. In contrast, supply-side shocks appear to play a more limited role in influencing the uncertainty of macroeconomic variables. In more recent studies, Kang et al. (2017), provide new empirical results that supply-side shocks significantly impact economic uncertainty. Their results indicate that fluctuations in supply, particularly in key sectors such as energy, can lead to increased volatility in energy market conditions. Focusing on the economies of United States and euro area, Thorbecke (2019) and Antonio & Luis (2022), document varying responses of economic uncertainty to crude oil price shocks across different time periods. Their research highlights that the impact of these shocks is not uniform, with fluctuations in crude oil prices affecting each economy in distinct ways depending on the specific economic context and period. Hailemariam et al. (2019) and Hashmi et al. (2022) investigated the association between real crude oil price shocks and economic uncertainty in G7countries. Their findings reveal that the impact of real crude oil price shocks on uncertainty exhibits notably different patterns before and after the global financial crisis (GFC) and COVID -19 pandemic. Prior to the crisis, crude oil price shocks tended to create moderate fluctuations in economic uncertainty. However, in the post-crisis period, these shocks led to more severe and unpredictable economic disruptions. Drawing inspiration from recent advancements in the field, this study explores the impact of crude oil price markets on macroeconomic uncertainty and financial market in Spain economy. Spain, as a significant importer of crude oil[1], has been particularly vulnerable to fluctuations in international energy prices. Given its reliance on imported energy, price volatility in the crude oil market has posed substantial risks to the country's economic stability.

This paper aims to investigate the long-term effects of crude oil price shocks on Spain's macroeconomic performance and stock market, particularly during periods of global economic crises such as global financial crisis (GFC), European debt crisis, COVID-19 pandemic, and Russia war I and II. By analyzing a comprehensive historical dataset between 1995 and 2023, the study seeks to understand how both international energy market developments and domestic economic conditions have influenced Spain's resilience and vulnerability to crude oil price shocks. The paper focuses on key macroeconomic indicators, such as unemployment rate, GDP growth, inflation, Interest rate, and stock market volatility, to assess the broader economic consequences of these energy disruptions. The volatility in crude oil prices had far-reaching implications for inflationary pressures, production costs, and overall economic growth. Furthermore, such crude oil price shocks influenced investor sentiment, driving fluctuations in the stock market. Previous studies have extensively explored the relationship between crude oil price shocks and economic performance in major industrialized countries, but little attention has been given to smaller, energy-import-dependent economies like Spain.

1 During the 2023s, according to CEIC (2023), Spain experienced significant fluctuations in crude oil exports and imports. For instance, in March 2023, Spain's crude oil exports reached €201 million (USD219.76 million), while imports amounted to €2.76 billion (USD 3.03 billion), resulting in a negative trade balance of €2.58 billion (USD 2.83 billion).

This study aims to fill that gap by focusing on Spain's experience, offering insights into how energy price volatility affects the macroeconomic and financial dynamics of smaller economies during periods of heightened global instability. A significant literature gap exists in understanding the long-term impact of crude oil price shocks on Spain's economy. While previous research has explored the short-term effects or focused on specific time periods, this paper provides a unique perspective by analyzing a four-decade dataset. This allows us to capture the evolving dynamics of Spain's economy and its interactions with the international energy market. The study will contribute to the existing literature by: (1) Analyzing the long-term trends in crude oil prices and their correlation with Spain's macroeconomic indicators and stock market performance, (2) Investigating the impact of crude oil price shocks during specific global crises, such as the 1990s recession, the global financial crisis (2008-2009), COVID-19 pandemic (2020-2021), and Russia war (2022-2023), (3) Evaluating the effectiveness of Spanish government policies in mitigating the adverse effects of crude oil price shocks. By addressing these research questions, this paper will provide valuable insights for policymakers, investors, and researchers seeking to understand the long-term implications of energy price fluctuations on Spain's economy.

The employ of GARCH-type family and Markov-switching GARCH (MS- GARCH) models in this paper provides several significant benefits for measuring the impact of crude oil price shocks on Spain's macroeconomic performance and stock market movements. GARCH-type family models are particularly useful for capturing volatility clustering and persistence, which are common features in macroeconomic variables and financial time series. By modeling conditional volatility over time, GARCH-type family allows for the analysis of how crude oil price shocks influence economic stability, unemployment rate, inflation, interest rate, and stock market fluctuations in Spain. This is especially relevant for energy-dependent countries like Spain, where fluctuations in energy prices can lead to persistent economic uncertainties (Engle, 1982; Bollerslev, 1986; Hou & Suardi, 2012; Dutta et al., 2021; Ng'ang'a & Oleche, 2022). Additionally, MS-GARCH models offer further advantages by capturing regime shifts, which are essential for understanding how economies transition between different states of volatility in response to external shocks. The ability to model regime changes is particularly valuable for analyzing economies during global crises or periods of structural change, allowing for the identification of different phases of volatility, such as low and high volatility regimes (Hamilton, 1989; Gong et al, 2021). This feature is especially important for Spain, which may experience shifts in macroeconomic behavior and financial market responses during periods of crude oil price shocks, reflecting different economic environments and responses to international energy trends.

Furthermore, both GARCH-type family and MS-GARCH-type family models allow for the analysis of non-linear relationships between energy price shocks and macroeconomic indicators. In the case of Spain, crude oil price shocks may have varying effects depending on whether the economy is in a growth or recession phase.

The regime-switching nature of the MS-GARCH-type model enables the study to capture these dynamics, providing a deeper understanding of how crude oil price fluctuations interact with broader economic conditions (Gray, 1996; Hong et al., 2022). In addition, these models provide strong forecasting capabilities, which are essential for both policymakers and investors in predicting future volatility and economic risks (Hamilton and Susmel, 1994; Poon & Granger, 2003; Živkov et al., 2021). Finally, the models are well-suited for handling high-frequency data, enabling the analysis of short-term impacts of energy price shocks, as well as their long-term consequences (Klaassen, 2002; Andersen et al., 2003).

The key findings of the study are as follows. Firstly, the empirical results indicate that the effects of crude oil price shocks on macroeconomic uncertainty are highly dependent on the prevailing regime. These impacts vary based on investor sentiment and the level of perceived volatility within financial markets. In periods of heightened uncertainty or pessimistic investor outlooks, the influence of these shocks is more pronounced, while during more stable periods, the effects tend to be less significant. This indicates that the state of financial market conditions and investor behavior plays a critical role in shaping the relationship between crude oil price disruptions and broader economic uncertainty. Secondly, the findings reveal that macroeconomic uncertainty tends to increase significantly during periods of high crude oil price volatility. The heightened volatility in crude oil prices amplifies market instability, leading to greater fluctuations in key macroeconomic indicators in Spain such as economic growth, production costs, and inflation. This positive reaction reflects the broader economic risks related with crude oil price shocks, particularly in economy like Spain that are heavily reliant on crude oil imports. Finally, the impact of crude oil shocks on macroeconomic uncertainties undergoes significant shifts in the aftermath of major global events, such as the post-global financial crisis (GFC), COVID-19 pandemic, and the Russia-Ukrainian war. During these periods of heightened geopolitical tension and economic instability, the effects of crude oil price volatility on macroeconomic uncertainty became more pronounced. It is important to note that our findings carry significant implications for policymakers and financial market investors. Existing literature provides evidence that macroeconomic uncertainty plays a leading role in shaping overall economic performance. Therefore, understanding how crude oil price shocks influence and predict future uncertainties is crucial. The ability of crude oil price shocks to serve as predictors of macroeconomic volatility highlights their importance for both investors and policymakers. Policymakers can use this insight to design strategies aimed at mitigating the adverse effects of crude oil price shocks, while investors can adjust their risk management approaches accordingly.

Following this introduction, the study is organized as follows. Section 2 delves into an extensive review of the existing literature on the Spanish economy. Section 3 provides the data and methodology. Section 4 describes empirical results and discussion. Section 5 concludes with summary remarks and policy implications.

## 2. LITERATURE REVIEW

### *2.1. heoretical Framework*

The theoretical framework for analyzing the relationship between crude oil price shocks and macroeconomic variables is rooted in various economic theories. A key approach is the cost-push inflation theory, which emphasizes how increases in the cost of input cost, such as crude oil, can drive overall price levels higher within an economy. In the case of Spain, where crude oil plays a significant role in both international exports and domestic consumption, rising crude oil prices can trigger inflationary pressures. This occurs because the higher costs of energy inputs raise production costs across sectors, ultimately leading to higher prices for products and services throughout the economy, which potentially affecting economic growth, trade balances, and employment. Cost-push inflation theory describes a phenomenon in which rising production costs, often resulting from increases in both wages and the prices of key inputs, lead to an overall increase in the price level within an economy. This theory has been extensively studied, with a significant body of literature focusing on how cost reductions in essential inputs affect inflation dynamics. Crude oil prices, in particular, are highlighted as a major factor influencing inflationary pressures.

Blanchard & Galí (2010) argue that the classical cost-push inflation model posits that when production costs rise, firms tend to pass these costs onto consumers in the form of higher prices. This increase in prices can result in a general increase in inflation, reflecting an upward trend in inflation rate. Numerous studies have directly connected the cost-push inflation concept to fluctuations in energy prices, with a particular focus on crude oil prices. For example, Gordon (1975) concluded that crude oil price fluctuations in the early 1970s were a major factor contributing to the inflation experienced by several developed economies, particularly in U.S. They explain that disruptions in the supply of crude oil led to significant price increases, which cascaded through various industries. The rising cost of crude oil, a critical energy input, caused production costs to escalate across sectors, including the products and services industries. As energy costs surged, businesses faced higher operational expenses, which were ultimately passed on to consumers in the form of higher prices for products and services. This inflationary impact illustrates how energy market fluctuations can directly influence the overall price level in an economy, particularly when key inputs like crude oil experience significant fluctuations. This notion is further reinforced by the research of Darrat & Lopez (1989), and the more recent work of Ahmed et al. (2023). Both studies demonstrate that sharp increases in crude oil prices can generate significant inflationary pressures, particularly in crude oil-importing economies. Further studies by Ball and Mankiw (1995) introduced the concept of asymmetric price adjustment, which indicates that firms are more likely to pass on cost increases to consumers than they are to reduce prices when costs decline.

This behavior is significant in explaining why inflationary pressures may persist even after crude oil price shocks subside. Another theoretical approach, known as Real Business Cycle (RBC) theory, developed by Kim & Loungani (1992) focuses on how external shocks to the economy, such as crude oil price fluctuations, can have short-lasting effects on labour, capital, and ultimately, economic growth. The Real Business Cycles (RBC) theory posits that fluctuations in business cycles are largely driven by real shocks, which in turn influence market dynamics. According to this theory, economic crises and volatility often result from external real shocks, particularly technology shocks. Earlier studies have shown that numerous cyclical events cannot be adequately explained by models that solely rely on technology shocks. This has led to the development of models that incorporate additional disturbances, such as natural disasters, political conflicts, bad weather, energy shocks particularly crude oil, safety policies, and stricter environmental (Stadler, 1994). This model aims to provide a more comprehensive understanding of the factors contributing to economic fluctuations beyond traditional technology shocks.

Stadler (1994) suggests another approach to classifying RBC model is by identifying the primary forces driving the economic cycle: Are the impulses originating from supply or demand shocks within the economy? Some economists attribute the recent crude oil shock to supply constraints imposed by organizations like OPEC, while others link it to increasing demand from Asian and African countries. The fundamental concept behind the Real Business Cycles (RBC) theory is that when an external shock happens, it can directly impact the efficiency of labour and capital activities. According to Sergio (2005) and Binbin (2009), this process influences the decisions made by both firms and workers, leading to changes in their production and consumption patterns. These shifts, in turn, impact overall economic activity, ultimately contributing to a negative effect on output. RBC theory carries important implications for the results, as it suggests that a significant crude oil shocks will have a direct impact on economic output. Business cycles can vary significantly in both duration and magnitude, which explains why economic cycles often differ from one another. The price shocks, such as those seen in recent crude oil disruptions, can fluctuate, with the scale of the impact in previous crude oil shocks differing from that of the current shock. Based on the Real Business Cycles (RBC) model presented, it can be concluded that fluctuations in economic output may result from a crude oil price shock. To develop a theory that incorporates the variable of crude oil, into an economic growth model, the framework proposed by Kydland & Prescott (1982) serves as a foundational starting point. Their model demonstrates that the neoclassical growth model established by Solow (1956) effectively replicates many characteristics of contemporary business cycles.

## *2.2. Crude oil price volatility and macroeconomic impact*

This part of the literature aims to investigate the impact of crude oil price shocks on various macroeconomic variables, including the stock market, within the Spanish economic context. It analyzes the impact of crude oil prices on economic growth, interest rates, inflation rates, unemployment rates, and stock prices in Spain. By examining existing literature, this paper provides an insightful understanding of the complex interplay between oil prices and these key macroeconomic variables. A surge in oil prices can initially act as a stimulant for the Spanish economy. Increased global demand for commodities often translates into higher export earnings for resource-rich countries, which in turn, generates revenue that fuels domestic spending and investments. This "Dutch Disease" effect, aptly named after the natural gas discoveries in the Netherlands, can accelerate economic growth through its multiplier effect (Dekker & Missemer, 2024). However, sustained high oil prices can also act as a dampener. As energy costs rise, businesses face higher production costs, impacting profitability and competitiveness. Consumers grapple with increased living expenses, leading to a decline in disposable income and aggregate demand. This vicious cycle ultimately curbs economic growth (Hamilton, 1983).

The Spanish economic trajectory encapsulates a complex interplay. During the early 2000s, soaring oil prices fueled rapid economic expansion, contributing to a construction boom and inflating asset bubbles. However, the subsequent oil shock in 2008 precipitated a severe recession, ushering Spain into a prolonged period of austerity and sluggish growth (Frias-Pinedo, 2013). The correlation between oil prices and economic growth has been a subject of extensive research since Hamilton's seminal study in 1983, where he established a negative relationship between oil prices and real output. This connection is deemed significant due to the profound implications of crude oil price fluctuations on global welfare (Borozan and Cipcic, 2022). Jiménez-Rodríguez and Sánchez (2005) conducted a study revealing that an upswing in oil prices correlates with a downturn in real GDP growth in Spain. They contend that elevated oil prices escalate production costs, curtailing households' disposable income and, consequently, diminishing consumption and investment, thereby exerting a negative impact on economic growth. The direct and substantial influence of oil prices on Spain's economic growth is evident as a net oil-importing nation. Elevated oil prices elevate production costs for industries, leading to reduced profitability and diminished output levels, thereby adversely affecting overall economic growth. Choi et al. (2017) quantified this impact, indicating that a 10% increase in oil prices can curtail Spain's GDP growth by approximately 0.25% in the short run. Contrary to the notion of an unequivocally negative impact, some studies argue that the implementation of effective economic policies can mitigate the effects of crude oil price shocks on real output (Gershon et al., 2019; Majumder et al., 2020). In a comprehensive literature review, Akinsola and Odhiambo (2020) highlight the varying effects of crude oil price fluctuations on economic growth, emphasizing that these effects are contingent on specific countries or sample contexts. This nuanced understanding underscores the need for tailored approaches in assessing the intricate relationship between oil prices and economic growth across diverse economic landscapes. Within the Spanish context, ongoing discussions within the literature delve into the nuanced impact of oil prices on economic growth. A prevailing argument posits that Spain, as a net importer of oil, views oil prices as a crucial determinant of production costs. Consequently, when oil prices rise, there is a cascading effect on income levels. This, in turn, results in a reduction in both consumption expenditures and investment, ultimately translating to lower levels of GDP growth (Abdelsalam, 2023; Wang et al., 2022; Salisu et al., 2022; Aladwani, 2025b).

According to this perspective, an escalation in global oil prices tends to diminish incomes for countries that heavily rely on oil imports. The magnitude of this income reduction is contingent upon the crude oil price elasticity and the sustained nature of the crude oil price changes (Moghaddam, 2023). Additionally, central banks may adopt counteractive policies to mitigate domestic price surges, introducing further constraints on the real production side. Empirical studies conducted by Miguel et al. (2003) and Jiménez-Rodríguez and Sánchez (2005) revealed a negative correlation between changes in oil prices and GDP growth. Similarly, Shehabi (2022) reported that a 9% higher increase in global oil prices results in a 6.2% decline in GDP growth. These findings underscore the intricate relationship between crude oil price dynamics and economic growth, demonstrating the nuanced impact on different economies based on their specific circumstances. The literature also extensively delves into the volatility of oil prices Alqaralleh (2024) contends that oil prices exhibit higher volatility compared to other commodities, leading to undesirable negative impacts on the real economy. A study by Pazouki and Zhu (2022) suggests that the volatility of oil revenue significantly and negatively affects GDP growth, with this effect being mitigated in the presence of mature institutions and a more qualified fiscal regime. Aladwani (2024a) found a significant negative effect of crude oil price volatility on GDP growth. However, contrasting findings exist, with studies like that of Hooker (1996) and Cantavella (2020) argued a positive correlation between changes in oil prices and GDP growth. Some studies propose that the impact of crude oil price volatility can be moderated; for instance, Van Eyden et al. (2019) suggest that financial institutions can mitigate the potential adverse effects of crude oil price volatility on certain oil-producing countries. These diverse findings underscore the complexity of the relationship between crude oil price volatility and economic growth, with contextual factors playing a crucial role in shaping the results. Fernández-Villaverde and Rubio-Ramírez (2004) investigated the consequences of increasing oil prices on the Spanish economy through a dynamic equilibrium model. Their findings suggest that surges in oil prices contribute to heightened uncertainty and a subsequent decline in economic growth, underscoring the adverse correlation between oil prices and economic growth.

Crude oil is a pivotal element in the global economic functioning, and alterations in oil prices wield substantial influence over various economic variables, notably inflation rates. Spain, being highly dependent on imported oil, is susceptible to the repercussions of crude oil price fluctuations, which can reverberate throughout the broader inflationary context. The objective of this essay is to scrutinize the correlation between oil prices and inflation rates in Spain, delving into historical patterns, potential mechanisms, and the current scenario. Historically, there exists empirical evidence indicating a positive correlation between oil prices and inflation rates in Spain. Pérez-Quiros and Timmermann (2001) found that during the 1970s, notable upswings in oil prices coincided with a marked escalation in inflation rates in Spain. Likewise, in a study encompassing the years 1970 to 2009, Topan et al. (2020) identified a cointegrating relationship between oil prices and the Consumer Price Index (CPI) inflation in the Spanish economy. The relationship between oil prices and inflation rates can be elucidated through various mechanisms. Firstly, an upswing in oil prices translates to elevated production and transportation costs, compelling businesses, particularly in oil-dependent sectors like transportation and manufacturing, to transfer these expenses to consumers in the form of heightened prices. Secondly, the escalation in oil prices may instigate increased consumer expectations, contributing to wage-price spiral dynamics that intensify inflationary pressures (Keane & Prasad, 1995). According to current data, the relationship between oil prices and inflation rates remains evident in Spain. In 2021, Spain encountered a spike in oil prices attributed to geopolitical tensions and supply-demand imbalances stemming from the COVID-19 pandemic. The upswing in oil prices has resulted in a rise in consumer prices in Spain, exemplified by a 2.5% year-on-year surge in the consumer price index (CPI) in June 2021 (INE, 2021). This indicates that fluctuations in oil prices continue to exert a noteworthy influence on inflation rates in Spain.

As previously mentioned, Spain heavily depends on imported oil for its energy and transportation requirements. Changes in oil prices can significantly impact on the country's economy, particularly regarding unemployment rates. Higher oil prices result in heightened production costs for industries, posing obstacles to economic growth and exerting a detrimental influence on employment rates. In response to surges in oil prices, companies frequently opt to downsize their workforce or halt new hiring initiatives, leading to increased levels of unemployment. A study by Blanchard and Gali (2007) serves to exemplify this correlation, revealing that a 10% upswing in oil prices corresponded to a 0.25% reduction in economic growth in Spain. This decrease in economic growth implies a potential uptick in the unemployment rate. Given its heavy reliance on imported oil, the transportation sector faces substantial cost increases during periods of rising oil prices. Companies operating within this sector frequently resort to measures such as downsizing their workforce or implementing cost-cutting strategies to counteract the elevated expenses. As a result, the transportation industry witnesses an upswing in unemployment when oil prices experience a surge. A study carried out by Ordóñez et al. (2019) delves into the repercussions of fuel price escalations on the operational expenses of diverse freight transport vehicles. The findings indicate that increases in diesel prices directly correlate with augmented fuel costs, representing a substantial portion of the overall operating expenditures for trucks, buses, and ships. Additionally, Dieaconescu et al. (2022) corroborate these insights, underscoring the global ramifications of crude oil price influences and emphasizing that the transport sector accounts for approximately 60% of the global oil supply. Escalating fuel expenses consequently result in heightened transportation costs for businesses, thereby impacting overall logistics expenses. Cuestas & Gil-Alana (2018) conducted a study exploring the consequences of crude oil price fluctuations on unemployment. Their findings revealed a positive correlation between elevated oil prices and heightened unemployment rates, with a more pronounced impact observed in the short run as opposed to the long run. In a separate empirical analysis, Cuestas (2016) utilized a Vector Autoregressive model to examine the repercussions of sudden crude oil price increases on Spanish unemployment. Their conclusions underscored the labor market's susceptibility to crude oil price shocks, highlighting that a surge in oil prices resulted in an uptick in unemployment in Spain. In a comprehensive study conducted by Józwik et al. (2024), the focus was on exploring the repercussions of crude oil price shocks on the unemployment rate—an essential indicator of economic growth. The findings of this study revealed a discernible increase in the unemployment rate in response to crude oil price shocks, suggesting a negative correlation between oil prices and economic growth. Gómez-Loscos et al. (2011) employed a distinctive methodology in their study, examining the connection between crude oil price shocks and the unemployment rate in Spain. Utilizing Vector Autoregressive (VAR) models, they identified a strong positive relationship between oil prices and the unemployment rate. This indicates that elevated oil prices contribute to an increase in the unemployment rate in Spain.

The intricate relationship between oil prices and stock prices is a topic of considerable interest for economists, policymakers, and global investors. In Spain, a nation highly reliant on imported oil, unraveling the interplay between oil and stock prices holds paramount importance in grasping economic trends and making well-informed financial decisions. Historically, the connection between oil prices and stock prices has been a topic of extensive research. The oil shocks of the 1970s were pivotal moments that underscored the vulnerability of stock markets to crude oil price fluctuations. In Spain, during this period, sharp increases in oil prices were associated with declines in stock prices. Anand & Paul (2021) found empirical evidence supporting this negative relationship during the 1970s. The interplay between oil prices and stock prices is influenced by several underlying mechanisms. Firstly, the impact of oil prices on production costs affects corporate profitability, subsequently impacting stock prices. As oil prices rise, companies in energy-intensive sectors face increased operational costs, potentially leading to reduced profits and diminished stock values (Ziadat et al., 2022). Secondly, oil prices can influence investor sentiment and market expectations. Geopolitical events, supply-demand imbalances, and global economic uncertainties, all of which can affect oil prices, contribute to market volatility. Investor reactions to these factors can result in fluctuations in stock prices (Alamgir & Bin Amin, 2021).

Finally, oil, as a crucial input in production processes and transportation costs, plays a fundamental role in influencing various economic factors, particularly interest rates. The intricate relationship between oil prices and interest rates has been the subject of extensive studies, offering insights into the dynamics of economic systems. Here, we delve into the multifaceted connections and provide references to relevant studies that illuminate this complex interplay. Fluctuations in oil prices can directly impact input costs, later affecting the overall price levels in an economy. When oil prices rise, businesses face increased production and transportation expenses, leading to higher costs for goods and services. This phenomenon often triggers inflationary pressures as companies pass on elevated costs to consumers. Several studies have explored the relationship between oil prices and interest rates. The study conducted by Cuñado & Pérez de Gracia (2003) investigated the correlation between oil prices and interest rates in Spain through the application of a Vector Autoregressive Model. The findings indicated that an escalation in oil prices resulted in elevated interest rates in the short term, substantiating the inflationary impact linked to heightened oil prices. Similarly, Kilian & Zhou (2022) conducted a study examining the relationship between oil prices and interest rates in seven European countries, including Spain. The findings suggested that upswings in oil prices contributed to increased short-term interest rates, implying a responsive strategy by central banks to counteract inflationary tendencies stemming from higher oil prices. Additionally supported by the study carried out by Cologni & Manera (2008), which investigated into the relationship between oil prices, interest, and inflation rates in Spain through a structural vector autoregression model. The results unveiled a noteworthy positive association between oil prices and both inflation and short-term interest rates, indicating that crude oil price shocks impact interest rate policy. Central bank in Spain, as custodians of monetary policy, often respond to inflationary pressures induced by crude oil price fluctuations by adjusting interest rates. The relationship between oil prices, inflation, and interest rates is a complex one, involving considerations of both short-term and long-term effects. Notable studies exploring this relationship, for instance, an early investigation conducted by Mork (1989) identified a positive correlation between the increase of oil prices and subsequent inflation, prompting central banks to implement higher interest rates in response. Additionally, these results were corroborated by Barsky and Kilian (2004) and Kilian (2008), who investigated the relationship between crude oil price shocks and the reactions of monetary policy. They highlighted the challenges encountered by central banks in distinguishing between temporary and persistent components of crude oil price fluctuations when formulating policy responses. Moya-Martínez et al. (2014), in a pioneering study, explored the relationship between oil prices volatility and interest rates in Spain. Their findings revealed a negative relationship, indicating that elevated oil prices diminish expectations of economic growth, resulting in higher interest rates. This dynamic may have adverse implications for Spain's economy over the long term. The collective evidence from these studies underscores the negative impact of high oil prices on economic growth, stock prices, and interest rates in Spain, emphasizing the potential long-term consequences on the country's economy.

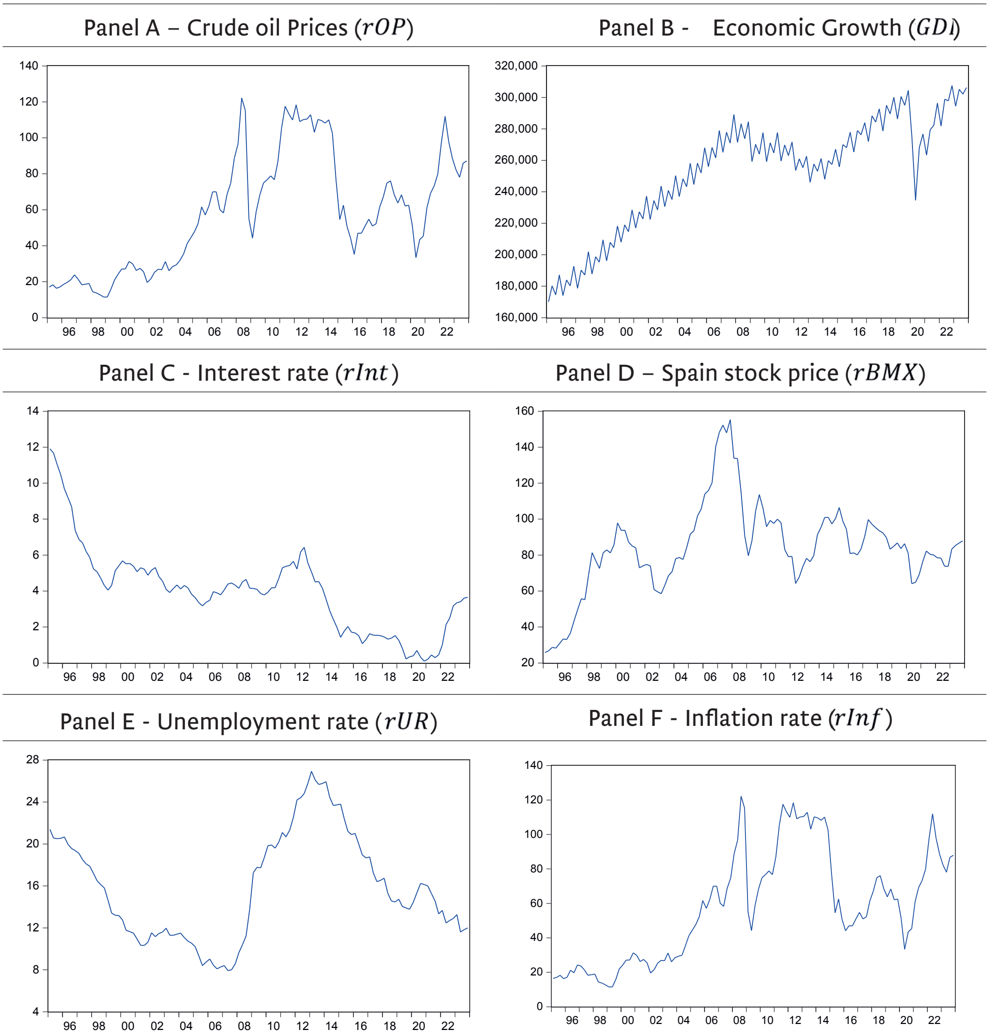
## 3. BEHAVIOUR OF SPAIN ECONOMIC AND SOME SIGNIFICANT EVENTS

Figure 1 - Panel A shows the tumultuous journey of crude oil prices from 1995 to 2023, shaped by a series of crises and economic disruptions. The period before 2008 witnessed a remarkable surge driven by a global demand for energy and speculative bubbles in resource markets. This upward trend peaked at a record $148 per barrel in 2008, only to sharply decline during the global financial crisis. The subsequent recovery was slow and uneven, with the US shale oil boom contributing to temporary price suppression through increased supply. However, geopolitical events such as the 2014 Ukrainian conflict and the 2022 Russian invasion caused prices to spike once again, emphasizing the delicate balance between political instability and energy security. Throughout these crises, crude oil demonstrated its sensitivity to global economic trends, geopolitical uncertainties, and technological changes, serving as a gauge of international risk and resilience. As we emerge from the aftermath of the COVID-19 pandemic, the future trajectory of crude oil prices remains uncertain, contingent on factors such as economic recovery, climate change policies, and the evolving geopolitical landscape. A comprehensive understanding of the historical dynamics between crises and oil prices is essential for navigating the intricate complexities of the global energy market in the years ahead. Figure 1, Panel B shows Spain's GDP growth from 1995 to 2023, highlighting a tumultuous journey intertwined with crises and upheavals. Prior to the 2008 financial crisis, Spain engaged in a flourishing dance with a booming economy, reaching a remarkable 5.5% growth in 2007, primarily driven by construction and credit expansion. However, the financial crisis acted as an unforeseen stumbling block in 2008, causing GDP to plunge to -3.8%, accompanied by surging unemployment and escalating debt. The aftermath of the crisis necessitated bitter austerity measures, constraining growth to a meager 0.3% in 2013. The subsequent recovery was slow and precarious, with GDP sluggishly returning to positive territory in 2014 but remaining below pre-crisis levels. The introduction of shale oil disrupted the economic rhythm temporarily, only to be compensated by the graceful intervention of the tourism sector, facilitating a more elegant 3.2% growth in 2017. Geopolitical uncertainties, such as the Ukraine war, threatened to interrupt the economic dance, but Spain adeptly found its footing, maintaining modest growth at 0.3% in 2023 amid global uncertainties.

In Figure 1, Panel C displays the narrative of Spain's interest rate dynamics from 1995 to 2023, portraying a captivating dance intertwined with economic fluctuations. The pre-crisis era witnessed a graceful sashay to the melody of record-low rates, contributing to a real estate boom and the inflation of asset bubbles. However, as the music abruptly stopped in 2008, rates engaged in a desperate waltz, aiming to restrain inflation and mitigate the fallout of the crisis. The subsequent austerity measures led to a somber cha-cha, with high rates suppressing growth and constricting borrowing. The recovery foxtrot unfolded slowly, with rates gradually lowering in each tentative step, yet remaining elevated due to persistent debt concerns. The entrance of shale oil introduced a shift in the dance's pace, further dampening rates, until the tourism sector's quickstep brought a brief, bouncy interlude. However, geopolitical tremors, such as the Ukraine conflict, rattled the dance floor, prompting rates to rise again in a hesitant two-step. Today, amid ongoing uncertainties, Spain's interest rate finds itself entangled in a complex rhythm, uncertain whether to lead or follow the economic melody. In Figure 1, Panel D unfolds the tumultuous narrative of Spain's stock market journey from 1995 to 2023, portraying a wild rollercoaster ride marked by the highs of euphoria and the lows of despair during various crises. The pre-2008 era witnessed a dizzying ascent, driven by real estate speculation and easy credit, with the IBEX 35 benchmark index waltzing to record highs, reaching an ecstatic 16,000 points in 2007. However, the financial crisis abruptly halted the joyous dance, plunging stocks into a dark tango and causing a staggering loss of over 70% of their value by 2009. Austerity measures added a bitter undertone, further dampening market sentiment and locking the index into a slow foxtrot for several years. The recovery was a hesitant two-step, with the IBEX gradually regaining ground but remaining distant from its pre-crisis peak. The entrance of shale oil disrupted the rhythm, introducing temporary instability, until the cha-cha of tourism provided a glimmer of hope, propelling the market to 10,000 points in 2017. However, geopolitical tremors, such as the Ukraine war, cast a shadow on the dance, causing another dip in 2023. In Figure 1, Panel E depicts the nuanced narrative of Spain's unemployment dynamics from 1995 to 2023, unfolding as a dramatic play in three distinct acts. During the boom years, it played out as a lighthearted comedy, with unemployment dipping to a mere 8% in 2007, fueled by the construction boom's job creation. However, the 2008 financial crisis abruptly brought down the curtain, transforming the narrative into a tragic drama. Unemployment soared to a heart-wrenching 26% in 2013 as businesses closed their doors, and austerity measures slashed public spending.

The recovery act that followed was slow and agonizing, with unemployment stubbornly refusing to retreat for years. Even the optimism fueled by tourism in 2017 left it lingering around 19%, serving as a persistent reminder of the deep scars left by the crisis. The recent energy crisis and geopolitical tensions added another layer of tension, pushing unemployment back up to 13% in 2023. In Figure 1, Panel F displays the captivating narrative of Spain's inflation rate from 1995 to 2023, drawing parallels to a temperamental dancer swaying to the music of crises and economic shifts. The pre-boom era set the stage for a gentle waltz with inflation around 2%, reflecting a stable global environment. However, as the construction frenzy escalated, the rhythm transformed into a lively mambo, pushing inflation to 4% in 2007, driven by surging energy costs and asset bubbles. The financial crisis then abruptly crashed the party, steering inflation into a somber cha-cha. Demand plummeted, and oil prices collapsed, causing inflation to dip below 1% in 2009. Austerity measures added another layer of austerity to the dance, keeping inflation subdued for years. The recovery took the form of a hesitant two-step, with inflation gradually inching back up but remaining well below pre-crisis levels. The entrance of shale oil added a twist, temporarily dampening inflation, until the tourism cha-cha brought a brief rise in 2017. Just as the music seemed to calm, geopolitical tremors like the Ukraine war and the energy crisis threw inflation into a wild tango in 2023, pushed it above 10% and which threatened to disrupt the fragile economic recovery.

**Figure 1.** Macroeconomic trends of Spain from 1995-2023




Sources: Author's design

## 4. METHODOLOGY

The continuous compounded returns of the time series can be determined by analyzing their respective returns. This return is denoted as $r_t$ with the subscript $t$ indicating time as follows:

$$r_t = Ln(V_t) - ln(V_{t-1}) \tag{1}$$

where, $V_t$ is the time series index of the variable at time $t$.

Modeling the dynamics in the conditional mean for return time series, denoted as $y_t$, can be accomplished through estimating Autoregressive Moving Average – ARMA(p,q) models. These models filter the time series data (residuals) and are characterized by having a zero mean and no serial correlation. Additionally, to understand the conditional variance ($h_t$), either standard GARCH-type models or MS-GARCH-type models can be employed. In the empirical part of the paper, only two of the many standard GARCH-type models, namely GARCH and GJR-GARCH models, will be discussed. The GARCH-type models are widely used for modeling the time-varying volatility and conditional variances in both financial and economic data. These models are essential for capturing persistence and asymmetry in volatility, which holds significance in risk management and asset pricing. The GARCH model assumes that the variance at a given time is a function of past variances and past squared errors, while the GJR-GARCH model introduces an asymmetric term, allowing for different responses to positive and negative shocks. These models' estimation helps understand the dynamics and forecasting of financial and economic variables and assess the impact of various factors on returns and volatility. The GARCH (1,1) model, proposed by Bollerslev (1986), is defined as follows:

$$h_t = \beta_0 + \beta_1 y_{t-1}^2 + \beta_2 h_{t-1} \tag{2}$$

where the term $\beta_0, \beta$ and $\beta_2$ indicate unknown parameters that will be estimated from sample time series. To ensure that $h_t$ remains positive, it is necessary for $\beta_0, \beta$ and $\beta_2$ to be greater than zero, with both $\beta_0, \beta$ and $\beta_2$ being non-negative. Additionally, Covariance-stationarity is assured when the $\beta_2$. The unconditional volatility[1], denoted by $\sigma$, can be calculated as follows:

$$\sigma = \sqrt{\frac{\beta_0}{(1 - \beta_1 - \beta_2)}} \tag{3}$$

The GJR-GARCH model, developed by Glosten et al. in 1993, is notable for its ability to capture asymmetric effects in fluctuations, commonly referred to as the leverage effect. This highlights the tendency of volatility to respond more intensely to negative shocks, such as bad news, than to positive shocks, like good news of the same magnitude of both shocks is equivalent. This implies that negative and positive news have distinct impacts on the conditional volatility. Specifically, the GJR-GARCH

(1,1) model consists of a combination of GARCH (1,1) and asymmetric terms. The GJR-GARCH (1,1) model is outlined as follows:

$$h_t = \beta_0 + [\beta_1 + \delta I(y_{t-1} < 0)y_{t-1}^2 + \beta_2 h_{t-1}] \tag{4}$$

The indicator function, denoted as $I(.)$, is used to assigns value 1 if $y_{t-1} < 0$ and 0 if $y_{t-1} \geq 0$.

To ensure that $h_t$ remains positive, it is necessary for $\beta_0, \beta_1, \beta_2$ and $\delta$ parameters greater than zero, Covariance-stationarity is satisfied when dealing with a symmetric distribution $\delta + \beta_2 < 1$ (Ardia et al., 2019). In contrast to the GARCH model, the GJR-GARCH model can account for the empirically observed asymmetry—specifically, the phenomenon where negative shocks at time $t-1$ exert a greater influence on $h_t$ than positive shocks of equivalent magnitude, commonly referred to as a leverage effect. The un-conditional volatility for GJR-GARCH model is defined as follows:

$$\sigma = \sqrt{\frac{\beta_0}{(1 - \beta_1 - 0.5\,\delta - \beta_2)}} \tag{5}$$

The standardized innovations, denoted as $z_t$ , in both models [4] and [6] are calculated as

$$z_t = \frac{y_t}{\sqrt{h_t}} \sim i.i.d\ N(0,1) \tag{6}$$

Regarding the conditional distribution of the standardized innovations $z_t$ in equation [6], several alternative distributions can be taken into consideration. While the normal distribution is one option, commonly employed alternatives include the student's t distribution and the generalized error distribution (GED), especially when modeling fat-tailed distributions. Additionally, skewed versions of these distributions can also be utilized. This diverse set of distributional choices provides flexibility in capturing different characteristics of financial and economic data and is crucial for robust modeling in various contexts.

As previously noted, standard GARCH-type models frequently suggest a substantial persistence of volatility associated with individual shocks. Klaassen (2002) highlighted a limitation in standard GARCH-type models. Specifically, when the variance is consistently high or low, yet homoskedastic during certain periods, these models may fail to capture the persistence of such elevated or subdued volatility. In such cases, standard GARCH-type models may incorrectly attribute the persistence of volatility solely to the enduring impact of individual shocks. This underscores the need for more nuanced modeling approaches that can accurately capture the dynamics of volatility under different conditions, including periods of consistently low or high variance.

Introducing regime-switching into the conditional variance, we can present the MS-GARCH-type model. If we denote the information set at time $t-1$ as $I_{t-1}$, the MS-GARCH specification, as outlined by Haas et al. (2004), is as follows:

$$y_t|[s_t = k, I_{t-1}] \sim D\big(0, h_{k,t}, \mu_k\big) \tag{7}$$

The notation $D(0, h_{k,t}$ represents a continuous distribution characterized by a zero mean, time-varying conditional variance (denoted as $h_t$), and additional shape parameters incorporated in the vector $\mu_k$. The stochastic regime variable $s_t$ takes on discrete integer values from the set $\{1, 2, \ldots, k$ and follows a first-order Markov process. The transition probability matrix $P$ with dimensions $K \times K$ includes transition probabilities $P_{ij} = P\{s_t = j|s_{t-1} = i\}$, indicating the probability that regime $i$ at time $t-1$ will be followed by regime $j$ at time $t$. Given that the variable should be in one of the $K$ considered regimes at any time, it holds that $\sum_{j=1}^{k} P_{ij} = 1$ for all $i \in \{1, 2, \ldots, k\}$.

The anticipated duration in each regime, denoted as$E(D_i)$ for $i \in K$, representing the average duration of being in a particular regime, can be computed using the following method (refer to, for instance, Rotta and Pereira, 2016):

$$E(D_i) = \frac{1}{1 - P_{ii}} \tag{8}$$

In contrast to standard GARCH-type models, MS-GARCH-type models provide the capability to capture two primary contributors to volatility persistence: within-regime persistence and the persistence of regimes (Klaassen, 2002; Sajjad et al., 2008; Raihan, 2017; and Chocholata, 2022). This extended modeling approach allows for a more comprehensive understanding of the dynamics influencing volatility, encompassing both the behavior within individual regimes and the transitions between different volatility states. As highlighted by researchers such as Haas and Paolella (2012), applications of MS-GARCH-type models typically rely on the assumption of a normal distribution. However, the studies conducted by Klaassen (2002) and Haas and Paolella (2012) have demonstrated that a MS-GARCH model with a normality assumption tends to trigger frequent identification of regime switches, particularly when confronted with large innovations (outliers) in an otherwise low or high volatility regime. Introducing leptokurtic components, such as the student's t-distribution, proves beneficial in better accommodating extreme realizations within a given regime, thereby improving the stability of identified regimes. This adjustment contributes to a more accurate representation of the underlying volatility dynamics in financial time series.

Regarding the empirical segment of the study utilizing the MS-GARCH specification proposed by Haas et al. (2004), the conditional variances $h_{k,t}$ for $k \in K$ (where$K = 1{,}2$) can adhere to $K$ distinct GARCH-type models. In other words, the conditional variance of $y_t$ is articulated as a GARCH-type model, as outlined, for instance, in equations [4] or [6]. Additionally, the conditional distribution can be uniquely defined for each regime. In our investigation, we consider only two potential regimes, denoted as $K = 2$, representing low volatility and high volatility states, and assume a student's t-distribution. The unconditional probabilities, or stable probabilities $\omega_i$ of being in a particular regime$(i = 1,2)$, can be derived as follows:

$$\omega_i = \frac{(1 - P_{ii})}{(2 - P_{ii} - P_{jj})} \tag{9}$$

To measure the time series of macroeconomic variables, including uncertainty in oil prices, employing the optimal model under two distinct regimes, it is crucial to eliminate the predictable component of variation from optimal models. This is achieved by quantifying the conditional variance series. Subsequently, after determining macroeconomic variables, including uncertainty in oil prices, we proceed to assess the impact of changes in oil prices on macroeconomic variables' uncertainty using the ARDL model. The ARDL(p;q) model plays a pivotal role in comprehending relationships and dynamics within our data, discerning causality, mitigating endogeneity, making forecasts, and selecting an appropriate model. The specification of the ARDL(p;q) model is presented as follows:

$$D(L,p)y_t = \vartheta + F(L,q)x_t + \varepsilon_t \tag{10}$$

Both terms, $D(L,p)$and $F(L,q)$represent lag polynomials. The lag operator L refers to the backward shift operator, and $p$ and $q$ are the maximum lags for the dependent and independent variables, respectively. The time series $y_t$ represents bivariate macroeconomic variable uncertainty under investigation, while $x_t$ denotes crude oil price returns. The vector $\varepsilon_t$ encompasses other parameters, including the intercept term and time trends.

The Lag Polynomials can be defined as follows:

$$D(L,p) = 1 - c_1L - c_2L^2 - c_pL^p \tag{11}$$

and

$$F(L,p) = b_0 - b_1L - b_2L^2 - b_qL^q \tag{12}$$

These lag polynomials allow for the inclusion of lagged terms up to order $p$ for the dependent variable $y_t$ and up to order $q$ for the independent variable $x_t$. In the ARDL model, the expression for the long-term effect is as follows:

$$\frac{F(L,q)}{D(L,p)} = \frac{\sum_{j=0}^{q} b_j}{1 - \sum_{j=1}^{p} c_j} \tag{13}$$

The short-term effect is calculated form below equation:

$$\Delta y_t = \alpha_0 \Delta x_t + \theta \varepsilon_{t-1} + \mu_t \tag{14}$$

where, $\alpha_0$ represents short-term effect and $\mu_{t-1} = y_{t-1} - \frac{\vartheta-(b_0+b_1+\cdots+b_q)}{1-(c_1+\cdots+c_p)} x_{t-1}$

Utilizing the Schwarz Information Criterion (SIC), optimal lag values ($p$ and $q$) are chosen to model the relationship between macroeconomic variables uncertainty and oil prices. The SIC is employed as a criterion for selecting the most suitable lags in the modeling process.

For model selection, we employ evaluation metrics such as the root mean squared error (RMSE) and mean absolute percentage error (MAPE). These metrics serve as criteria to assess the goodness of fit and identify the best-fitted models. The RMSE measures the average magnitude of prediction errors, while MAPE provides a percentage-based assessment of the accuracy of the models. These metrics contribute to a comprehensive evaluation process, aiding in the identification of the most appropriate models for the given dataset. MAPE and RMSE can computed as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\bar{y}_t - y_t)^2} \tag{15}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\bar{y}_t - y_t}{y_t}\right| \tag{16}$$

which, $\bar{y}_t$ indicates for predicted values and $y_t$ indicates for actual values.

## 4.1. Data Source

To analyze the impact of the crude oil price shocks on Spain economic activity, this study examines four key macroeconomic and Spain stock market index, including GDP, inflation rate, unemployment rate, and the interest rate. These variables are commonly regarded as significant indicators of the business cycle, reflecting both the supply and demand dynamics in the Spain economy. The selection of these macroeconomic and stock market index—such as gross domestic product (GDP), inflation rate, unemployment rate, the interest rate, Spain stock market index — was made not only due to their relevance as business cycle indicators but also for practical reasons related to key macroeconomic variables such as economic growth, unemployment, and inflation in Spain. These variables are essential in measuring the impact of crude oil price shocks on Spain's economic stability. GDP, for example, is directly influenced by changes in energy prices, particularly crude oil, as energy is a key input in production. When energy costs increase, production costs follow, which can slow economic expansion. Unemployment may also be influenced as energy-dependent industries might reduce production (output) or lay off workers in response to higher costs. Meanwhile, inflation is highly sensitive to energy price shocks, as increasing crude oil prices can higher costs for products and services throughout the economy, thereby driving up the overall price level (Hamilton, 1983; Zulfigarov & Neuenkirch, 2020).

Data are quarter and cover the period from Q2-1995 to Q3-2023 (i.e., 115 observations). Quarterly time series is particularly well-suited for the application of standard GARCH-type family, MS-GARCH and ADRL models, especially in the context of financial and economic analysis. This time series frequency provides an optimal balance between capturing long-term trends and maintaining enough granularity to capture volatility patterns without becoming overwhelmed by noise. Unlike high-frequency time series, which may result in overfitting by modeling random fluctuations, quarterly time series offers a broader view of macroeconomic variables such as inflation and GDP, which tend to evolve over time (see, e.g., Engle, 1982; Bollerslev, 1986). Moreover, quarterly time series enhances the ability of MR-GARCH-type models to identify regime shifts, such as transitions between periods of low and high volatility. These regime changes, which are essential for understanding macroeconomic behavior during structural changes or crises, are better captured over quarterly intervals rather than shorter-term fluctuations (see, e.g., Hamilton, 1989). Finally, quarterly time provides sufficient observations for robust estimation, making it preferable to annual time series, which may lack the necessary granularity. Its alignment with economic cycles and policy reporting, such as monetary and fiscal decisions, further strengthens the model's applicability for analyzing shifts in market conditions (Gray, 1996; Skott, 2023). Consequently, quarterly time series enables a more comprehensive analysis of the impact of macroeconomic and financial shocks while avoiding the common challenges associated with higher-frequency datasets (Denton, 1971; Poon & Granger, 2003; Deschamps et al., 2020).

The use of standard GARCH and MRS-GARCH models on quarterly datasets, particularly in small sample sizes, is well-supported in the econometric literature. Bollerslev (1986) & Hamilton (1994) presented the standard GARCH model, demonstrating its effectiveness in capturing volatility clustering in economic and financial sample data, making it applicable even when time series data is limited. Similarity, Engle (1982) provided foundational evidence by applying standard GARCH models to UK inflation time series, emphasizing their capacity to model volatility accurately in small time series data, while Zakoian (1994) investigated threshold GARCH and MRS-TGARCH models and emphasized their effectiveness in estimating volatility with limited sample sizes, a critical advantage for quarterly datasets. Davidson & MacKinnon (2004) concentrated on the performance of standard GARCH model in small time series data, demonstrating their dependability in producing estimates even with limited time series, underscoring their appropriateness for empirical analyses in both economics and finance. In addition, Bock & Mestel (2009) argued a comprehensive review of recent developments in standard GARCH and MRS-GARCH models, affirming their robustness across various applications, including those involving limited data sizes. Bauwens et al, (2006) presented empirical evidence demonstrating the efficacy of standard GARCH-type family models in capturing time-varying volatility in small time series data, particularly for financial and economic variables, supporting the concept that standard GARCH can be advantageous even with limited sample data. Cummins & Bucca (2011) compared between standard GARCH and standard EGARCH models and found that both models maintain good forecasting performance, therefore reinforcing the argument for their use in small time series data scenarios. Recently research have continued to support the use of GARCH models in small sample contexts. For instance, Vasudevan & Vetrivel (2016) and Leong (2018) examined double regime MRS-GARCH-type family models applied to financial and economic indicators with small time series data sizes, emphasizing the importance of model selection criteria that enhance predictive accuracy in limited datasets. Likewise, Do & Faff (2010) examined the performance of standard GARCH-type family models in forecasting U.S. real stock market returns volatility with small time series data, confirming their effectiveness compared to other volatility models.

Regarding crude oil, the analysis utilizes crude oil prices sourced from the U.S Energy Information Administration (EIA). This publication is recognized as a reliable and comprehensive source of historical energy data, providing accurate information on crude oil pricing trends. For the remaining macroeconomic variables, such as GDP, inflation rate, unemployment rate, the interest rate, Spain stock market index, data were primarily collected from FRED. Table 1 provides the definitions and abbreviations of the macroeconomic variables being analyzed.

**Table 1.** The specific definitions and abbreviations of variables.

| Variable type | Variables | abbreviations |
|---|---|---|
| Dependent variable | Crude oil price | $rOP$ |
| Explanatory variable | Gross Product Demand | $rGDP$ |
| Explanatory variable | Inflation | $rInf$ |
| Explanatory variable | Interest rate | $rInt$ |
| Explanatory variable | Unemployment rate | $rUR$ |
| Explanatory variable | Spain Stock Exchange | $rBME$ |

Source: Author's design.

## 5. EMPIRICAL RESULTS AND DISCUSSION

### *5.1. Descriptive statistics and conditional mean equations*

Table 2 provides descriptive statistics for the time series data under consideration, including the results of normality testing using Jarque-Bera statistics. The mean returns for all-time series hovered around zero. The crude oil prices exhibited the highest quarterly percentage return at 1.42%, followed by the stock prices, interest rate, inflation rate, unemployment rate and economic growth with 1.06%, 1.05%, 0.90%, 0.52%, and 0.5%, respectively. Regarding standard deviations, the inflation rate and interest rate demonstrated the highest volatility at 128.32% and 26.51% respectively. The sampling distributions of all the analyzed return time series exhibited a negatively skewed pattern, accompanied by higher kurtosis (greater than 3) compared to that of a normal distribution. These characteristics are indicative of fat-tailed returns, suggesting a propensity for extreme values and heightened volatility in the data. This phenomenon is often observed in economic factors and financial markets, reflecting the occurrence of significant market events and outliers, contributing to a more comprehensive understanding of the return distribution dynamics. Except for the inflation rate, which displays a positively skewed distribution and lower kurtosis, the other analyzed return time series exhibit negatively skewed patterns and higher kurtosis. The positive skewness in the inflation rate indicates a prevalence of more positive returns, while the lower kurtosis indicates a distribution with lighter tails and fewer extreme values compared to a normal distribution. These distinct characteristics in the inflation rate return distribution may be attributed to specific economic and market dynamics unique to inflation rate fluctuations, highlighting the need for a nuanced understanding of the underlying factors influencing each financial metric. The deviation from normality in the distribution was validated by the Jarque-Bera statistics, which exhibited statistical significance at the 1% level for all returns, except for the inflation rate, which showed significance at the 5% level. This observation underscores the departure from a normal distribution in the returns of the analyzed variables. Consequently, to accommodate the fat-tailed nature of the time series, both GARCH-type and MS-GARCH-type models were employed. The estimation process utilized the maximum likelihood method, assuming a student's t-distributed error to better capture the characteristics of the return distributions. As emphasized in several studies conducted by FrÖmmel (2010), Nikolaev et al. (2013), and more recently by Bauwens et al. (2012), the utilization of the t-distribution is widespread in the estimation of GARCH-type models. Its popularity extends to regime-switching models due to its capacity to improve the stability of identified regimes. This feature adds robustness to the modeling process, contributing to a more accurate representation of the underlying dynamics in financial and economic time series.

**Table 2.** Descriptive statistics of time series

| | $rOP_t$ | $rGDP_t$ | $rUR_t$ | $rInt_t$ | $rMBE_t$ | $rInf_t$ |
|---|---|---|---|---|---|---|
| Mean | 0.014191 | 0.005042 | 0.005197 | 0.010484 | 0.010631 | 0.008978 |
| Maximum | 0.315569 | 0.133516 | 0.224109 | 0.791066 | 0.219423 | 3.663435 |
| Minimum | -0.739758 | -0.156244 | -0.134250 | -1.277809 | -0.234353 | -4.239915 |
| Std. Dev. | 0.154273 | 0.051770 | 0.053343 | 0.265056 | 0.084443 | 1.283209 |
| Skewness | -1.277171 | -0.336890 | 1.081552 | -0.940072 | -0.549741 | 0.028305 |
| Kurtosis | 7.268065 | 2.440259 | 6.763942 | 11.23749 | 3.844879 | 1.468359 |
| Jarque-Bera | 117.5200* | 3.644620* | 89.51982* | 339.1078* | 9.132738* | 11.06048** |
| Observations | 114 | 114 | 114 | 114 | 114 | 114 |

Note: All macroeconomic variables including the crude oil price values are all taken as a logarithm.
*Means statistically significant at 1% level.
Source: Author's design.

Given that the time series returns under consideration exhibited serially uncorrelated behavior, the rejection of the null hypothesis of no serial correlation was robustly supported by the values of the Ljung-Box Q-statistics. Consequently, it was assumed that the conditional mean for time series remained constant. The conditional mean equation specifications, along with the associated Ljung-Box Q-statistics for 10 and 21 lags, and the ARCH *LM* diagnostics for 1 lag, are compiled in Table 3. The results presented strongly assert that, at the 5% level of significance, there was no serial correlation in the filtered returns. However, the confirmation of conditional heteroscedasticity was evident.

**Table 3.** Conditional mean equations and residual diagnostics

| | $rOP_t$ | $rGDP_t$ | $rUR_t$ | $rInt_t$ | $rMBE_t$ | $rInf_t$ |
|---|---|---|---|---|---|---|
| Model | - | - | - | - | - | - |
| Ljung-Box Q (10) | 5.2498* | 5.0249* | 20.043* | 154.92* | 6.8303* | 39.977* |
| Ljung-Box Q (21) | 6.8057 | 5. 7860 | 27.490 | 158.85 | 17.840 | 81.074 |
| ARCH LM (1) | 11.55* | 1.09* | 11.47* | 4.63* | 0.003* | 0.705* |

Note: The purpose of the regression is to display the conditional mean equations and assess the adequacy of the model through residual diagnostics. * indicates statistically significant at 5% level.
Source: Author's design.

The filtered returns, designated in this paper with the prefix $(y_t)$ were employed for estimating univariate GARCH (1,1) and GJR-GARCH (1,1) models, with the assumption of Student's t-distributed innovations. This distributional choice is consistent with previous studies, as it accommodates the observed non-normality and fat-tailed characteristics of the returns.

## 5.2. Estimation of the GARCH-type models

Tables 4 and 5 present the estimated parameters for both the GARCH and GJR-GARCH models, derived from equations (2) and (3), respectively. These tables also include the degrees of freedom (υ) associated with the standardized Student's t-distribution and the log-likelihood (LL). Upon careful examination, it is evident from Table 3 that all estimated parameters demonstrate statistical significance, affirming their relevance within the analyzed series. However, it is noteworthy that in the case of the GARCH model, two exceptions emerge concerning the $\beta_0$ parameter associated with interest and money supply. This particular parameter did not attain statistical significance, indicating a nuanced aspect in the model's performance for this specific variable. In contrast, Table 4 reveals a distinct pattern in the statistical significance of parameters within the time series under consideration. Notably, all parameters the economic growth ($rGDP_t$), unemplyment rate ($rUR_t$) and intetest rate ($rInt_t$) time series demonstrate statistical significance. However, it is crucial to emphasize that this significance is not uniformly observed across all parameters in the remaining time series. Moreover, an insightful observation from the estimation of the $\delta$ parameter in GJR-GARCH models for all time series indicates a consistently positive value.

This positive sign implies the existence of an asymmetric impact of past returns on conditional volatility. Notably, the time series exhibiting the most robust volatility reaction to past negative returns are the crude oil market, economic growth, interest rate, unempoyrment, stock pirces, and infaltion rate returns. Conversely, unemployment rate retuens exhibits a significantly weaker leverage effect in comparison. This nuanced understanding of asymmetric effects across different maceconomic factors enriches our comprehension of the dynamics within each factor segment. Regarding the log-likelihood ($LL$) values, it is noteworthy that the asymmetric GJR-GARCH models consistently demonstrated higher values compared to the GARCH models across all analyzed time series returns. This trend can be attributed to the enhanced ability of the GJR-GARCH models to capture and accommodate the asymmetry inherent in the return dynamics, leading to improved model fitting and representation of the observed data.

**Table 4.** Estimation results of GARCH (1,1) model

| Coeff | $rOP_t$ | $rGDP_t$ | $rUR_t$ | $rInt_t$ | $rMBE_t$ | $rInf_t$ |
|---|---|---|---|---|---|---|
| $\beta_0$ | 0.000749*** | 0.000263* | 0.000132* | 0.002808*** | 0.000972 | 0.000409 |
| $\beta_1$ | 0.297330*** | 0.459198* | 0.224889*** | 0.171123* | 0.015730** | 0.106200* |
| $\beta_2$ | 0.439711*** | 0.333961* | 0.752548* | 0.755900 | 0.843524*** | 0.775725** |
| $\upsilon$ | 4.500064** | 5.60337** | 7.84742** | 3.72548** | 5.771562** | 11.62995** |
| $\beta_1 + \beta_2$ | 0.737041 | 0.793159 | 0.977437 | 0.927023 | 0.859254 | 0.881925 |

| | | | | | | |
|---|---|---|---|---|---|---|
| $LL$ | 53.65752 | 231.5616 | 193.0829 | 81.84664 | 115.7013 | 95.03320 |
| $\sigma$ | 0.053362 | 0.035658 | 0.076487 | 0.072977 | 0.0831027 | 0.058839 |

Note: *, **, and*** indicate statistically significant at 1%, 5%, and 10% levels respectively. $LL$ represents log-likelihood, $\upsilon$ denotes degrees of freedom of the $t - distribution$, $\sigma$ denotes GARGH model unconditional volatility. Source: Author's design.

**Table 5.** Estimation results of GJR-GARCH (1,1) model

| **Coeff** | $rOP_t$ | $rGDP_t$ | $rUR_t$ | $rInt_t$ | $rMBE_t$ | $rInf_t$ |
|---|---|---|---|---|---|---|
| $\beta_0$ | 0.001219*** | 0.000320* | 0.000274* | 0.002521* | 0.002888 | 0.004433 |
| $\beta_1$ | 0.030562 | -0.188668** | 1.177746* | -0.194752* | -0.037835 | 0.133245 |
| $\beta_2$ | 0.464583 | 0.833141* | -0.461666 | 0.158281* | 0.119993 | 0.140693 |
| $\delta$ | 0.213252* | 0.486788* | 0.091642* | 0.606384* | 0.519892* | 0.722026* |
| $\upsilon$ | 4.700943* | 5.880966*** | 5.65381** | 8.927593** | 6.682184** | 10.43758** |
| $\beta_1 + \beta_2 + \frac{1}{2}\delta$ | 0.601771 | 0.887867 | 0.761901 | 0.266721 | 0.342104 | 0.634951 |
| LL | 62.24931 | 142.0167 | 119.7821 | 87.56874 | 125.9000 | 86.8696 |
| $\sigma$ | 0.055329 | 0.053421 | 0.033923 | 0.058634 | 0.066255 | 0.110203 |

Note: *, **, and*** indicate statistically significant at 1%, 5%, and 10% levels respectively. $LL$ represents log-likelihood, $\upsilon$ denotes degrees of freedom of the $t - distribution$, $\sigma$ denotes GJR-GARGH model unconditional volatility.
Source: Author's design.

The condition of covariance-stationarity, indicated by Eq. (2) for the GARCH model and Eq. (4) for the GJR-GARCH model, was satisfied across all-time series returns. This fulfillment implies that the models successfully adhere to the stipulated criteria, emphasizing stability and suitability for capturing the dynamics of the observed data. Moreover, these summations pointed to a notable degree of volatility persistence, ranging from 0.74 to 0.98 for GARCH models. In contrast, GJR-GARCH models showed significantly lower values, ranging from 0.27 to 0.89, except GDP returns, which registered a higher value. This observation underscores the sustained influence of past volatility on the current conditional volatility, highlighting the enduring impact of historical market fluctuations. This result is consistent with earlier studies, such as Sharma et al. (2014).

The estimation of denotes degrees ($\upsilon$) in the crude oil market yielded the lowest values, suggesting a distribution with considerably fat tails. Subsequently, the stock price returns, unemployment returns, economic growth returns, interest rate returns, in contrast, the inflation rate returns demonstrated notably high values, indicating a distribution with relatively less pronounced fat-tailed characteristics. This insight emphasizes the nuanced differences in tail thickness across the distributions of these variables, contributing to a comprehensive understanding of their statistical profiles.

The appropriateness of opting for the student's t-distribution was validated, as the relatively low degrees of freedom parameters (υ) indicated a substantial deviation from normality. This confirmation aligns with findings from previous studies (Haas et al., 2004; Ardia et al., 2019), further supporting the choice of the student's t-distribution as an accurate representation of the underlying data distribution. Tables 4 and 5 show that the computed unconditional volatilities (σ) were notably consistent for both the GARCH and GJR-GARCH models. However, in contrast, the inflation rate returns exhibited the highest values of unconditional volatilities (σ), specifically in the GJR-GARCH model as compared to the GARCH model. This observation points to variations in volatility levels, emphasizing the distinct characteristics of the inflation rate returns, particularly in the context of the GJR-GARCH model. These findings align with previous studies conducted by Duan et al., (2006) and Alexander et al., (2021).

## *5.3. Estimation of the MS-GARCH-type models*

Table 6 and 7 present the results of the MS-GARCH and MS-GJR-GARCH models, respectively. Both models assumed that the innovations follow a student's t-distribution with two regimes, namely a high volatility regime (regime 1) and a low volatility regime (regime 2). The degrees of freedom parameter υ, which determines the shape of the t-distribution, was kept constant across both regimes. The estimated values of υ, ranging from 4.3 to 19.5, indicated that the modeled distributions had finite variance (as υ is greater than 2) and heavier tails compared to the normal distribution (see e.g., Hamilton, 1994; Johnson et al., 1995). Upon analyzing the results, it was observed that a majority of the estimated parameters associated with regime 1 and 2 demonstrated statistical significance, underscoring their substantial influence on both models (except.$\beta_{01}$ parameter in interest rate and unemployment rate returns). This suggests that the MRS-GARCH and JGR-GARCH models were employed in this analysis, providing a robust framework to capture the nuanced dynamics within the data. However, the parameters defining regime 1, particularly concerning interest rate returns in MRS-GJR-GARCH model specifications, were found to be statistically insignificant. This suggests that these specific parameters did not have a significant impact on the model's dynamics in the context of Hungarian interest returns. The lack of statistical significance implies that the variables associated with regime 1 in the MRS-GJR-GARCH model for Spain interest rate returns may not play a crucial role in influencing the volatility dynamics, highlighting a less substantial contribution to the model's overall behavior. The asymmetry parameters exhibited distinct values across individual regimes. In the case of the inflation rate, interest rate, and stock price returns, a more pronounced impact of bad news was evident in both regimes. However, for the crude oil prices and economic growths returns, the reaction to bad news was notably stronger during the turbulent regime 2 in comparison to the calm regime 1 in MRS-GJR- GARCH model. This variation in asymmetry parameters underscores the differential responses of these markets to negative information, with the crude oil prices and economic growths returns showing heightened sensitivity during periods of increased turbulence in regime 2. These findings are aligned with previous research conducted by De la Torre-Torres et al. (2020).

**Table 6.** Estimation results of MS-GARCH (1,1) model

| **Coeff** | $rOP_t$ | $rGDP_t$ | $rUR_t$ | $rInt_t$ | $rMBE_t$ | $rInf_t$ |
|---|---|---|---|---|---|---|
| Regime 1 – low volatility regime | | | | | | |
| $\beta_{01}$ | 0.026323** | -0.091535* | 0.045086 | 0.014249 | 0.019779** | 1.389521* |
| $\beta_{11}$ | 0.252583** | 0.763899* | 0.818180** | 0.144743* | -0.274381** | -0.184556* |
| $\beta_1$ | 0231345* | 0.372983* | 0.301883* | 0.628125* | 0.304844* | 0.730634* |
| $\beta_{11}+\beta_1$ | 0.483928 | 0.736882 | 0.920063 | 0.772868 | 0.030463 | 0.546078 |
| Regime 2 – high volatility regime | | | | | | |
| $\beta_{01}$ | 0.006045 | 0.012082* | 0.010654** | 0.012420 | 0.025260 | 0.003870* |
| $\beta_{11}$ | 0.053743* | 0.133584* | 0.199345** | 0.410587* | 0.147354* | 0.193298* |
| $\beta_1$ | 0.396917* | 0.378090* | 0.321092* | 0.266108* | 0.238958* | 0.661529* |
| $\beta_{11}+\beta_1$ | 0.450660 | 0.244506 | 0.520437 | 0.676695 | 0.386312 | 0.854827 |
| $\upsilon$ | 18.18910* | 17.93604* | 14.78644* | 18.76163* | 13.55685* | 12.39938* |
| $p_{11}$ | 0.921281* | 0.946309* | 0.777209* | 0.903073* | 0.660642* | 0.984895* |
| $p_{21}$ | 0.078719* | 0.187867** | 0.016308** | 0.024352* | 0.470200** | 0.030679 |
| $LL$ | 64.89741 | 259.6149 | 194.0176 | 75.29121 | 128.3714 | 90.49771 |
| $\sigma_1$ | 0.051006 | 0.074244 | 0.021382 | 0.062734 | 0.020400 | 0.055812 |
| $\sigma_2$ | 0.011004 | 0.024742 | 0.022216 | 0.038416 | 0.041161 | 0.086659 |
| $\omega_1$ | 0.078719 | 0.062011 | 0.184662 | 0.090369 | 0.609555 | 0.984656 |
| $\omega_2$ | 0.921281 | 0.937989 | 0.815338 | 0.909631 | 0.390445 | 0.015344 |
| $E(D_1)$ | 3.582298 | 1.231325 | 4.488507 | 10.31706 | 2.946744 | 66.20186 |
| $E(D_2)$ | 12.70346 | 18.62527 | 61.32023 | 41.06484 | 1.887506 | 32.59540 |

Note: *, **, and*** indicate statistically significant at 1%, 5%, and 10% levels respectively. $LL$ represents log-likelihood, $\upsilon$ denotes degrees of freedom of the $t-distribution$, $\sigma$ denotes GJR-GARGH model unconditional volatility.
Source: Author's design.

**Table 7.** Estimation results of MS-GJR-GARCH (1,1) model

| Coeff | $rOP_t$ | $rGDP_t$ | $rUR_t$ | $rInt_t$ | $rMBE_t$ | $rInf_t$ |
|---|---|---|---|---|---|---|
| Regime 1 – low volatility regime | | | | | | |
| $\beta_{01}$ | 0.001835* | 0.001582* | 0.001975* | 0.002015 | 0.002758*** | 0.001571* |
| $\beta_{11}$ | 0.006087* | 0.254392* | 0.296686* | 0.215614 | 0.276612*** | 0.131467* |
| $\delta$ | 0.965234* | 0.183345* | 0.253738** | 0.291744 | 0.587047*** | 0.898222** |
| $\beta_1$ | 0.451405* | 0.403321* | 0.386021** | 0.462344 | 0.330319* | 0.359495** |
| $\beta_1 + \beta_2 + \frac{1}{2}\delta$ | 0.940109 | 0.749385 | 0.809576 | 0.823830 | 0.896674 | 0.940073 |
| Regime 2 – high volatility regime | | | | | | |
| $\beta_{01}$ | 0.0033686* | 0.0010851* | 0.001480* | 0.000949 | 0.000832 | 0.000201* |
| $\beta_{11}$ | 0.019954* | 0.087337* | 0.111322* | 0.257528* | 0.282641*** | 0.167017* |
| $\delta$ | 0.893760* | 0.760380* | 0.837787* | 0.616370* | 0.704048** | 0.884125* |
| $\beta_1$ | 0.503097* | 0.373301* | 0.270084* | 0.266657* | 0.243744* | 0.360926* |
| $\beta_1 + \beta_2 + \frac{1}{2}\delta$ | 0.969931 | 0.840828 | 0.800299 | 0.832370 | 0.878409 | 0.970006 |
| $v$ | 19.494032* | 18.914041* | 4.315586* | 6.668617* | 15.269386* | 15.539379* |
| $p_{11}$ | 0.925131* | 0.988861* | 0.893168* | 0.896003* | 0.905677* | 0.979855* |
| $p_{21}$ | 0.453033* | 0.296966* | 0.201150** | 0.026541** | 0.432279* | 0.102001** |
| $LL$ | 379.3611 | 251.8591 | 137.74875 | 76.00866 | 132.0597 | 249.9102 |
| $\sigma_1$ | 0.075035 | 0.079441 | 0.051839 | 0.069581 | 0.063372 | 0.061885 |
| $\sigma_2$ | 0.034705 | 0.082566 | 0.086092 | 0.075261 | 0.082715 | 0.081861 |
| $\omega_1$ | 0.120400 | 0.015597 | 0.117958 | 0.096521 | 0.142472 | 0.978059 |
| $\omega_2$ | 0.879600 | 0.984403 | 0.882042 | 0.903479 | 0.857528 | 0.021941 |
| $E(D_1)$ | 2.207343 | 3.367387 | 4.971403 | 9.615639 | 1.111111 | 49.64058 |
| $E(D_2)$ | 13.35674 | 89.77088 | 9.360475 | 37.67805 | 1.761428 | 9.803791 |

Note: *, **, and*** indicate statistically significant at 1%, 5%, and 10% levels respectively. $LL$ represents log-likelihood, $v$ denotes degrees of freedom of the $t - distribution$, $\sigma$ denotes GJR-GARGH model unconditional volatility.
Source: Author's design.

In a broader context, the estimated parameters confirmed the heterogeneous nature of the volatility process across both regimes. To elaborate, the regimes exhibited differences in terms of unconditional volatility values. The calculation of unconditional volatilities for individual regimes (1 and 2) followed distinct formulations: for the MS-GARCH model, it was calculated by using E.g. [3] in the case of regime i, and for the

MS-GJR-GARCH model, it was calculated by using E.g. [5] in the case of regime i. It's essential to note that the within-regime volatility persistence of the MS-GARCH-type model aligns with the volatility persistence observed in standard GARCH-type models. This differentiation in unconditional volatility values and persistence patterns emphasizes the heterogeneous characteristics inherent in the volatility process across the identified regimes. The findings demonstrated variations in within-regime volatility persistence, as measured by MS-GARCH and MS-GJR-GARCH, across the identified regimes $(i = 1, 2)$. Notably, Regime 2, characterized as a high volatility regime, exhibited significantly higher within-regime volatility persistence when compared to low volatility regime 1, for both model specifications. This distinction underscores the dynamic nature of volatility persistence within the identified regimes. The observed differences can be attributed to the inherent characteristics and conditions associated with each regime, contributing to distinct volatility behaviors across the specified periods. However, concerning the crude oil price and interest rate returns, the initial effect of a shock on conditional volatility is more pronounced in the low volatility regime 1 compared to the high volatility regime 2. This suggests that the primary contributor to volatility clustering in the low volatility regime may be attributed to persistence of a singular shock rather than regime persistence, as outlined by Angelini et al. (2017). The distinctive response patterns in these markets highlight the role of singular persistence as a key factor influencing volatility dynamics in specific regions.

The second factor contributing to volatility persistence is the endurance 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. The study found that the probabilities of remaining in the low volatility regime were extremely high and statistically significant for all returns in both MS-GARCH-type models. Conversely, the probabilities of remaining in the high volatility regime were generally lower and, in some instances, not statistically significant. Additional analysis indicated that the probability of transitioning from low to high volatility $(p_{22} = 1 - p_{21})$ was consistently lower than the probability of remaining in the low volatility regime $p_{11}$. This suggests that the low volatility regime was more persistent compared to the high volatility regime. Therefore, regime 1 has been shown to exhibit greater durability compared to regime 2 in most cases. This finding suggests that regime 1 has a higher likelihood of long-term stability.

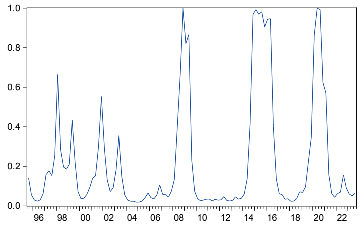
The stability stable probabilities (ω) and the expected durations $(ED_i)$are computed using E.q. (8) and E.q. (9), respectively. In Tables 5 and 6, it is evident that all-time series under consideration except stock price and inflation rate returns, as analyzed through the MS-GARCH and MS-GJR-GARCH models, exhibit stable probabilities of being in the high volatility regime 2. Additionally, the expected durations of regime 2 were higher when compared to the values associated with the low volatility regime 1. This suggests that, according to the stability stable probabilities and expected durations, the economic variables in Spain tend to persist in a state of higher volatility, providing insights into the temporal characteristics of the volatility regimes. This suggests that shocks to volatility have a more enduring effect. Deviations in volatility from the average tend to endure for longer periods, leading to more extended phases of either high or low volatility. Contrastingly, the rates of inflation rate returns exhibited higher stable probabilities of being in the low volatility regime 1, along with longer expected durations for regime 1, in comparison to the corresponding values for the high volatility regime 2. In this regime, the expected duration is shorter. This suggests that shocks to volatility dissipate rapidly, indicating that significant deviations in volatility do not persist for an extended period. The volatility reverts to its long-run average relatively quickly. For stock price returns, the estimation outcomes from the MS-GARCH and MS-GJR-GARCH models yielded disparate results. According to MS-GARCH model, the stable probabilities distinctly pointed to a significantly higher likelihood of being in the low volatility regime 1, exceeding 0.61. The expected duration in this regime was observed to be 9 months. In contrast, the probability for regime 1 was approximately 0.39, with an expected duration ($ED$) of approximately 3 months. This discrepancy underscores the distinct characteristics of the two volatility regimes, with regime 1 exhibiting a prolonged period of stability compared to the shorter and less probable stability period in regime 2. However, the estimation results of the MS-GJR-GARCH model, considering the important leverage effect, showed a greater likelihood of the high volatility regime 2 with a probability of approximately 0.86 and an average duration of 6 months. On the other hand, the probability of regime 1 was around 0.14 with an expected duration of 3 months. This highlights a more stable and persistent pattern of high volatility in regime 2 compared to regime 1.

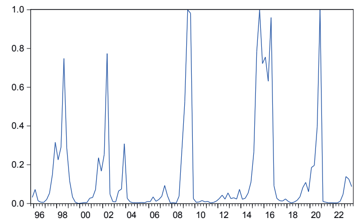
The log-likelihood values ($LL$) provide an initial perspective for evaluating the significance of regime persistence as a contributor to volatility persistence, a concept explored by researchers like Klaassen in 2002. These values serve as a valuable indicator in assessing the extent to which the persistence of regimes influences the overall persistence of volatility in the analyzed context. For the al time series returns under consideration, the log-likelihoods associated with MS-GARCH-type models surpassed those of their standard GARCH-type model equivalents. This observation suggests that the MS-GARCH-type models provide a better fit or capture the underlying dynamics more effectively for these markets compared to the standard GARCH-type models. The higher log-likelihood values signify a superior ability of the MS-GARCH-type models to represent the observed data patterns. In general, the examination of log-likelihoods indicates that incorporating regimes into the analysis can enhance the ability to capture volatility persistence. This suggests that acknowledging and accounting for different regimes in the modeling process contributes to a more accurate representation of the underlying dynamics influencing volatility.

The smoothed probabilities for the low volatility regime 2 of the MS GARCH and MS-GJR-GARCH model are presented in Figure 2. These probabilities provide insights into the behavior of specific time series. The results reveal distinct characteristics among the variables analyzed. In the analysis of unemployment rate, interest rate, and inflation rate returns, both MS-GARCH-type models produced consistent results, indicating that the market predominantly underwent tranquil periods with intermittent abrupt shifts to the high volatility regime. These transitions coincided notably with well-known turmoil periods, such as the global financial crisis in 2007 and the emergence of the Covid-19 pandemic in 2020 for the unemployment rate returns. However, in the case of interest rates, the transitions were observed during the Covid-19 pandemic and the Russia-Ukraine war in 2022. This detailed examination enhances our understanding of market dynamics during remarkable events, highlighting the MS-GARCH models' capacity to capture subtle variations in volatility regimes. In the analysis of crude oil price, stock price, and economic growth returns in Spain from 2000 to 2023, both MS-GARCH-type models consistently revealed similar outcomes. These findings indicate that, for most of the time, the market experienced relatively tranquil periods, punctuated by occasional abrupt shifts to the high volatility regime. These transitions aligned notably with well-known turmoil periods, encompassing various crises and global events. The identified turmoil periods, as captured by the volatility regime switches, coincide with significant global influences. The analysis accounts for the impact of the global financial crisis (GFC) in 2008, speculative bubbles 2000-2004, the European debt crisis in the summer of 2011, the onset of the Covid-19 pandemic in March 2020, and the Russia-Ukraine war in 2022, which involved economic sanctions on Russia. Each of these events has had a profound influence on global financial markets, triggering fluctuations and uncertainties that reverberated into the Spanish stock and crude oil markets. The MS-GARCH-type models, by discerning periods of heightened volatility and calmness, provide valuable insights into the market's response to these crises and global events. Understanding how external factors contribute to volatility dynamics allows for a nuanced interpretation of market behavior, aiding in the identification of key drivers during specific periods. This detailed analysis contributes to a comprehensive understanding of Spain's financial markets, particularly in relation to significant global and domestic events that have shaped market conditions over the years.

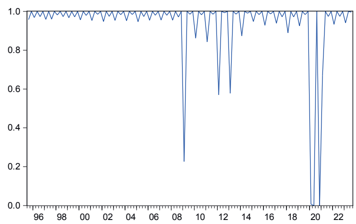
**Figure 2.** Smoothed probabilities for the regime 2

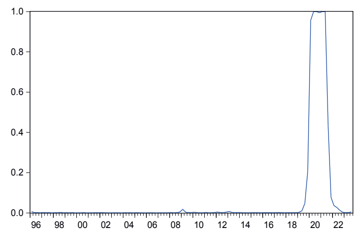
$rCOP_t$ – MS GARCH | Crude oil prices– MS-GJR -GARCH



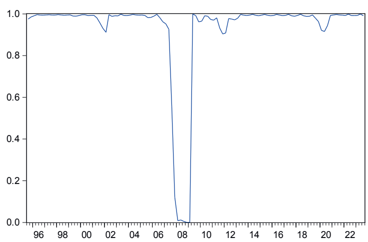



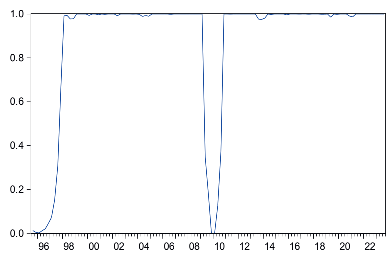

GDP – MS GARCH | GDP – MS-GJR -GARCH



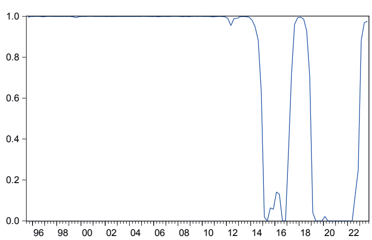



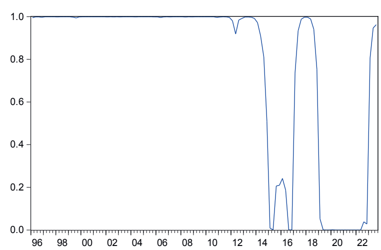

Unemployment rates – MS GARCH | Unemployment rates MS GJR GARCH



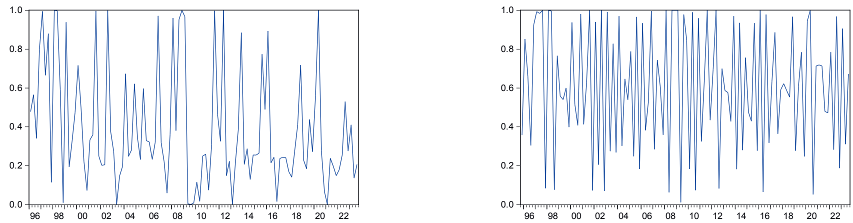




Interest rates – MS GARCH | Interest rates – MS-GJR -GARCH



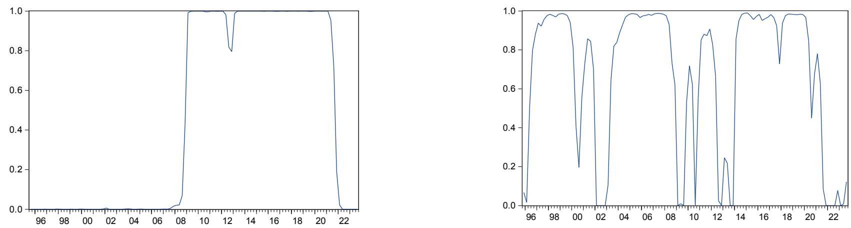




Stock price – MS GARCH | Stock Prices – MS-GJR -GARCH




Inflation rates – MS GARCH

Inflation rates – MS-GJR -GARCH




Source: Author's design

Table 8 presents the dynamics of conditional volatilities in individual markets over the next three quarters, with a particular focus on the period coinciding with the Russia-Ukraine war. The estimated MS-GARCH model and MS-GJR-GARCH model were employed to compute the five-step ahead conditional volatilities. Notably, the forecasted values from both model specifications revealed that the crude oil prices, economic growth (GDP) rates, stock prices exhibited the highest conditional volatility, followed by the interest rates, unemployment rates, and inflation rates. This information offers insights into the anticipated volatility patterns in these markets, emphasizing the heightened volatility expected during the specified period, as captured by the models.

**Table 8.** Five-step ahead conditional volatilities of MS-GARCH-type models

| | $rOP_t$ | $rGDP_t$ | $rUR_t$ | $rInt_t$ | $rMBE_t$ | $rInf_t$ |
|---|---|---|---|---|---|---|
| | | | **MS-GARCH Model** | | | |
| 2024Q1 | 0.0357 | 0.0254 | 0.0035 | 0.0162 | 0.0266 | 0.0259 |
| 2024Q2 | 0.0377 | 0.0190 | 0.0046 | 0.0146 | 0.0256 | 0.0391 |
| 2024Q3 | 0.0334 | 0.0148 | 0.0021 | 0.0042 | 0.0268 | 0.0350 |
| 2024Q4 | 0.0307 | 0.0159 | 0.0014 | 0.0076 | 0.0327 | 0.0419 |
| | | | **MS-GJR-GARCH Model** | | | |
| 2024Q1 | 0.0379 | 0.0122 | 0.0074 | 0.0312 | 0.0243 | 0.0353 |
| 2024Q2 | 0.0329 | 0.0206 | 0.0058 | 0.0608 | 0.0261 | 0.0442 |
| 2024Q3 | 0.0342 | 0.0191 | 0.0096 | 0.0023 | 0.0294 | 0.0416 |
| 2024Q4 | 0.0297 | 0.0137 | 0.0018 | 0.0146 | 0.0245 | 0.0353 |

Source: Author's design.

Table 9 shows the most suitable model for the variables under investigation that exhibit the ARCH effect, determined through information criteria, and forecast accuracy measures. According to the results of the Schwarz Information Criterion (SIC) and Akaike Information Criterion (AIC) presented in Table 9, the optimal model for all variables under consideration aligns with the MS-GARCH models. This selection is based on the rigorous evaluation of information criteria and forecast accuracy, highlighting the MS-GARCH models as the best-fitted choice for capturing the volatility characteristics of the variables in question. Indeed, the SIC and AIC values in MS-GARCH-type models are notably lower than those in standard GARCH-type models. This is further illustrated in Table 8, where MS-GARCH-type models across all variables under investigation demonstrate smaller root mean square error (RMSE) and mean absolute percentage error (MAPE) values compared to their standard GARCH-type counterparts. The observed smaller prediction errors in the selected MS-GARCH-type models, as indicated by these two evaluation criteria, underscore their effectiveness in providing accurate predictions across various variables. Hence, compelling evidence emerges supporting the superior performance of MS-GARCH models over the standard GARCH-type models in effectively capturing the characteristics of all-time series. This observation underscores the robustness and efficacy of the MS-GARCH-type models in accurately representing the dynamics inherent in all-time series under investigation.

**Table 9.** The optimal model of variables that have the ARCH effect.

| | $rOP_t$ | $rGDP_t$ | $rUR_t$ | $rInt_t$ | $rMBE_t$ | $rInf_t$ |
|---|---|---|---|---|---|---|
| **Standard GARCH-type Models** | | | | | | |
| Model | GARCH | GARCH | GJR-GARCH | GARCH | GARCH | GJR-GARCH |
| SIC | -0.747523 | -3.960141 | -3.166384 | -1.197601 | -1.890002 | 1.949798 |
| AIC | -0.868884 | -4.082191 | -3.252436 | -1.342418 | -2.012751 | 1.804164 |
| RMSE | 0.155450 | 0.044486 | 0.054552 | 0.265184 | 0.084955 | 1.272941 |
| MAPE | 0..112366 | 0.037921 | 0.039523 | 0.145400 | 0.063608 | 1.120705 |
| **MS- GARCH-type Models** | | | | | | |
| Model | MS-GARCH | MS-GARCH | MS-GJR-GARCH | MS-GARCH | MS-GARCH | MS-GJR-GARCH |
| SIC | -0.796689 | -4.032470 | -3.739648 | -1.298877 | -1.977308 | 1.702755 |
| AIC | -0.895115 | -4.177287 | -3.886947 | -1.443694 | -2.122125 | 1.631884 |
| RMSE | 0.150545 | 0.041026 | 0.052756 | 0.255774 | 0.081103 | 1.254403 |
| MAPE | 0.110164 | 0.030995 | 0.034918 | 0.143534 | 0.061211 | 1.113095 |

Source: Author's design.

## *5.4. Estimation of the ADRL models*

In this section, initially, the time series of variables uncertainty is quantified utilizing the optimal model that encompasses two distinct regimes. To gauge uncertainty, the predictable component of variation is eliminated from optimal models by assessing the conditional variance time series. Following the quantification of variables associated with uncertainty, the impact of crude oil prices changes on variables associated with uncertainty is estimated through the ARDL model. We employ the SIC to determine the optimal lags (p;q) for modeling the relationship between variables uncertainty and crude oil prices. SIC serves as a critical criterion in the selection process, aiding in the identification of the most suitable lag structure to effectively capture and model the intricate dynamics between variables associated with uncertainty and crude oil price fluctuations. Table 10 shows the conclusive ARDL (p; q) model, encapsulating both short-term and long-term effects of crude oil prices on the variables associated with uncertainty within two distinct regimes. The estimation of long-term and short-term effects was derived from Eq. (13) and Eq. (14) within the finalized ARDL(p; q) model. This comprehensive model allows for a nuanced examination of the temporal dynamics, enabling the exploration of both immediate and prolonged impacts of crude oil price changes on the uncertainty variables under consideration.

**Table 10.** Short-term and long-term effect of the crude oil price shocks on the macroeconomic variables.

| Variables | Short- term | | Long- term | |
|---|---|---|---|---|
| | Regime 1 | Regime 2 | Regime 1 | Regime 2 |
| $rGDP_t$ | -0.441331 | -0.642236 | -2.120272* | -1.330152** |
| $rUR_t$ | 0.082016 | 0.343891 | 0.821393** | 0.795413** |
| $rIint_t$ | -0.115312 | -0.344120 | -1.080912** | -1.227014** |
| $rMBE_t$ | -0.056131* | -0.276371** | -0.543713* | -0.610047* |
| $rInf_t$ | 0.050364** | 0.061310** | 1.642236* | 2.003347* |

Note: * indicates significance at the 10% level; **, at the 5% level; and *** at the 1% level.
Source: Author's design.

Table 10 shows a comprehensive examination of the impact of crude oil price changes on uncertainty of stock prices and the uncertainty of inflation rate returns in both systems, specifically focusing on the short term within the Spanish context. The statistical analysis reveals a significant negative relationship between oil prices and stock prices, indicating that higher oil prices are associated with a downturn in stock prices. This negative correlation can be attributed to increased operational costs for businesses, potentially leading to reduced profit margins and consumer spending constraints. Concurrently, a statistically significant positive relationship is observed between oil prices and inflation rate uncertainty. Elevated oil prices contribute to cost-push inflation, leading to higher production costs that may be passed on to consumers, resulting in increased uncertainty in inflation rates. Additionally, global economic dynamics and geopolitical events influencing oil prices can contribute to broader economic uncertainties, further impacting inflation rate uncertainty in Spain. The evidence aligns with numerous studies, including Ioannidis & Ka (2018) and Garzon & Hierro (2021), all of which affirm the negative relationship between oil prices and stocks, as well as the positive relationship between oil prices and inflation. Furthermore, the correlation between oil prices fluctuation and economic indicators such as economic growth, unemployment, and interest rate returns does not exhibit statistical significance in both systems over the short term. Despite this, the study reveals a positive association between oil prices fluctuation and uncertainty in the unemployment rate returns, alongside negative associations between oil prices fluctuation and uncertainty in both interest rate and economic growth returns. These findings highlight the nuanced nature of the relationships between oil prices and various economic factors, emphasizing the importance of considering temporal dynamics for a comprehensive understanding of these associations.

Over the long term, there exists a statistically significant negative relationship between oil prices fluctuation and the uncertainty surrounding economic growth, interest rates, and stock prices returns in both systems. Notably, the substantial size of these parameters indicates a significant impact on the economic landscape of Spain. The negative relationship between oil prices fluctuation and economic indicators can be attributed to various factors. Firstly, high oil prices increase production for many industries, including manufacturing and transportation. This leads to higher prices for goods and services, reducing consumer demand and overall economic growth. Uncertainty surrounding crude oil prices can also lead to cautious business investment, as companies are unsure about future costs and profitability. Secondly, the impact of high oil prices extends to the negative influence on uncertainty of stock price returns. Crude oil serves as a crucial input cost for numerous companies, and as prices surge, it diminishes their profitability and cash flow. The ensuing decrease in earnings, coupled with the uncertainty associated with oil prices, can result in a reduction in stock prices. Finally, high crude oil prices typically contribute to an escalation in interest rates. As oil prices surge, inflationary pressures intensify, prompting Spain central bank to raise interest rates in a bid to mitigate inflation. The subsequent increase in interest rates can hinder economic growth, as the cost of borrowing becomes more expensive for both individuals and businesses. In general, the negative relationship between oil prices fluctuation and uncertainty of economic growth, interest rate, and stock price returns implies that high oil prices can have detrimental effects on Spain's economy in the long term. These empirical results align with existing studies investigating the nexus between oil prices and economic growth, stock prices, and interest rates, in the context of Spain. Notable studies, including those conducted by Aladwani. (2024a), substantiate the concurrence of these findings, contributing to a growing body of literature that underscores the interconnectedness of oil prices with various economic indicators in the Spanish setting.

Furthermore, a robust positive statistical significance is observed at the 1% level for the interdependence between oil prices fluctuations and uncertainty in the inflation rate returns, while a notably stronger positive statistical significance is evident at the 5% level for the interdependence between oil prices fluctuations and uncertainty in the interest rate returns. This finding can be elucidated by four key factors. Firstly, Spain's substantial dependence on imported oil plays a pivotal role. The country relies heavily on oil imports to fulfill its energy requirements, and consequently, any shifts in global oil prices have a direct impact on the domestic economy. Higher oil prices contribute to heightened costs in production, consumption, and transportation, thereby inducing inflationary pressures within the economy. Secondly, Spain has a notable presence of energy-intensive sectors, including manufacturing, chemical industry, automotive, and transportation. These industries have a substantial dependence on oil and petroleum products as crucial inputs for their operations. Therefore, any upswing in oil prices exerts a direct impact on the cost dynamics of these industries, potentially resulting in job losses and layoffs, thereby contributing to an escalation in unemployment rates. Thirdly, Spain is one of the global top tourist destinations, with its economy significantly influenced by the tourism industry. Higher oil prices contribute to escalated transportation costs, including airfares and fuel costs for tourist vehicles, directly influencing the affordability of travel for both domestic and international tourists. Thus, a reduction in tourist arrivals has adverse implications for the hospitality sector, resulting in diminished employment opportunities. Finally, High oil prices exert pressure on household budgets, especially for those in lower-income brackets, as they contend with elevated expenses related to consumer goods, heating, and transportation. This heightened financial burden can result in a decrease in discretionary spending, impacting overall consumption levels and, consequently, hindering economic growth. The decrease in consumer spending frequently prompts companies to implement cost-cutting measures, potentially involving layoffs or a halt in new hires, thereby contributing to higher unemployment rates. The confirmation of a substantial interconnection between crude oil price shocks and both unemployment rates and inflation rates in Spain, as demonstrated in this study, is consistent with the findings of previous studies conducted by Charfeddine et al., (2020).

## 6. CONCLUSION, LIMITATIONS, AND FUTURE DIRECTIONS

This study's main objective is to enhance the measurement of selected macroeconomic variables uncertainty by refining models within the MS-GARCH and MRS-GJR-GARCH models. Additionally, we aim to assess the influence of crude oil prices fluctuations on the uncertainty of selected macroeconomic variables, specifically economic growth, interest rate, inflation rate, unemployment rate and stock prices. The methodologies involve the application of MS-GARCH and MS-GJR-GARCH models to estimate the volatility of macroeconomic variables, including crude oil prices. Subsequently, we conducted a comparative analysis of their performance against GARCH and JGR-GARCH models, considering various distribution assumptions such as Student's-t distributions. The empirical results of the study clearly confirm that MS-GARCH-type models extend beyond the capabilities of standard GARCH-type models, providing enhanced flexibility in modeling the volatility process. Beyond specific outcomes for each factor, several overarching conclusions can be drawn. The estimated MS-GARCH-type models effectively identify breakpoints in all macroeconomic variables volatilities, specifically during significant events such as the global financial crisis (GFC) in 2008, the European debt crisis in 2011, and the Covid-19 pandemic of 2020, Russia-Ukraine War in 2022. However, these models did not indicate a switch in volatility regimes for other crises, such as the OPEC conflict with Russia and the USA. Moreover, the forecasted five-step ahead conditional volatilities, derived from both the estimated MS-GARCH and MS-GJR-GARCH models, highlighted the highest volatility for the crude oil prices, followed by the inflation rate, stock prices, interest rate, and unemployment rate. Given the significant leverage effect identified in all analyzed time series and the intriguing findings related to switching volatility regimes in Spain, future research could face a challenging task of exploring within-regime volatility persistence and regime persistence across a diverse set of macroeconomic variables using various MS-GARCH-type models. In the second section of the study, we found the impact of crude oil price fluctuations on the uncertainty of macroeconomic variables within a regime-switching framework. The results indicate a negative impact of crude oil price fluctuations on the uncertainty of inflation rate and unemployment rate returns. Conversely, other macroeconomic variables demonstrate a positive impact under both regimes. The results of the study carry significant economic and financial implications. Understanding the trends of macroeconomic variables in Spain under different regimes, along with the transition probabilities between these regimes, provides investors with valuable insights for more accurate predictions. Furthermore, gaining a comprehensive understanding of uncertainty and its magnitude empowers investors to effectively gauge and manage risks associated with macroeconomic variables.

**Limitations and Future Directions**

This research investigates the impact of crude oil price volatility on key macroeconomic variables, such as inflation, GDP, inflation, unemployment, and interest rates, and the Spanish stock market, spanning the period from 1995 to 2023. By using advanced econometric models, including standard GARCH-type, MS-GARCH-type family (double regimes), and ADRL models, this analysis captures the dynamic volatility patterns in crude oil price shocks and their broader economic implications. The research's temporal scope includes major global economic crises such as the international war oil price, GFC, the COVID-19 pandemic, and the Russia-Ukraine war I and II, which add to the richness of the analysis. However, several limitations must be acknowledged. First, although the GARCH-type models are proficient in modeling volatility, they may struggle to capture the full extent of structural breaks and regime shifts caused by unprecedented exogenous shocks like the financial crisis, COVID-19 pandemic or geopolitical conflicts. MS-GARCH-type models provide some flexibility in capturing regime shifts; however, they may still fall short in addressing sudden and persistent shocks that redefine long-term economic structures. Furthermore, the reliance on historical data over more than three decades introduces challenges related to the stationarity and homogeneity of variables, which could affect the reliability of model estimates. Second limitation concerns the exclusion of critical external factors such as advancements in renewable energy technologies, global energy policy changes, or shifts in international energy markets, all of which could have a profound impact on crude oil prices and macroeconomic outcomes. Furthermore, while this research focuses on the Spanish economy, the results may not be fully generalizable to other countries with different energy market structures, macroeconomic conditions, or policy frameworks. Third, A further dimension of the research involves examining the impact of crude oil price shocks on the stock returns of energy companies listed on the Spanish stock market. This is an important extension, as the stock performance of energy companies can directly influence the general market index, given the weight of these companies in the market portfolio. The sensitivity of energy companies' stock prices to crude oil price shocks could amplify the overall stock market risk, which further complicates the macroeconomic implications. However, this aspect introduces further limitations, particularly regarding the potential for endogeneity between crude oil price shocks and energy company stock performance, which could bias the results. Addressing this issue requires advanced econometric techniques to disentangle the feedback effects between these variables.

Future research should aim to address these limitations by considering more sophisticated econometric approaches that can better account for structural breaks and non-linearities, such as Transition Autoregressive (STAR) models, vector autoregressive (VAR) models, or Threshold GARCH (TGARCH) models, which might capture asymmetric responses to shocks. Additionally, the integration of time-varying parameter models could offer more nuanced insights into how the relationship between crude oil prices and macroeconomic variables evolves over time. Expanding the dataset to include other energy sources, such as renewable energy prices, would also allow for a more comprehensive understanding of how energy market dynamics influence macroeconomic stability in Spain. Furthermore, comparative studies across multiple economies or regions could yield insights into the heterogeneous effects of crude oil price shocks, particularly in economies with different energy dependencies, economic structures, and fiscal policies. Future studies might also include microeconomic perspectives, such as the impact of energy price volatility on productivity, firm-level investment decisions, or sectoral performance, more enriching the understanding of the economic consequences. Finally, future research should consider the implications of the global transition toward decarbonization and the adoption of greener technologies, which are likely to alter the relationship between crude oil price shocks and macroeconomic variables. Understanding how the transition to renewable energy will affect traditional energy markets, and consequently stock market performance, will be critical as economies strive for both economic growth and energy security in a rapidly changing international energy landscape.

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