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The impact of oil and global markets on Saudi stock market predictability: A machine learning approach

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ABSTRACT

This study investigates the predictability power of oil prices and six international stock markets namely, China, France, UK, Germany, Japan, and the USA, on the Saudi stock market using five Machine Learning (ML) techniques and the Generalized Method of Moments (GMM). Our analysis reveals that prior to the 2006 collapse, oil exerted the least influence on the Saudi market, while the UK and Japan were the most influential stock markets. However, after the collapse, oil became the most influential factor, highlighting the strong dependence of Saudi Arabia's economic structure on oil production. This finding is particularly noteworthy given Saudi Arabia's efforts to reduce its reliance on oil through Vision 2030. We further demonstrate that China's influence on the Saudi market increased significantly after the 2006 collapse, surpassing that of the UK. This is attributable to the substantial trade between China, Japan, and Saudi Arabia, as well as the rise in Saudi foreign direct investment in China, and the decline in such investment in the UK post-collapse. Our results carry important implications for stock market investors and policymakers alike. We suggest that policymakers in Saudi Arabia should continue to diversify their economy away from oil and strengthen economic ties with emerging markets, particularly China, to reduce their vulnerability to oil price fluctuations and ensure sustainable economic growth.

1. Introduction

In recent decades, the landscape of financial markets has undergone a profound transformation, evolving into a highly interconnected and globally integrated "single market." This metamorphosis, driven by the increasing interdependence of global supply chains and the adoption of standardized financial instruments and networks by financial institutions worldwide (Abdelkader et al., 2024; Abdou et al., 2019; Albitar et al., 2020; Bilal et al., 2023; Matar et al., 2021), has brought forth a new era of challenges and opportunities. The financial world also has faced significant challenges, including the stock market crash of October 1987, the Asian financial crisis of 1997, Russia's economic turbulence in 1998, and the global financial crisis of 2008 (GFC). These crises have spurred research into the intricate relationships among stock markets across different countries (Anyikwa and le Roux, 2020; Ezeani et al., 2022; Ezeani et al., 2023a, 2023b; Liu et al., 2023; Syllignakis and Kouretas, 2011). Moreover, the COVID-19 pandemic introduced disruptions to both crude oil and stock exchange markets, adding a layer of complexity to global financial dynamics. Within this context, the aim of this study is to investigate the co-movement of various stock markets, particularly focusing on the Saudi stock market, and its relationship with international stock markets and oil prices.

Co-movement, which refers to the simultaneous movements of multiple markets, has emerged as a crucial phenomenon in empirical literature (Cross, 1973; French, 1980; Gibbons and Hess, 1981; Keim, 1983; Tinic and West, 1984). The degree of co-movement signifies the

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extent of risk spillover among these markets and carries significant implications for investors and policymakers alike. Specifically, the influence of specific markets on the Saudi market has profound implications. For instance, stocks in markets with a strong positive influence on the Saudi market may not be ideal for international diversification. Conversely, stocks from markets with an adverse impact can be crucial for risk reduction or hedging. The time lag between global market closings and the Saudi market offers unique forecasting opportunities, aiding strategic decision-making in portfolio management. This study aims to unravel the factors driving co-movement and its characteristics, shedding light on how one stock market influences another and to what extent such insights are invaluable for portfolio managers and investors, helping them make informed decisions regarding international diversification, risk management, and strategic deployment of stocks.

The escalating trade war between the United States and China, starting in 2018, has added a new layer of complexity to the global economic and political order. This trade war, characterized by tariffs imposed by both nations on each other's goods, has created uncertainties impacting businesses and the global economy. The anticipation of a global economic slowdown and declining oil prices have further exacerbated these uncertainties, with significant repercussions for oil-dependent countries like Saudi Arabia, where the oil sector contributes substantially to the GDP. Despite Saudi Arabia's Vision 2030 initiative to reduce oil dependency, the relationship between oil prices and the Saudi stock market remains significant. Thus, understanding the relationship between oil and stock markets, especially within the Saudi context, is of paramount importance for economic stability and decision-making.

Saudi Arabia, as the largest economy among Arab countries and the Gulf Cooperation Council (GCC) nations, holds a pivotal role in the global economic landscape as shown in Table 1. Specifically, according to the Organization of the Petroleum Exporting Countries (OPEC, 2021), Kingdom of Saudi Arabia (KSA) possessed proven oil reserves equivalent to 16.9% of the total global proven reserves in 2020, making it a significant contributor to the world's oil supply. Additionally, KSA produced 13.33% of the daily world production in 2020, further solidifying its role as a major player in the global oil industry. These figures illustrate the importance of KSA's oil reserves and production levels in the global market and underscore the need for continued attention to the country's oil-related activities. Its stock market boasts the largest market capitalization and average company size among its peers. Given its economic prominence, comprehending the dynamics of the Saudi stock market within the context of global financial markets is essential.

While prior research has established relationships between stock markets across different regions and time periods (Ahmed and Huo, 2018; Antoniou et al., 2003; Bekaert et al., 2009; Beirne and Gieck, 2014; Chow et al., 2011; Graham et al., 2013; Glick and Hutchison, 2013; Loh, 2013; Shen et al., 2015; X. Zhang et al., 2017), recent studies have suggested nuanced connections between the Saudi stock market and international stock markets like the US, UK, China, Japan, Germany, and France (Matar et al., 2021; Saâdaoui, 2021). However, disparities in these relationships arise due to differences in market operational hours. International stock markets operate 24 hours across various time zones, whereas the Saudi stock market follows a different schedule, closing on Thursday evening and Friday. This gap in the literature calls for further investigation to gain a deeper understanding of these relationships and their implications for investors and policymakers.

The relationship between oil and stock markets has been a subject of extensive research globally, with numerous empirical investigations exploring this nexus (Arouri, 2011; Bagirov and Mateus, 2019; Basher et al., 2018; Creti et al., 2014; Cunado and Perez de Gracia, 2014; Jammazi and Aloui, 2010; Mensi et al., 2021a; Naser and Alaali, 2018; Scholtens and Yurtsever, 2012; Wang et al., 2013). Additionally, there is evidence of a relationship between oil and the stock markets of GCC countries (Alqahtani et al., 2019; Arouri and Rault, 2012; Cheikh et al., 2021; Boubaker and Sghaier, 2014; Maghyereh and Al-Kandari, 2007; Mokni and Youssef, 2019). Specifically, the relationship between oil and the Saudi stock market has been investigated in various studies (Azar and Basmajian, 2013; Basher et al., 2018; Cheikh et al., 2021; Bouri and Demirer, 2016; Cevik et al., 2021; Finta et al., 2019; Hamdan and Hamdan, 2020; Jiang and Yoon, 2020; Jouini and Khallouli, 2019; Mensi et al., 2015; Mensi, 2019; Mokni and Youssef, 2019; Wang et al., 2013). This relationship is especially critical for oil-dependent countries like Saudi Arabia, as it can significantly impact economic performance and decision-making strategies.

In light of these considerations, the primary objective of this study is to forecast the weekly returns of the Tadawul All Share Index (TASI), the primary stock market index in Saudi Arabia. To achieve this objective, we aim to investigate the impact of international stock market indices (China, US, Japan, UK, Germany, France) on the Saudi stock market, examine the influence of combined oil prices (West Texas Intermediate and Brent crude oil) on the Saudi stock market, and assess how the influence of international stock markets and oil on the Saudi market has evolved over time, specifically before and after the 2006 collapse of the

Table 1
Key Indicators of Arab Capital Markets in 2020.

Country	Market capitalization (million USD)	No. of listed companies	GDP at current prices (billion USD)	Average company size (million USD)	Market capitalization to GDP
Saudi Arabia	2426,632	203	701.5	11,954	345.9
Kuwait	106,249	216	107.9	492	98.4
Qatar	165,371	45	146.1	3675	113.2
Egypt	41,195	256	361.8	161	11.4
Morocco	65,715	75	113.5	876	57.9
Bahrain	24,608	44	33.9	559	72.6
Jordan	24,608	180	43.5	101	41.8
Oman	52,576	111	63.2	474	83.2
Tunisia	8387	81	39.6	104	21.2
Lebanon	6724	28	19.1	240	35.2
Abu Dhabi	202,218	69	354.3	2931	57.1
Algeria	326	5.0	144.3	65	0.2
Dubai	92,887	67	354.3	1386	26.2
Sudan	1313	67	34.4	20	3.8
Palestine	3447	48		72	
Syria	2808	24		117	

Note: This Table showcases that Kingdom of Saudi Arabia (KSA) has the most substantial economy among Arab nations and specifically within the Gulf Cooperation Council (GCC) nations. KSA's gross domestic product in 2020 was recorded at $701.5B, and it had the highest market capitalization of $2426B, with an average company size of $11,954 M. In addition to the largest market capitalization to GDP ratio of 345.9, compared to other Arab and GCC nations (*Source*: Saudi Central Bank, Annual Report, 2021, P. 139).

Saudi stock market. The Saudi stock market index experienced a significant collapse in 2006, dropping 54% from a peak of 20,744 to 9471 within two months. This decline was attributed to irrational margin buying, with stock prices far exceeding their fair value. Since this collapse, the highest index value recorded was 13,949 on May 9, 2022, still 32% below the 2006 peak. This study aims to analyze the impact of international stock markets and oil on the Saudi market before and after the 2006 collapse. It seeks to understand changes in investor behavior and the varying influences of global markets and oil on the Saudi stock market in different periods, providing more accurate insights post-collapse. To fulfill these objectives, this study employs advanced Machine Learning (ML) techniques, namely Support Vector Machine (SVM), General Regression Neural Network (GRNN), Radial Basis Function Neural Network (RBFNN), Decision Tree Forest (DTF), Tree Boost (TB), and the Generalized Method of Moments (GMM).

The study of Tissaoui and Azibi (2019) is the sole endeavor predicting the returns of the Saudi stock market based on the stock market indices of China, Japan, Germany, and France. Nonetheless, our investigation introduces distinctive contributions by deviating from their methodology in three major dimensions. Firstly, in contrast to our reliance on stock market indices and oil prices, Tissaoui and Azibi adopted a different approach by employing volatility indices derived from market options. This methodological difference underscores the diverse perspectives employed in assessing market dynamics. Secondly, their study, spanning from January 8, 2009, to October 31, 2016, represents a relatively limited temporal scope. In contrast, our research encompasses a more comprehensive timeframe, extending from January 9, 2000, to December 29, 2019. This extended duration captures crucial market events, including the 2006 market collapse in the Saudi market and the era of the trade war between the United States and China, providing a more nuanced understanding of market behavior over time. Thirdly, our methodology distinguishes itself by employing five distinct machine learning models in conjunction with the GMM model. This innovative approach enables us not only to gauge the impact of each market on the Saudi stock market relative to others but also to discern the direction of this impact—a nuanced aspect unexplored in the findings of Tissaoui and Azibi. These methodological disparities position our study as both an extension and a complement to their work, thereby enriching the scholarly and practical dimensions of the research.

We conducted five models before and after the collapse of the Saudi Arabian stock market. Our pre-collapse findings indicated that the British stock market was the most significant influencer on the Saudi stock market, followed by the German stock market, the Japanese stock market, the French stock market, the Chinese stock market, and oil, respectively. We also observed that there was no impact from the US stock market. In our post-collapse results, oil was found to be the most influential factor, followed by the Japanese stock market, the Chinese stock market in third place, and the British stock market in fourth place. The German stock market was ranked fifth, followed by the French stock market in sixth place, with the US stock market having the least influence.

This research makes several significant contributions to the existing literature. First, it extends the temporal scope of the study to cover a substantial timeframe from January 9, 2000, to December 29, 2019. This extended duration allows for a deeper understanding of market behavior, encompassing critical events such as the 2006 market collapse in Saudi Arabia and the US-China trade war, which were not adequately explored in prior studies. Second, the study introduces methodological innovation by incorporating five distinct ML models in conjunction with the GMM model. This methodological diversity not only evaluates the impact of various markets on the Saudi stock market but also discerns the direction of this impact, offering a nuanced perspective that was previously unexplored. Particularly, neural networks, excel in identifying complex patterns in market data, adapt to changing conditions, and effectively handle non-linear and non-normal market characteristics. Third, while past research predominantly focused on the relationship between the Saudi stock market and US or UK stock markets, this study broadens the scope by examining relations with the stock market indices of China, Japan, Germany, and France. This comprehensive approach provides a more holistic view of international market influences on the Saudi stock market. Fourth, despite Saudi Arabia's Vision 2030 initiative aimed at reducing oil dependency, this research underscores the ongoing significance of oil prices in influencing the Saudi stock market. This finding holds implications for investors and policymakers in Saudi Arabia as they make critical decisions. Finally, the study conducts a meticulous pre-and post-collapse analysis of the Saudi stock market, shedding light on how international stock markets and oil impacted the market before and after the 2006 market collapse. This comparative analysis enhances the accuracy of the results, offering a more precise understanding of the influence of global markets and oil on the Saudi stock market.

The structure of the paper proceeds as follows: In Section two, we review the relevant literature, highlighting gaps and prior weaknesses. Section three outlines our dataset and methodology, explaining how we approach our analysis. Section four presents and discusses our results, shedding light on the implications. Finally, in Section five, we conclude our work, underscore its contributions to the literature, and suggest avenues for future research.

2. Literature review

A large body of literature addresses the dependence between comovement among stock markets, and the literature can be broadly classified into three groups. The first group presents the theoretical connection between oil and stock markets, as well as the interrelationships between stock markets. The second group focuses on studying the empirical relationship between stock markets and their impact on each other. The objective of this group is to identify the extent of the relationship between stock markets globally, followed by the Gulf Cooperation Council (GCC) countries, and finally, in KSA. The third group is interested in examining the empirical impact of oil prices on stock markets. The objective of this group's research is to identify the extent of the relationship between oil and stock markets in previous studies at the global level, followed by the GCC countries, and finally, in KSA.

2.1. Oil's impact on stock markets and interconnections among stock markets in theory

Numerous theoretical pathways illuminate the intricate relationship between oil and the stock market dynamics (Degiannakis et al., 2018). Initially, the stock valuation process elucidates this connection, rooted in economic theory, which posits stock value as the anticipated discounted cash flow (Huang et al., 1996). The impact of oil prices on stock cash flows varies, contingent upon the relationship between the issuing company and oil. Companies, as producers or consumers of oil, experience consequential effects on their revenues or expenses, thereby influencing their cash flows. This, in turn, affects how investors appraise their stocks, subsequently impacting stock prices (Bohi, 1991; Oberndorfer, 2009; Mohanty et al., 2011; Mork et al., 1994).

The subsequent pathway stems from the influence of oil prices on inflation rates, subsequently affecting interest rates, both of which have a direct impact on the discount rate used in stock valuation (Degiannakis et al., 2018). Escalating oil prices drive up production costs, leading to increased prices for goods and services, ultimately raising inflation rates. This prompts central banks to raise interest rates to counter inflation (Abel and Bernanke, 2001; Basher and Sadorsky, 2006; Hamilton, 1996). Higher interest rates translate to increased borrowing costs and an upward adjustment in the discount rate used for stock valuation, which adversely affects the stock market (Degiannakis et al., 2018).

Another pathway relates to oil-exporting countries, which rely significantly on oil revenues to fund their infrastructure (Farzanegan, 2011). These countries' incomes from oil exports directly impact their governmental expenditures, both short- and long-term (Hassan, 2021). A surge in oil prices prompts increased government spending, leading to amplified corporate cash flows and subsequently driving up stock prices. Conversely, declining oil prices trigger reduced government spending, resulting in diminished corporate cash flows, ultimately leading to a decline in share prices.

The existence of relationships between stock markets can be attributed to various factors (Mahran and Elamer, 2023; Salem et al., 2021; Selmey and Elamer, 2023; Ullah et al., 2022). One fundamental cause involves common shocks, such as significant economic shifts in industrialized nations, fluctuations in commodity prices, or declines in global economic growth. Such impactful events can trigger crises, leading to substantial capital outflows from emerging markets, resulting in heightened simultaneous movements in asset prices and capital flows (Calvo and Reinhart, 1996; Masson, 1998). Trade linkages, including direct trade and competitive devaluations, also contribute to contagion. A crisis in a particular country may lead to reduced income and subsequently lower demand for imports, affecting exports, trade balances, and associated economic fundamentals (Corsetti et al., 2005; Gerlach and Smets, 1995). Additionally, financial interconnections play a role. In a highly integrated region, a crisis in one country can directly impact other nations through reductions in trade credit, foreign direct investment, and various capital flows (Goldfajn and Valdes, 1997).

Besides these fundamental causes, the relationships can also be explained through theories of investor behavior (Claessens and Forbes, 2013). One such theory revolves around liquidity problems; losses in one country may prompt investors to sell securities in other markets to raise funds, anticipating increased redemptions (Valdés, 2000). Moreover, if banks experience significant deterioration in loans to a specific country, they may aim to reduce overall portfolio risk by minimizing exposure to other high-risk investments, which might encompass other markets. Faced with liquidity issues, investors may need to sell other assets in their portfolios, potentially causing price declines in markets beyond the crisis-affected country, thereby transmitting the disturbance across multiple markets. Additionally, incentive structures and risk aversion contribute to these relationships (Broner et al., 2006; Schinasi and Smith, 2000). A crisis in one market could prompt investors to sell holdings in other markets to maintain a specific proportion of a country's or region's stock in their portfolio. Similarly, risk aversion might cause investors to sell assets in which they are overly invested to remain close to their benchmarks. Furthermore, if many investors have similar benchmarks or fixed country weights in their portfolios, this could lead to significant price declines following a shock in one asset. Lastly, information asymmetries and imperfect information may lead investors to believe that a crisis in one country could be followed by similar problems in a related or neighboring country. Consequently, if a crisis uncovers weak fundamentals, investors may logically infer that similar countries might face equivalent challenges, contributing to contagion.

2.2. *The empirical relationship between stock markets*

An increasing body of literature focuses on studying the relationship between global stock markets. Glick and Hutchison (2013) concluded that there is a relationship between the Chinese stock market and the Asian stock markets (India, Indonesia, Korea, Malaysia, Philippines, Singapore, Taiwan, and Thailand) and the US stock market during and after the 2008 global financial crisis. They found that this relationship has become stronger until the time of conducting the study in 2013. Along similar lines, the findings from the research conducted by Uddin et al. (2022) underscored an interconnection among the stock markets of China, Hong Kong, Japan, and Korea. In a similar vein, the findings of the study by Ouyang et al. (2023) illuminate the presence of contagion within the global stock markets, demonstrating diverse behavioral characteristics across short, medium, and long-term periods. This contagion intensifies during financial stress periods in the medium and long terms, but its impact diminishes in the short term.

Ahmed and Huo (2018) studied the price movement and volatility in the Chinese stock market and 15 stock markets in Africa and concluded that there is an effect of price movement and volatility in the Chinese stock market on the African stock markets. Their results of the price movement indicate that there is a two-way relationship between China and most African stock markets, which suggests that Chinese and African stock markets can influence each other. X. Zhang et al. (2017) examined the dynamic correlation between 27 stock markets in 24 countries from three different continents, including Asia, America, and Europe during the period 2006–2015. They found that there is a strong influence of US stock indices on the rest of the indices in other continents, and this effect increased between America and Europe during the 2008 financial crisis. It was found in the study conducted by Beirne and Gieck (2014) during the period 1998–2011 that there was an effect of contagion of stock markets inside and outside countries during the 2008 financial crisis, especially in the United States, Latin America, and Asia. Shen et al. (2015) found that contagion occurs between the stock markets in the countries in which there is a large trade exchange.

Bekaert et al. (2009) pointed out that the share prices of companies that achieve large growth rates are related to each other in different countries, unlike those that achieve low growth rates. Antoniou et al. (2003) studied the relationship between the UK, French, and German stock markets. They found that there is a relationship between the three markets in general and that there is a two-way relationship between the UK and French stock markets. The study conducted by Sheng et al. (2024) delved into the interrelationship among the stock markets of Shanghai, Hong Kong, and the United States. Their investigation revealed that the nature of this tripartite market connection fluctuates over time and intensifies during periods of heightened market volatility. Notably, this relationship exhibited increased strength following the linkage of stocks between Shanghai and Hong Kong. Mao et al. (2024) research, following a comparable line of inquiry, indicates the existence of return spillover among the stock markets of the United States, China, and India across short and long-term durations. Chow et al. (2011) studied the relationship between New York and Shanghai stock returns from 1992 to 2010. They concluded that the effect of New York returns on their Shanghai counterpart increased after the 1997 Asian crisis and became substantial and positive after 2002. On the other hand, they found that Shanghai's influence in New York became substantial and positive also after 2002.

Yao et al. (2024) show dynamic and asymmetric risk transmissions among the stock markets of Shanghai, Shenzhen, Hong Kong, and London spanning from January 2013 to January 2022. Yuan and Du (2023) study reveals discernible variations in spillover effects between emerging and developed markets. Notably, the findings emphasize the substantial interdependency among developed markets, leading to a notably higher average dynamic total connectedness when compared to emerging markets. In a study conducted by Graham et al. (2013) to examine the co-movement between equity returns in the United States and the Middle East and North Africa region (MENA) during the period from June 2002 to June 2010, it was found that there was a long-term co-movement between the United States and Kuwait, KSA, and Egypt. The strongest co-movement was between Egypt and the United States. Loh (2013) investigated the co-movement of equity returns in 13 stock markets in the Asia-Pacific region, Europe, and the United States and found that there is a strong co-movement between most of the Asia-Pacific region, the United States of America, and Europe stock markets in the long term.

On a smaller scale, other researchers were interested in studying the impact of the GCC stock markets on each other. Abraham and Madani (2012) concluded that there is a correlation between the stock markets of the GCC countries, where the markets of Saudi Arabia, Kuwait, and Qatar are linked to each other in one direction, while Oman and Dubai are linked in another direction. In the same vein, Aloui and Hkiri (2014) results reveal frequent changes in the pattern of the co-movements, especially after 2007 for the GCC stock markets at relatively higher frequencies. They further note an increasing strength of dependence among the GCC stock markets during the 2008 financial crisis.

In the case of the Saudi stock market, it is highly concentrated and dominated by the financial industry, which has strong connections with American and European financial markets (Arouri and Rault, 2012). Therefore, researchers have also examined the impact of the US and UK stock markets on the Saudi stock market. The research conducted by Tissaoui and Azibi (2019) presents compelling evidence illustrating the enduring impact of shocks on the dynamic conditional correlation within TASI returns across diverse VIX peers. This investigation delineates the coexistence of short-term and long-term persistence in the identified shocks. Long-term persistence manifests in approximately half of the sample, while a conspicuous absence of such persistence characterizes the short-term level concerning TASI returns connected to HSI, Japan, Britain, and French VIX peers. Notably, within the shorter temporal domain, the discernible persistence of shocks on the dynamic conditional correlation is exclusively observable in TASI returns associated with the Chinese VIX peer. Intriguingly, no discernible conditional correlation surfaces between TASI returns and information concerning oil volatility risk, particularly in the context of Oil VIX. Moreover, the study emphasizes the valuable predictive nature of lagged values pertaining to global volatility risk in forecasting TASI returns. Saâdaoui (2021) concluded that there is a confirmed interdependence between TASI and DJI during various periods and frequencies. However, the TASI-FTSE nexus was slightly less significant, particularly in short-run horizons.

2.3. The empirical impact of oil prices on stock markets

The relationship between oil and the stock market has been extensively studied in the literature. Mensi et al. (2021a, 2021b) found a strong co-movement between oil returns and the stock market in Brazil, India, China, Russia, and South Africa (BRICS). Similarly, several studies have shown a relationship between oil and the US stock market (Chkili et al., 2014; Cunado and Perez de Gracia, 2014; Naser and Alaali, 2018; Rahman, 2020; Sakaki, 2019) and in European countries.

(Arouri, 2011; Bagirov and Mateus, 2019; Chkili et al., 2014; Cunado and Perez de Gracia, 2014; Naser and Alaali, 2018; Park and Ratti, 2008; Rahman, 2020; Sakaki, 2019; Scholtens and Yurtsever, 2012; W. Zhang et al., 2020). The findings presented by Liu et al. (2022) echo analogous conclusions, emphasizing the spillover risks transferring exclusively from the oil market to the G20 stock markets during crisis periods. Significantly, their research underscores the substantial impact on the stock markets of the United States, Canada, and Mexico. The study conducted by Guru et al. (2023) presents contrasting outcomes; however, their findings suggest a limited spillover effect from the oil market to the G7 stock markets, as well as India and China.

Wang et al. (2013) demonstrated that the stock market's reaction to oil price fluctuations hinges on two crucial factors: a country's net oil import or export status and the underlying cause of the oil price change, whether it is due to a shift in supply or aggregate demand. Notably, the study revealed that the influence of aggregate demand uncertainty on stock markets is considerably more profound and persistent in oil-exporting nations as opposed to oil-importing countries. Specifically, positive shifts in aggregate demand and precautionary measures were found to result in a heightened degree of co-movement among the stock markets in oil-exporting nations. These findings emphasize the importance of carefully considering the interplay between oil markets and stock markets in developing and implementing effective policy measures aimed at stabilizing financial markets.

Basher et al. (2018) found the existence of regime-switching for the impacts of oil-market shocks on stock returns in oil-exporting nations. The study conducted by Wen et al. (2022) suggested a more substantial transmission of risks from global oil markets to the Chinese stock market, particularly noticeable at the medium-term investment horizon compared to the short-term investment horizon. Jammazi and Aloui (2010) observed negative and temporary responses of stock market variables to crude oil changes during moderate and expansion phases, but not during recession phases. Bjørnland (2009) found that higher oil prices stimulate the Norwegian economy, increasing stock returns immediately by 2–3% following a 10% increase in oil prices, reaching a maximum effect after 14–15 months, and gradually dying out. Chiou and Lee (2009) confirmed a negative impact of oil prices on stock returns (S&P 500), with asymmetric effects being statistically significant only in high-fluctuation states for both spot and futures oil price contracts. Creti et al. (2014) conducted a study that shed light on the correlation between oil prices and stock prices, with a particular focus on the impact of demand and supply shocks, as well as the net oil import or export status of a given country. Their findings revealed that a rise in oil prices resulting from demand shocks was accompanied by an increase in stock prices, especially in oil-exporting nations. Conversely, coherence among stock prices due to supply shocks was only noticeable in countries that export oil. Additionally, their long-term cointegration analysis revealed that oil shocks were more persistent in countries that import oil than in those that export it. These findings highlight the importance of carefully considering the drivers of oil price changes and the net oil import or export status of a country when examining the relationship between oil and stock markets. Such insights are crucial in developing effective policies aimed at promoting financial market stability.

Several studies have explored the relationship between oil prices and stock markets in GCC countries. Alqahtani et al. (2019) found that uncertainty in the global oil market negatively affects stock returns in GCC markets, with Bahrain and Oman being less sensitive to this effect compared to other countries. Mokni and Youssef (2019) identified a direct relationship between oil prices and stock markets in GCC countries, with the Saudi stock market exhibiting the highest degree of stability in dependency on oil prices. Similarly, Boubaker and Sghaier (2014) observed that daily oil price changes influence the returns of GCC stock markets. Meanwhile, ben Cheikh et al., 2021 discovered that GCC stock markets exhibit differing sensitivities to oil price changes, with four out of six markets being more sensitive to large oil deviations than small ones. In addition, Arouri and Rault (2012) found evidence for cointegration between oil prices and GCC stock markets, with oil price increases having a positive impact on stock prices, except in Saudi Arabia. Contrary to expectations and within a different context, the findings of Ben Douissa and Azrak (2023) do not support the transmission of bubbles from the oil market to the stock markets of the Gulf Cooperation Council (GCC) countries, except for the market in Dubai, throughout the COVID-19 pandemic.

Several studies have specifically focused on the relationship between oil and the Saudi stock market. The empirical findings by Cevik et al. (2021) indicate a reciprocal causal association between the Saudi stock market and the oil market. Jiang and Yoon (2020) found a strong relationship between oil and the Saudi stock market during the global financial crisis of 2008, with the relationship being stronger in oil-exporting countries. Mensi (2019) investigated the impact of oil on various sectors of the Saudi stock market, while ben Cheikh et al., 2021 discovered that the Saudi stock market is sensitive only to negative oil deviations and exhibits higher sensitivities to large oil price changes compared to small ones. Similarly, Mokni and Youssef (2019) found that the Saudi stock market has the strongest link and persistence of dependence on the crude market compared to other GCC countries. Basher et al. (2018) also observed that oil-demand and idiosyncratic oil-market shocks have a statistically significant impact on Saudi stock returns.

Hammoudeh and Aleisa (2004) found evidence of a bidirectional relationship between SAUDI and NYMEX futures price at a 5% significance level. Bouri and Demirer (2016) discovered unidirectional volatility transmissions from oil prices to stock markets, especially in the net exporting nations of Kuwait, Saudi Arabia, and UAE. Jouini and Khallouli (2019) observed asymmetric reactions of the Saudi stock index returns and the probabilities of transition from one state to another to oil price variations, with diverse impacts across sectors and regimes. The Saudi stock market was found to be more sensitive to oil price decreases than to oil price increases. Elamer et al. (2022) confirm the presence of a correlation between oil and every sector within the Saudi stock market, displaying fluctuations in strengths across different time periods. Notably, their study emphasizes notably strong connections between oil and various sectors, specifically energy, materials, utilities, transportation, banks, and telecommunication services. In line with this, Bin Amin and Rehman (2022) discovered that positive fluctuations in oil prices had a more substantial impact compared to negative ones on sectors like building and construction, energy and utilities, and petrochemicals within the Saudi stock market. Conversely, higher oil prices negatively affected the stock prices of the banking and financial service sectors in the same market. Wang et al. (2013) discovered that the impact of oil demand shocks on the Saudi stock market is less persistent than in other oil-exporting countries. Additionally, several studies have reported a relationship between oil and the Saudi stock market (Azar and Basmajian, 2013; Cevik et al., 2021; Finta et al., 2019; Hamdan and Hamdan, 2020; Jouini, 2013; Mensi et al., 2015).

In general, there is a substantial body of literature on the relationship between stock markets globally, and this relationship may vary over time, before and after crises such as the 1997 Asian crisis and the 2008 financial crisis (Ahmed and Huo, 2018; Antoniou et al., 2003; Beirne and Gieck, 2014; Bekaert et al., 2009; Chow et al., 2011; Glick and Hutchison, 2013; Graham et al., 2013; Loh, 2013; Shen et al., 2015; X. Zhang et al., 2017). In this study, we contribute to this literature by examining the impact of the six primary stock markets of the United States of America, China, Japan, Great Britain, Germany, and France on the Saudi stock market. To the best of our knowledge, there is no literature that investigates the collective impact of the stock markets of these countries on the Saudi stock market, despite the substantial trade exchange between KSA and these countries in 2020, as shown in Table 2.

Upon reviewing the methodologies utilized in the literature exploring the correlation between equity markets and oil, we have observed a reliance on conventional techniques. The prevailing corpus of research has heavily leaned on established methodologies, including a diverse array of approaches such as the multivariate VAR-EGARCH methodology, ARDL Model, DCC-GARCH Model, Granger causality tests, multifactor asset pricing model, regime-switching models, nonlinear smooth transition models, Univariate GARCH models, Causality-in-variance tests, Generalized impulse response functions, wavelet analysis, Markov switching vector autoregressive models, Vector Autoregressive (VAR) models, Vector Error Correction (VEC) models, nonlinear cointegration analysis, and multivariate VAR analysis (see for example, Ahmed and Huo, 2018; Alqahtani and Martinez, 2020; Antoniou et al., 2003; Anyikwa and le Roux, 2020; Arouri and Rault, 2012; Arouri, 2011; Bekaert et al., 2009; Cheikh et al., 2021; Bouri et al., 2017; Chiou and Lee, 2009; Chow et al., 2011; Ding et al., 2016; Hammoudeh and Aleisa, 2004; Jammazi and Aloui, 2010; Lee et al., 2012; Maghyereh and Al-Kandari, 2007; Park and Ratti, 2008; R. Aloui et al., 2013; Saâdaoui et al., 2017; Shen et al., 2015; Wang et al., 2013; X. Zhang et al., 2017).

Table 2
Kingdom of Saudi Arabia Exports and Imports 2020.

Country	Exports	Imports
China	\$8.18B	\$26.51B
United States	\$1.85B	\$14.10B
Japan	\$665.09 M	\$5.66B
United Kingdom	\$374.09 M	\$2.99B
Germany	\$310.39 M	\$6.81B
France	\$198.28 M	\$4.06B

Note: This table provides a detailed overview of the Kingdom of Saudi Arabia's (KSA) trade relationships with six countries in 2020. It highlights a significant trade exchange between KSA and China, Germany, France, Japan, and the United Kingdom. Notably, China emerged as KSA's largest trading partner, with imports from China reaching \$26.51B and exports totaling \$8.18B. The data also underscores the substantial trade with Japan and the UK, with imports from Japan at \$5.66B and from the UK at \$2.99B. Additionally, trade with Germany was noteworthy, featuring imports of \$6.81B and exports of \$310.39 M. These figures indicate a robust and diverse trade network between KSA and several key global economies (*Data source*: Trading Economics[a]).

[a] Available at: https://tradingeconomics.com

Recent studies have increasingly employed ML to predict global stock and oil markets, demonstrating its superiority over traditional methods in this field. Machine learning techniques excel over these methodologies in four key aspects: Firstly, ML, especially deep learning models like neural networks, excels in identifying complex, non-linear patterns within both oil and stock market data. This proficiency enables the detection of intricate relationships within these markets, which traditional models—often linear or predetermined—might fail to recognize. Secondly, ML models demonstrate adaptability to changing market conditions by continuously learning from new data, a feature lacking in traditional models that often require manual adjustments to accommodate shifts. Thirdly, ML models inherently manage nonlinearity and non-normality, prevalent characteristics in oil and stock market data, effectively capturing intricate relationships that may evade traditional methodologies. Fourthly, while traditional time-series models often rely on rigid assumptions, constraining their adaptability to evolving market dynamics, ML models excel in capturing subtle, time-varying patterns and intricate dependencies within the data (Behera et al., 2023; Chen et al., 2023; Kumbure et al., 2022; Yang et al., 2024).

Moreover, existing literature using neural networks to forecast the Saudi stock market has solely employed historical Saudi market data (Jarrah and Salim, 2019; Malibari et al., 2021). Therefore, our work aims to be the first to predict the Saudi stock market by integrating data from six international stock markets and oil into the machine learning including neural networks prediction process. Lastly, to our knowledge, this paper will be the first to examine the 2006 Saudi market collapse and compare the significance of international stock markets and oil in influencing the Saudi stock market before and after the event. Niu et al. (2023) delve into the impact of geopolitical risks on predicting volatility in the US stock market using machine learning models. Hanauer and Kalsbach (2023) compare various machine learning models in forecasting cross-sectional returns of emerging markets, revealing that incorporating non-linearities and interactions leads to better out-of-sample returns than conventional linear models. Dichtl et al. (2023) assess a broad range of predictor variables from the five largest Eurozone countries to predict stock market crashes, finding that a support vector machine-based model outperforms random classifiers, univariate benchmarks, and multivariate logistic regression models in terms of statistical predictive performance.

Campisi et al. (2023) explore volatility indices' predictive potential in determining future stock market directions using diverse machine learning methods. Their findings show that machine learning models outperform classical least squares linear regression in predicting S&P 500 returns, with random forests exhibiting superior predictive performance across all evaluation metrics. Li et al. (2022) analyze the dynamic risk interplay between crude oil and the stock market, influenced by systemic risk and investor heterogeneity, employing econophysics and machine learning techniques. Their in-sample and out-of-sample forecasting demonstrates that the proposed periodic model offers better fitting performance than benchmark models, supported by machine learning and predictive testing. Al-Maadid et al. (2022) investigate the impact of COVID-19-related news on stock markets in Gulf Cooperation Council (GCC) countries, using machine learning approaches to gauge the role of COVID-19 news in predicting stock returns in these markets. Additionally, Costa et al. (2021) explore machine learning techniques for short-term oil price forecasting, observing their good performance.

Some of these studies focus on the Saudi stock market, aiming to investigate specific factors influencing its performance or develop predictive models. Elamer et al. (2022) examine the influence of COVID-19 on the relationship between non-renewable energy and the Saudi stock market, utilizing Radial Basis Function Neural Network (RBFNN) models. Furthermore, Assous (2022) investigates the impact of Environmental, Social, and Governance (ESG) factors on Saudi stock return volatility from 2012 to 2020, employing linear regression, GLE algorithm, and neural network models. This motivated us to employ artificial intelligence (AI) to predict the Saudi stock index using the stock exchanges of the United States of America, China, Japan, Great Britain, Germany, and France, as well as two types of oil (WTI and Brent) and determine the importance of each one in the prediction process and thus determine the extent of the impact of each of them on the Saudi stock market.

3. Experimental data and methodology

3.1. Experimental data

The dataset used in this study was obtained from Investing[1] and consists of weekly historical data of the Shanghai Composite index (SSE), Dow Jones Industrial Average index (DOW), Nikkei 225 index (NIK), Thomson Reuters United Kingdom 50 index (UK), Frankfurt DAX Indication index (DAX), CAC 40 index (CAC), Tadawul All Share Index (TASI), and West Texas Intermediate futures (WTI) and Brent crude oil (BRT) as proxies for oil. The data covers a period of 20 years, from January 9, 2000, to December 29, 2019, with a total of 1024 observations for the eight independent variables represented by SSE, DOW, NIK, UK, DAX, CAC, WTI, and BRT, in addition to the dependent variable TASI.

To ensure consistency with the operating schedules of the six international stock markets and the oil market, weekly observations were utilized instead of monthly or daily observations. These markets operate five days a week, Monday to Friday. However, the Saudi stock market operates five days a week from Sunday to Thursday, resulting in the international markets and oil market being closed on Sundays while the Saudi stock market is operational. Similarly, on Fridays, the international markets and oil market are open while the Saudi stock market remains closed. Using weekly observations highlights the effect of what happens on Friday in the international markets and the oil market on prices in the Saudi market the following week more than daily or monthly observations. Additionally, using daily data would result in missing data on Friday and Sunday rows, which may lead to inaccurate results.

The reason for choosing Saudi Arabia among the Arab countries is that it has the largest economy and stock market among them, as shown in Table 1. The data is classified into three panels. The first panel includes the entire period covered by the dataset, as shown in the blue area of Fig. 1. The second panel covers the period before the 2006 Saudi stock market collapse, from January 9, 2000, to December 25, 2005, as shown in the green area in Fig. 1. The last panel covers the period after the 2006 collapse, from January 7, 2007, to December 29, 2019, as shown in the red area of Fig. 1. The year 2006 was excluded as the market collapsed, as suggested by Fig. 1.

3.2. Methodology

To construct our models, we utilized DTREG and STATA software. Five distinct ML modelling techniques were employed, namely Support Vector Machines (SVM/SVR), Generalized Regression Neural Networks (GRNN), Radial Bases Function Neural Network (RBFNN), Decision tree forest (DSF), and Tree boost (TB); and the Generalized Method of Moments (GMM).

3.2.1. Support vector machines

Support vector machines (SVMs) are supervised machine learning algorithm that holds significant promise in building accurate models for various types of problems. This modelling technique is relatively new and bears a close relation to neural networks, making it particularly well-suited for pattern recognition and a variety of modelling applications (Ibrahim et al., 2022; DTREG, 2021). SVMs employing the sigmoid kernel function can be equivalent to a two-layer multilayer perceptron neural network, such as a feed-forward neural network or radial basis function. SVMs are versatile and can be applied to both classification and regression modelling problems. These algorithms construct an N-dimensional hyperplane that optimally divides data into two or more clusters, depending on the type of dependent variable. This process employs quadratic programming problems with linear constraints to solve the weight of the network.

Within a SVM network, predictor variables are referred to as attributes, and a transformed attribute used to define the hyperplane is called a feature (Ibrahim et al., 2022; DTREG, 2021). The process of selecting the most suitable representation of data is known as feature selection. A vector is a set of features that describes a single row of predictor values. The goal of SVM modelling is to identify the optimal hyperplane that can segregate clusters of vectors. The vectors that are in close proximity to the hyperplane are referred to as support vectors. In this study, we employed the radial basis function as the recommended kernel function for constructing our SVM models (Ibrahim et al., 2022).

3.2.2. Generalized regression neural networks

The Generalized Regression Neural Network (GRNN) is a type of neural network that has a similar structure to the Probabilistic Neural Network (PNN), but with a key distinction: the GRNN is designed for regression analysis with a continuous dependent variable, while the PNN is used for classification. Although both networks share similarities with the k-Nearest Neighbors ($k-$NN) algorithm, they have distinct applications (Abdou et al., 2012, 2021).

According to Abdou et al. (2012, 2021), one of the advantages of GRNN is that it does not require various stationarity tests that are needed for regression models from the traditional statistical family. In terms of architecture, GRNN consists of four layers: input, pattern, summation, and output. The input layer receives the predictor variables, and the pattern layer transforms them into patterns. The summation layer calculates the sum of weighted differences between the input patterns and reference patterns, while the output layer generates the final output by taking the weighted average of the training outputs. Fig. 2 illustrates an example of the architecture of a GRNN.

3.2.3. Radial basis function neural network

The Radial Basis Function Neural Network (RBFNN) shares similarities with GRNN, which was previously discussed. However, RBFNN differs in that it has a smaller number of neurons compared to the number of training points, whereas GRNN has one neuron for each point in the training data (DTREG, 2021). It is also comparable to a feedforward neural network, where the input layer is fully connected to a hidden layer, which then generates outputs by performing a weighted sum (Guoa et al., 2012). The neurons in RBFNN's hidden layer consist of Gaussian transfer functions, whose outputs are inversely proportional to the distance from the center to the neuron, as depicted in Fig. 3 (DTREG, 2021, p. 261).

3.2.4. Decision tree forests

A decision tree forest is a collection of decision trees that work together to produce an overall forecast for the forest (DTREG, 2021). Each tree in the forest grows based on a specific random vector, and the data is trained accordingly. This process results in a higher degree of prediction accuracy than that achieved by using a large number of decision trees alone. To validate the model, the decision tree forest uses out-of-bag data rows. Moreover, it resists overfitting due to the presence

[1] Available at: https://www.investing.com

Fig. 1. Data panels.
This Figure shows that the data has been divided into three distinct panels based on the period covered by the dataset. The first panel encompasses the entire duration of the dataset, as indicated by the blue region in this Figure. The second panel focuses on the period preceding the collapse of the Saudi stock market in 2006, specifically spanning from January 9, 2000, to December 25, 2005, as shown by the green region in this Figure. The final panel pertains to the period after the 2006 market collapse, spanning from January 7, 2007, to December 29, 2019, as illustrated by the red region in this Figure. It is noteworthy that the year 2006 has been excluded from analysis due to the aforementioned market collapse (*Source*: TradingView). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of stochastic elements, which select rows of data used as input for each tree. Additionally, the independent variables data is considered as candidates for each node split (DTREG, 2021).

3.2.5. Tree boost

Tree boost is a machine learning algorithm that builds a group of trees in a sequential manner, where each tree is constructed after the previous tree is built. In contrast to the decision tree forest, where the trees are built in parallel. Tree boost is also known as stochastic gradient boosting (DTREG, 2021). The algorithm is based on the concept of gradient boosting, which constructs an additive regression model by sequentially fitting simple parameterized functions. The execution speed of gradient boosting and the approximation accuracy can be improved by incorporating randomization, which enhances the robustness against overfitting of the base learner (Friedman, 2002). Mathematically, tree boost can be described as follows:

$$P = S_0 + C_1{}^*D_1(X) + C_2{}^*D_2(X) + \ldots + C_M{}^*D_M(X)\ldots \tag{1}$$

where,

P is the predicted value, S_0 is the series starting value for, X is a vector of "pseudo-residual" values remaining at this point in the series, $D_1(X)$, $D_2(X)$ are trees fitted to the pseudo-residuals and $C_{1,}$ $C_{2,}$ etc. are the tree node predicted values coefficients that are computed by the Tree boost algorithm. The model can also be expressed in Fig. 4.

We utilized five machine learning modelling techniques to construct five models, one for each method. The independent variables, also known as predictors, in all five models include SSE, DOW, NIK, UK, DAX, CAC, WTI, and BRT, whereas the dependent variable is TASI. The goal of these models is to forecast the Saudi stock market and examine the most influential markets throughout the prediction procedure to investigate the co-movements between the Saudi stock market and these markets.

3.2.6. The generalized method of moments (GMM)

In order to enhance the accuracy of our findings, a GMM model has been developed. GMM offers several benefits over alternative estimation methods, primarily due to its ability to accommodate diverse forms of biases, including but not limited to, reverse causality, simultaneity, and omitted variable bias. Furthermore, GMM is capable of mitigating endogeneity biases that may arise when the independent variables are correlated with the error term. Our two-step system GMM model is presented in the following equation:

$$\begin{aligned} TASI_t = {} & TASI_{t-1} + TASI_{t-2} + BRT_t + CAC_t + DAX_t + DOW_t + NIK_t + SSE_t \\ & + UK_t + WTI_t\ldots \end{aligned} \tag{2}$$

where,

TAS_{t-1} indicates one lag of the dependent variable, and TAS_{t-2} denotes second lag of it. The GMM model controls for endogeneity by internally transforming the data and by including lagged values of the dependent variable (Ullah et al., 2018).

4. Results and discussion

4.1. The predictability power of oil and global stock markets on the Saudi stock market during the whole study period

We conducted five ML model runs using different samples for validation. The first run used the overall sample, while the remaining runs used various validation sets i.e. 2019 data; 2018–2019 data; 2017–2019 data; and a 20% random selection of the data automatically selected by the software. We employed oil and stock indices from China, the US, Japan, the UK, Germany, and France as predictors of the Saudi stock index from early 2000 to the end of 2019.

Table 3 and Fig. 5 reveal that BRT had the most significant influence on the Saudi stock market, followed by WTI using the entire data (i.e.

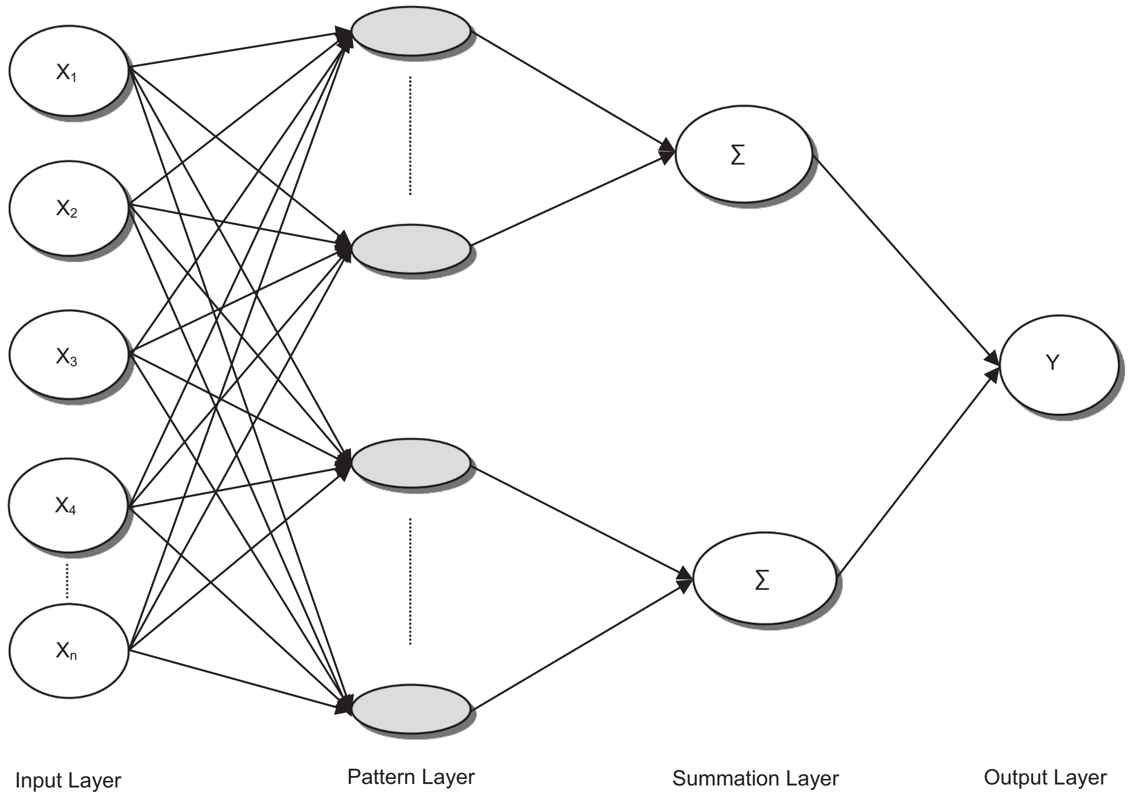

Fig. 2. Architecture of Generalized Regression Neural Network (GRNN).
Note: The presented architecture depicts a neural network model comprising four Generalized Regression Neural Network (GRNN) layers. The first layer, referred to as the input layer, consists of a single neuron for each independent predictor variable in the model. The second layer, known as the pattern layer, comprises a node for each training case that calculates the distance between the input values and the training values presented by each node. These values are then transmitted to each node in the third layer, referred to as the summation layer. The summation layer is composed of numerator and denominator nodes that function based on the distance in smoothing factors. In the third layer, one node is present for each dependent predictor variable, and each node computes a weighted average using the training cases in that category. The nodes in the summation layer add their inputs, and the output node divides them to generate the most accurate predictions (Abdou et al., 2021, p. 6285; Abdou et al., 2012, p. 800; Ibrahim et al., 2022).

Panel A). However, when using three years of validation (i.e. Panel D), the influence between the two was reversed, with WTI becoming the most influential, followed by BRT. Our findings are consistent with those of Jiang and Yoon (2020), who demonstrated a strong relationship between oil and the Saudi stock market, given that Saudi Arabia is a significant oil-exporting country. Moreover, our results support those of Mensi (2019), who observed the impact of oil on various sectors of the Saudi stock market. Mokni and Youssef (2019) also reported that the Saudi market is the most closely related and dependent on oil prices among the GCC, which our study supports.

However, our results contradict those of Wang et al. (2013), who concluded that the impact of oil demand shocks on the Saudi stock market was the least among the oil-exporting countries. This discrepancy could be attributed to the different study periods. Our study covered a period of twenty years, from early 2000 to the end of 2019, while their study only covered the period from early 1999 to late 2011.

According to our analysis, the Chinese stock market initially held the third rank in terms of its influence on the Saudi stock market. However, when we conducted a validation over two years (i.e. Panel C) and utilized a 20% validation, we found that the Japanese stock market occupied this rank. This finding supports the theory proposed by Shen et al. (2015) that contagion occurs between stock markets of countries with significant commercial exchange. Fig. 6 indicates a considerable trade between China and KSA, with Saudi exports to China valued at \$8.18B and imports from China valued at \$26.51B in 2020, as shown in Table 2.

Our results also show that the fourth influencer on the Saudi stock market is the Japanese stock market, which traded places with the Chinese stock market when we used two years of validation (i.e. Panel C). We found that the German stock market ranked fourth when we used a validation of two years, but the UK stock market took this place when we used a 20% validation. This result is consistent with the findings of Shen et al. (2015) and suggests that there is a considerable trade exchange between Saudi Arabia and Japan. In 2020, Saudi exports to Japan were valued at \$665.09 M, and imports from Japan were valued at \$5.66B, as shown in Table 2. Regarding the fifth influencer, our analysis indicates that the British stock market holds this position. However, when we used a one-year validation (i.e. Panel B), the French stock market occupied this rank, and when we used a 20% validation, the Japanese stock market ranked fourth, as mentioned previously. These results are in line with the findings of Saâdaoui (2021) and suggest that the British stock market has an interdependent relationship with the Saudi stock market but to a lesser extent than that with the US stock market. In 2020, Saudi exports to the UK were valued at \$374.09 M, and imports from the UK were valued at \$2.99B, as shown in Table 2. Finally, our analysis reveals that the sixth influencing factor on the Saudi stock market is the German stock market. However, when we used a one-year validation, the British stock market occupied this rank, while the Chinese stock market took this place when we used a two-year validation. These results support the findings of Shen et al. (2015), indicating that there is significant trade between Saudi Arabia and Germany, with Saudi exports to Germany valued at \$310.39 M and imports from Germany valued at \$6.81B in 2020, as shown in Table 2.

In our study, we found a shifting of influence between the seventh and eighth ranks of the Saudi stock market, with the US stock market ranking seventh when using the overall sample and 20% validation, and the French stock market ranking seventh when using two- and three-

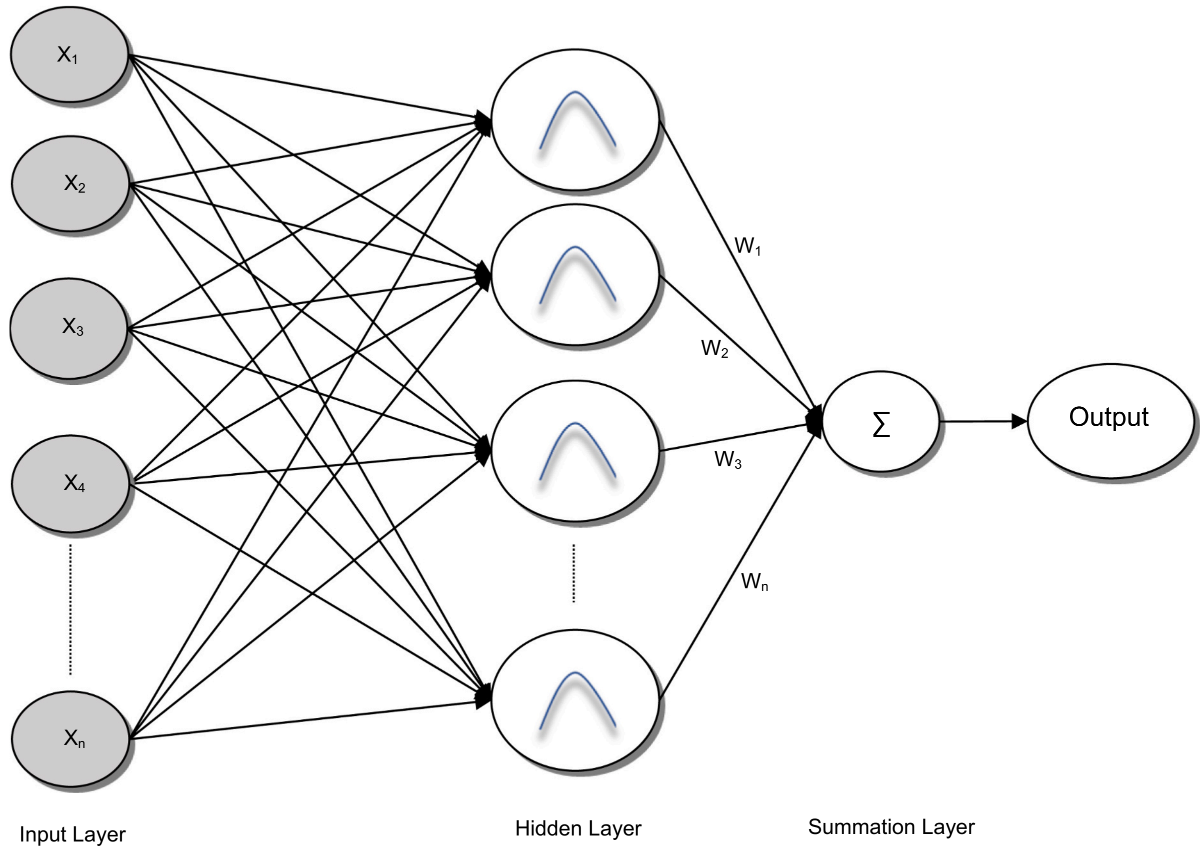

Fig. 3. Architecture of a Radial Basis Function Neural Network (RBFNN).
Note: This structure depicts a Radial Basis Function Neural Network (RBFNN) that consists of three layers. The first layer, known as the input layer, comprises a set of predictor variables, with each variable represented by one neuron. These neurons are responsible for normalizing a range of values, which are subsequently transmitted to the neurons in the next layer, i.e., the hidden layer. The optimal number of neurons in the hidden layer is established during the training phase, depending on the number of predictor variables and the size of the dataset. Each neuron in the hidden layer encompasses an RBFNN, which is centered on a point with numerous dimensions and interconnected with the predictor variables. The distribution of any RBFNN can vary for each dimension, and both the centers and the spreads are determined by the training process. The values obtained from the hidden layer are then multiplied by a weight connected to each of the neurons, represented as W1 … Wn, and then transmitted to the summation layer. The summation layer sums the weighted values and produces the output of the RBFNN in the form of an $\sum$ (DTREG, 2021, p. 266; Guoa et al., 2012, p. 520); own figure, modified.

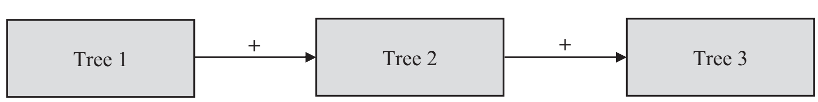

Fig. 4. Architecture of a Tree Boost.
Note: The initial step involves fitting the data to the first tree. The residuals of the first tree are then utilized as inputs to the second tree, resulting in a reduction in errors. This process is iteratively repeated through a sequence of consecutive trees. Finally, the predicted value is obtained by adding the weighted contribution of each tree. (DTREG, 2021, p. 245) modified.

year validation. The German stock market dropped to this rank when using one-year validation. The French stock market occupied the eighth rank when using the overall sample and 20% validation, while the US stock market occupied the same rank when using the other validation methods. Our findings partially contradict Shen et al. (2015) results, which showed that the US ranks second in terms of trade exchange with Saudi Arabia, but is the least influential in the Saudi stock market. However, our results are consistent with their findings regarding France, which ranks second to last in terms of trade with Saudi Arabia and also occupies the second to last rank in influencing the Saudi stock market. Our findings also contradict Saâdaoui (2021) results, which suggest that the relationship between the Saudi and UK stock markets is slightly less important than the relationship between the Saudi and US stock markets.

Our study extends the existing literature on the relationship between stock markets worldwide and the relationship between oil and stock markets, particularly in Saudi Arabia. We examined the influence of six international stock markets on the largest stock market in the GCC countries over a longer period of twenty years until the end of 2019. Our study highlights the importance of each stock market in influencing the Saudi stock market and identifies the strength of the impact of oil compared to the impact of the stock markets of China, the US, Japan, the UK, Germany, and France. Our results contribute to a better understanding of the interdependence between global stock markets and the factors that affect the Saudi stock market.

In addressing the broader context and theoretical underpinnings of these findings, our investigation significantly contributes to the existing body of knowledge on the interconnectedness of global financial markets and the pivotal role of commodities like oil in shaping market dynamics. The marked influence of oil prices on the Saudi stock market, as highlighted in our results, underscores the critical economic theory of commodity-dependent market behavior, especially in countries with

Table 3
SVM results.

Stock Indices & Oil Prices	Panel A	Panel B	Panel C	Panel D	Panel E	Panel F	Panel G
	Importance of variables						
BRT	100.00	100.00	100.00	99.832	100.00	2.366	100.00
CAC	–	23.503	21.278	30.623	4.604	35.091	3.87
DAX	21.493	14.608	35.196	27.073	11.077	66.67	15.025
DOW	10.945	6.571	12.266	12.359	8.23	–	2.125
NIK	46.57	39.428	52.313	34.797	59.067	45.92	30.689
SSE	57.481	45.36	23.874	71.24	28.254	8.736	24.466
UK	40.185	20.093	32.197	35.278	21.95	100.00	15.574
WTI	95.599	80.146	86.181	100.00	79.044	3.705	47.668
Model Parameters							
Number of points evaluated during search	1095	1095	1112	1100	1093	1105	1096
Minimum error found by search	0.001028	0.001048	0.001085	0.001132	0.000992	0.000597	0.000951
Epsilon	0.001	0.001	0.001	0.001	0.001	0.001	0.001
C	1.95363735	1.40814162	7375.8293	1.17613604	455.434919	0.22583537	2.01199314
Gamma	0.38662773	0.43560045	0.00331382	0.44297339	0.01107176	0.12258324	0.43560276
P	0.01389887	0.01359359	0.00137005	0.01	0.00999993	0.00013632	0.01359359
Number of support vectors used by the model	538	523	883	584	532	302	356

Analysis of Variance	Training	Training	Validation	Training	Validation	Training	Validation	Training	Validation	Training	Training
Mean target value for input data	0.002002	0.002037	0.0013462	0.0020652	0.0014423	0.0021338	0.0012739	0.0020391	0.0018537	0.0073203	0.0006597
Mean target value for predicted values	0.0026482	0.0026778	0.0050452	0.0032291	0.0043654	0.0032899	0.0053906	0.002562	0.0029506	0.00727	0.0007854
Variance in input data	0.0011072	0.0011335	0.0006155	0.0011731	0.0005239	0.0012251	0.0004557	0.0010631	0.0012834	0.0006118	0.0010727
Residual after model fit	0.0009755	0.0009974	0.0006056	0.001057	0.0004939	0.0010766	0.000448	0.0009469	0.0012637	0.000582	0.0008922
R^2	0.11893	0.12009	0.01604	0.09895	0.05728	0.12118	0.01679	0.10933	0.01536	0.04860	0.16831
CV	15.601551	15.503557	18.281280	15.742758	15.408163	15.377302	16.616243	15.091001	19.177359	3.295712	45.279311
NMSE	0.881066	0.879908	0.983961	0.901049	0.942724	0.878816	0.983208	0.890675	0.984640	0.951396	0.831694
Correlation between actual and predicted	0.347842	0.348988	0.198284	0.319556	0.277616	0.352464	0.233243	0.334079	0.144088	0.235325	0.412689
Maximum error	0.188489	0.1904308	0.0625606	0.1994409	0.0632209	0.1911896	0.0635063	0.190045	0.1967749	0.1590573	0.1883722
RMSE	0.0312336	0.0315813	0.0246094	0.0325122	0.0222233	0.032812	0.0211672	0.0307716	0.0355483	0.0241255	0.0298694
MSE	0.0009755	0.0009974	0.0006056	0.001057	0.0004939	0.0010766	0.000448	0.0009469	0.0012637	0.000582	0.0008922
MAE	0.0211255	0.0212479	0.0192848	0.0217919	0.0174088	0.0220025	0.0160262	0.0210979	0.0231814	0.0168694	0.0205134
MAPE	90.493734	90.421804	90.897256	90.349398	89.618341	89.152414	90.707514	90.823666	94.324867	85.31195	88.79302

Note. Panel A: encompasses results with overall sample for the entire study period; Panel B: represents results using 2019 data as a validation set; Panel C: denotes results using 2018–2019 data as a validation set; Panel D: signifies results using 2017–2019 data as a validation set; Panel E: shows results using 20% random selection of the data automatically selected by the software; Panel F: highlights results before 2006 TASI collapse; and Panel G: presents results after 2006 TASI collapse. R^2: is the proportion of variance explained by the model; CV: is the coefficient of variation; NMSE: refers to the normalized mean square error; RMSE: refers to the root mean squared error; MSE: refers to the mean squared error; MAE: refers to the mean absolute error; and MAPE: refers to the mean absolute percentage error. SVM results show that all the six stock markets have influence on the Saudi stock market (with exception of CAC on Panel A and DOW on Panel F). In particular, the results show that BRT and WTI have the most significant influence on the Saudi stock market among all stock markets. Interestingly Panel F results show that the UK has the most significant influence on the Saudi stock market in consistence with other models results. However, it is noteworthy that SVM uniquely captures subtle influences of other markets on the Saudi market prior to the 2006 collapse, a detail not detected by the GMM model, which only underscores the UK's significance at a 90% confidence level. This underscores the SVM model's sensitivity in capturing nuanced market influences, offering a more detailed perspective compared to the GMM model.

mono-commodity economies like Saudi Arabia. This phenomenon aligns with the core principles of market sensitivity to global economic forces and dependency theory, which posits that the economic prospects of commodity-rich countries are intricately tied to the global valuation of these commodities.

Furthermore, our empirical analysis provides nuanced insights into the evolving nature of global economic relationships, as evidenced by the shifting influence of various international stock markets on the Saudi market. This aligns with the empirical literature emphasizing the increasing globalization of financial markets and the complex web of interdependencies among them. The policy implications of our study are profound, especially for Saudi Arabia's Vision 2030 initiative. Our findings suggest that while diversification away from oil dependency is a strategic imperative, the country's financial market will continue to be significantly influenced by global oil dynamics in the short to medium term. For investors and policymakers alike, these insights offer a strategic vantage point for portfolio diversification, risk management, and aligning investment strategies with emerging global economic patterns.

4.2. Pre- and post-Saudi stock market collapse subperiods

In our study, we utilized SVM Model to examine the Saudi Arabian stock market before and after its collapse. Our analysis, as shown in Table 3 and Fig. 7, revealed that the British stock market was the most

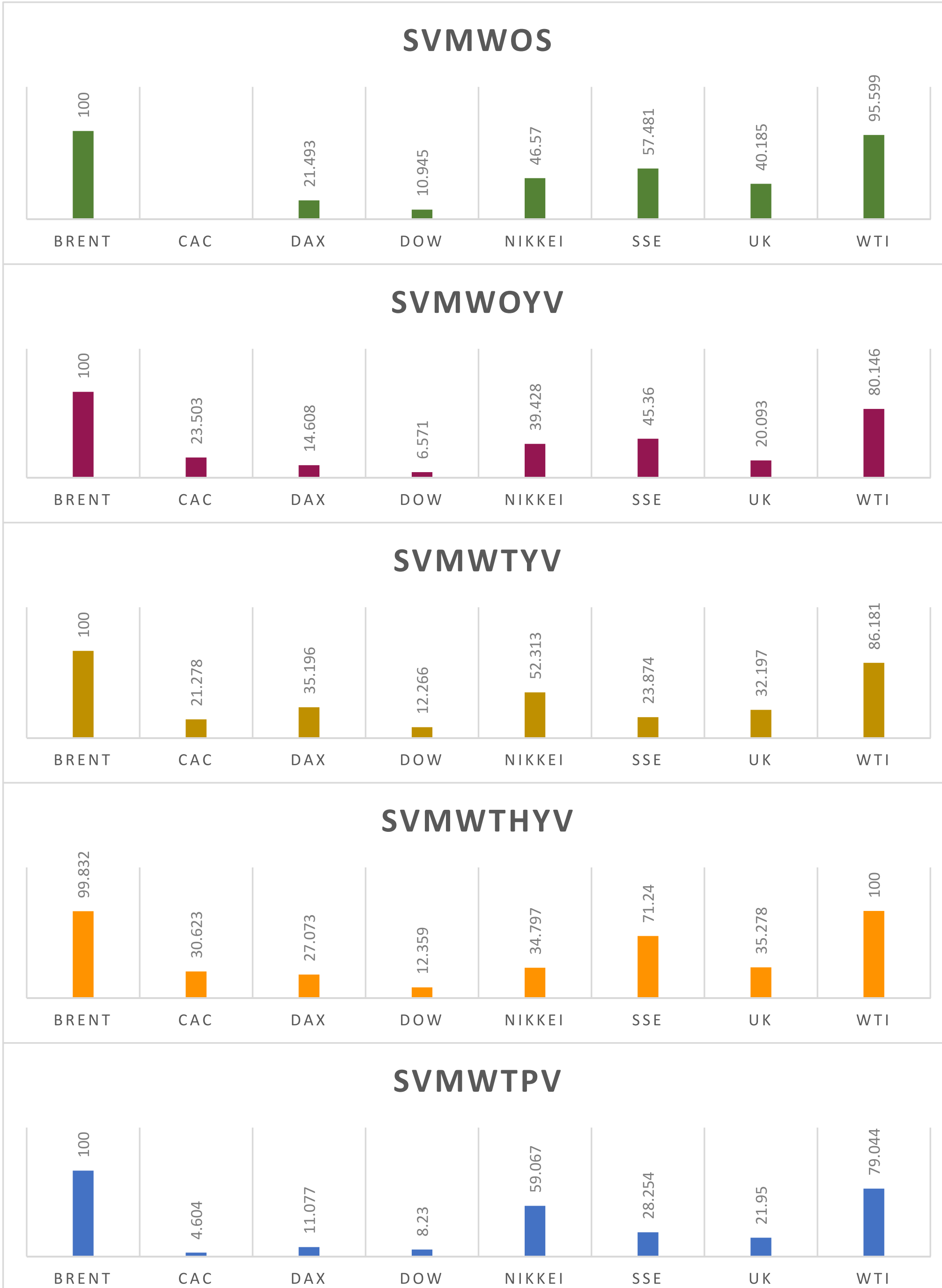

Fig. 5. The Importance of international stock indices and oil in predicting the Saudi stock index.
Note: SVMOS: importance with overall sample for the entire study period, SVMWOYV: importance with 2019 validation for the entire study period, SVMWTYV: importance with 2018 and 2019 validation for the entire study period, SVMWTHYV: importance with 2017–2019 validation for the entire study period, SVMWTPV: importance with 20% validation for the entire study period.

influential on the Saudi stock market before its collapse (i.e. Panel F), followed by the German, Japanese, French, and Chinese stock markets, respectively, with WTI and BRT being the least influential. Interestingly, we found that the US stock market had no influence on the Saudi stock market during this period. These findings are in contrast to the results obtained when applying the model to the entire study period, where oil was the most influential factor, and the Chinese stock market was more influential than the French and German stock markets. These results contradict Saâdaoui (2021) findings, which indicated that the nexus between the Saudi and UK stock markets is less important than the nexus between the Saudi and US stock markets. Our study contributes to the existing literature by highlighting the changing nature of the influence of international stock markets on the Saudi stock market before and after its 2006 collapse.

Based on our analysis presented in Table 3 and Fig. 7, our findings suggest that the Brent and WTI crude oil markets are the primary

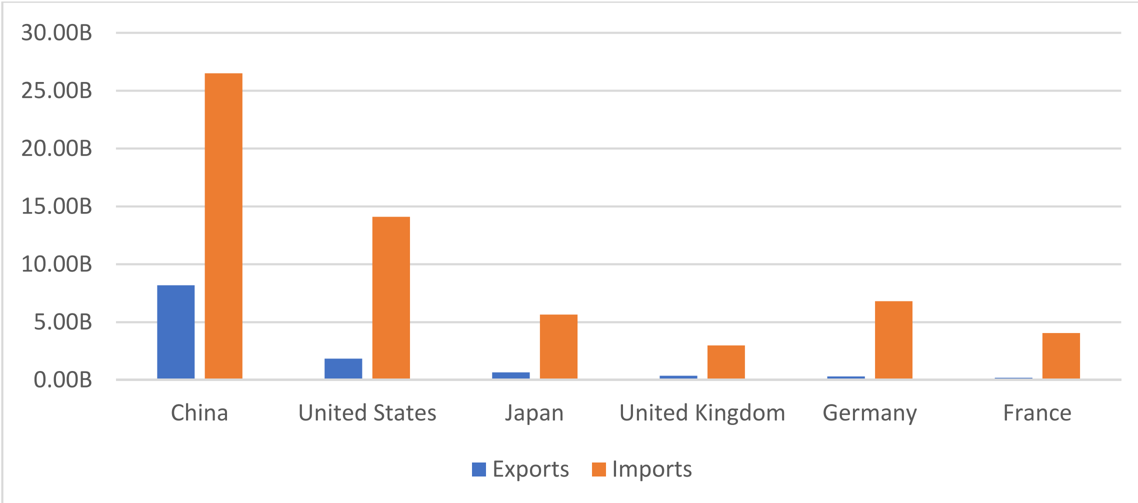

Fig. 6. Saudi Arabia Exports and Imports 2020.
Note: This Figure provides a clear illustration of the significant trade relationship between China and KSA, with a noteworthy Saudi export value of $8.18B and import value of $26.51B from China in 2020. Additionally, the US is identified as the second-highest importer from KSA in 2020 with a value of $14.10B, as demonstrated in Table 2.
Source: Trading Economics.

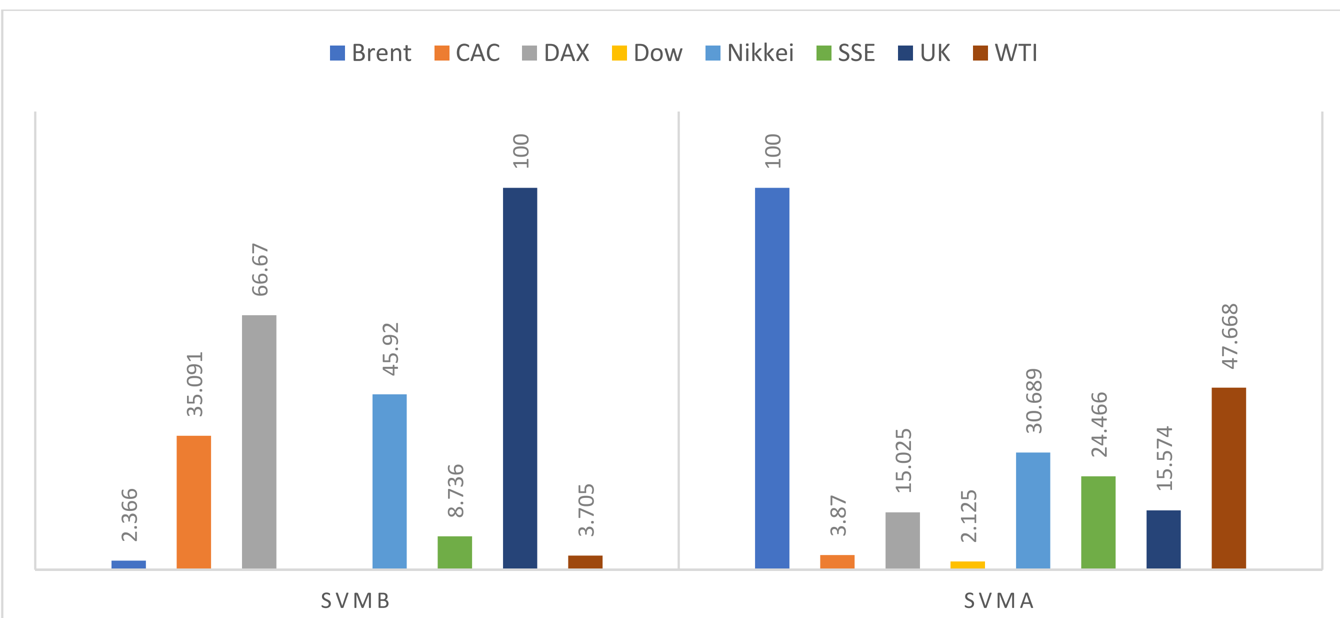

Fig. 7. The importance of international stock indices and oil in predicting the Saudi stock index before and after the 2006 Saudi stock market collapse.
Note: SVMB: importance before the 2006 Saudi stock market collapse, SVMA: importance after the 2006 Saudi stock market collapse. This Figure reveals the ranking of the influence of various stock markets on the Saudi stock market before and after the 2006 collapse. Before the collapse, the British stock market was the most influential, followed by the German, Japanese, French, and Chinese markets. After the collapse, the Brent and WTI crude oil markets become the primary influencers, with Brent having the most significant impact, followed by WTI, the Japanese stock market, and the Chinese stock market. The British stock market now ranks fifth, with the German and French markets in sixth and seventh place, respectively, and the US stock market has the least influence.

influencers of the Saudi stock market after the 2006 collapse (i.e. Panel G), with Brent having the most significant impact, followed by WTI, the Japanese stock market, and the Chinese stock market.[2] The British stock market follows in fifth place, with the German stock market ranking[3] sixth and the French stock market in seventh place. The US stock market has the least influence on the Saudi stock market. These results are consistent with our findings throughout the entire study period.

Our analysis also reveals four significant impacts of the 2006 collapse on the Saudi stock market. Firstly, the influence of oil on the Saudi market significantly increased after the collapse. This outcome corroborates established theoretical pathways, encompassing several channels: the stock evaluation channel, elucidating the connection between stock valuation and economic theory that defines stock value as the projected discounted cash flow (Huang et al., 1996). The influence of

[2] Available at: https://data.worldbank.org/indicator/NY.GDP.PETR.RT.ZS?locations=SA

[3] Available at: https://data.worldbank.org/indicator/BM.KLT.DINV.CD.WD?locations=SA&type=shaded&view=map&year=2019

oil prices on stock cash flows varies depending on the association between the company and oil, impacting revenues or expenses and, consequently, altering cash flows. Investors subsequently reassess stock valuation, thereby affecting stock prices (see for example, Mohanty et al., 2011; Oberndorfer, 2009; Mork et al., 1994; Bohi, 1991). Another channel, the monetary channel, emerges from oil price impacts on inflation rates, consequently influencing interest rates, a direct determinant in stock valuation discount rates (Degiannakis et al., 2018). Rising oil prices inflate production costs, triggering an upsurge in prices for goods and services, which in turn elevates inflation rates. Central banks respond by increasing interest rates to curb inflation (see for example, Abel and Bernanke, 2001; Basher and Sadorsky, 2006; Hamilton, 1996). Elevated interest rates translate into higher borrowing costs and an upward adjustment in the stock valuation discount rate, adversely affecting the stock market (Degiannakis et al., 2018). Furthermore, the fiscal channel pertains to oil-exporting nations highly reliant on oil revenues to finance their infrastructure (Farzanegan, 2011). Fluctuations in oil prices directly impact these countries' government expenditures, both in the short and long term (Hassan, 2021). Surges in oil prices prompt augmented government spending, thereby increasing corporate cash flows and subsequently boosting stock prices. Conversely, declining oil prices trigger reduced government spending, leading to decreased corporate cash flows and ultimately resulting in a decline in share prices.

Secondly, traders in the Saudi market became more rational, with their decisions being more affected by oil than stock markets. Given their growing conviction that oil prices have a more significant impact on the performance of companies operating in Saudi Arabia, consequently affecting their stock prices to a greater extent compared to the influence of changes occurring in other stock markets. Particularly notable is that the majority of emotionally driven traders, characterized by impulsive decision-making and margin trading, have incurred complete losses in their investments. This has imparted a harsh lesson to the remaining traders, emphasizing the importance of discipline and prudence in the market. Furthermore, those traders who have remained in the market have tended to exhibit greater prudence than those who exited due to the complete loss of their investments.

Thirdly, the Japanese stock market became the most influential, replacing the British market due to a decline in Saudi foreign direct investment in Britain and an increase in Saudi foreign direct investment in Japan. Finally, China's stock market has become more influential than Germany's due to a significant increase in Saudi foreign direct investment in China. Our findings have practical implications for individual investors, investment funds, institutional investors, and policy and decision-makers in the Saudi Capital Market Authority. These results can help investors diversify and hedge their investment portfolios while enabling decision-makers to take the necessary precautions during major movements in oil and global stock markets. Overall, our study provides empirical evidence on the relationship between the Saudi stock market and oil and six international stock markets that can help stakeholders make informed decisions.

This study's comprehensive analysis pre- and post-Saudi stock market collapse offers significant theoretical and empirical insights into the changing dynamics of stock market interdependencies. Our findings, particularly the increased influence of oil post-collapse, align with the economic theories of market sensitivity to global commodity prices and intermarket relationships. This sheds light on the shifting landscape of global financial interdependencies, where oil, as a crucial economic driver, significantly influences market behavior, especially in oil-centric economies like Saudi Arabia.

Moreover, the empirical evidence presented here underscores the evolving nature of international economic ties, evidenced by the changing influence rankings of various stock markets on the Saudi market. The practical implications are substantial for investors and policymakers, underscoring the need for diversified investment strategies that account for these dynamic intermarket relationships. This study not only contributes to the existing body of knowledge on global market interdependencies but also provides a strategic framework for stakeholders in navigating the increasingly interconnected global financial landscape.

4.3. Additional analysis

In order to ensure the reliability of our findings, we employed additional models, namely GRNN, RBFNN, DTF and TB models. Tables 3, 6, and 7, alongside Fig. 10, collectively illustrate a consistent pattern among the outcomes derived from the SVM, TB, and DTF models. These results strongly indicate that BRT exerts the most substantial influence on the Saudi stock market throughout the entirety of our study period. Correspondingly, these Tables, in conjunction with Fig. 10, suggest that while WTI also has a noteworthy impact on the same market, its influence appears to be comparatively less significant than that of BRT.

Moreover, Tables 3 and 5, along with Fig. 10, highlight how the SVM and RBFNN models delineate the subsequent influence of SSE on the Saudi stock market. Additionally, Tables 3, 5, and 6, coupled with Fig. 10, propose that the SVM, RBFNN, and TB models point to the subsequent effect of NIKKIE. Finally, Tables 3, 4, 5, and 6, in parallel with Fig. 10, illustrate that the SVM, GRNN, TB, and RBFNN models indicate the subsequent impact exerted by DAX.

These findings collectively demonstrate a significant alignment among the employed models. It is evident that the RBFNN and TB models closely mirror the patterns observed in the SVM model. Remarkably, the DTF model exhibited less conformity, primarily due to its higher predictive error measures (RMSE, MSE, MAE, and MAPE) compared to the other models, as revealed by Tables 3, 4, 5, 6, and 7. These results strongly imply the accuracy and reliability of our findings throughout the entire study duration.

Preceding the 2006 collapse, Tables 3, 5, 6, 7, along with Fig. 10 collectively underscore a significant impact from the British stock market on the Saudi stock market, as suggested by several models including SVM, RBFNN, TB, and DTF. However, there exists a disparity among these models regarding the prioritization of influence from oil and other markets on the Saudi stock market, highlighted in Fig. 8. This discrepancy could potentially be attributed to stock prices escalating to levels surpassing their fair valuation, notably witnessed when TASI reached a peak of 20,744 on February 26, 2006, as illustrated in Fig. 9. Moreover, during this period, investors leaned more towards speculative activities rather than embracing a buy-and-hold strategy (Benjelloun and Abdullah, 2009), which might account for the divergent outcomes observed from the five models utilized at that time.

In contrast, following the collapse, an analysis of Tables 3, 4, 5, and Fig. 10 reveals SVM, TB, and DTF models highlighting BRT as the predominant driver in the Saudi market. Moreover, Tables 3, 5, and Fig. 10 suggest SVM and RBFNN models positioning WTI as following BRT in its influence on the same market. These specific tables, alongside Fig. 10, identify NIKKIE as the third influential factor, succeeded by SSE in the fourth position and UK in the fifth.

The significant consistency observed among the machine learning models underscores the accuracy of our findings, particularly emphasizing the alignment of RBFNN and TB models with the SVM model. These results emphasize that preceding the 2006 collapse, the British stock market played a central role in influencing the Saudi stock market. However, post-collapse, this influence transitioned towards oil, the Japanese, and Chinese stock markets.

Our additional analysis using GRNN, RBFNN, DTF, and TB models offers robust empirical support for our initial findings, reinforcing the theoretical underpinnings regarding market influences and interdependencies. The consistency across models strengthens the reliability of our results, highlighting BRT's predominant influence on the Saudi stock market, a finding that aligns with economic theories on commodity market impacts. This consistency is critical in understanding

Table 4
GRNN results.

Stock Indices & Oil Prices	Panel A	Panel B		Panel C		Panel D		Panel E		Panel F	Panel G
	Importance of variables										
BRT	42.076	45.794		52.187		52.004		59.753		34.108	100.00
CAC	18.349	18.947		19.887		16.834		28.123		73.036	10.436
DAX	14.837	15.098		17.429		17.254		22.704		77.728	15.726
DOW	8.022	12.55		12.602		12.613		15.172		31.317	8.311
NIK	98.531	91.875		94.029		85.034		100.00		32.835	72.601
SSE	100.00	100.00		100.00		100.00		83.051		18.046	91.964
UK	67.912	67.427		58.665		59.268		45.508		100.00	29.765
WTI	24.643	29.507		20.696		29.778		31.676		26.488	51.843
Model Parameters (Neural Network Parameters)											
Starting Parameters Evaluations	20,480	20,480		20,480		20,480		20,480		5800	13,340
Conjugate Gradient Evaluations	43,008	43,008		43,008		43,008		44,032		3190	17,342
Starting Parameters Error	1.0455e-003	1.0455e-003		1.0455e-003		1.0455e-003		1.0456e-003		6.1757e-004	9.8440–004
Conjugate Gradient Error	1.0215e-003	1.0215e-003		1.0215e-003		1.0215e-003		1.0217e-003		6.1648e-004	9.6027–003
Analysis of Variance	Training	Training	Validation	Training	Validation	Training	Validation	Training	Validation	Validation	Validation
Mean target value for input data	0.002002	0.002037	0.0013462	0.0020652	0.0014423	0.0021338	0.0012739	0.0020391	0.0018537	0.0074267	0.0006597
Mean target value for predicted values	0.0023977	0.0023123	0.0041678	0.0023203	0.0032815	0.0022092	0.0040376	0.0024931	0.0034768	0.009045	0.0013169
Variance in input data	0.0011072	0.0011335	0.0006155	0.0011731	0.0005239	0.0012251	0.0004557	0.0010631	0.0012834	0.0006132	0.0010727
Residual (unexplained) variance after model fit	0.0008544	0.0008684	0.0006044	0.0008968	0.0004991	0.0009312	0.0004463	0.0008457	0.0012483	0.0005544	0.0007779
R^2	0.22836	0.23387	0.01804	0.23555	0.04740	0.23986	0.02060	0.20450	0.02735	0.09589	0.27488
CV	14.600605	14.466554	18.262701	14.500431	15.488695	14.301415	16.584035	14.261914	19.060276	3.170538	42.278713
NMSE	0.771640	0.766134	0.981962	0.764449	0.952604	0.760143	0.979400	0.795497	0.972653	0.904113	0.725116
Correlation between actual and predicted	0.494631	0.500288	0.245770	0.502365	0.234986	0.507143	0.199217	0.466596	0.176720	0.272716	0.538481
Maximum error	0.1607616	0.1607616	0.0640935	0.1607616	0.0641806	0.1607616	0.0646498	0.1607616	0.1951583	0.1598532	0.1636398
RMSE	0.0292297	0.0294689	0.0245844	0.0299465	0.0223395	0.0305163	0.0211262	0.0290811	0.0353312	0.0235467	0.02789
MSE	0.0008544	0.0008684	0.0006044	0.0008968	0.0004991	0.0009312	0.0004463	0.0008457	0.0012483	0.0005544	0.0007779
MAE	0.0198475	0.0198867	0.0192875	0.0201339	0.0177436	0.0205566	0.0162657	0.0197817	0.0232279	0.0169783	0.0193557
MAPE	87.681914	87.41798	93.138882	87.106356	94.547978	86.426735	96.037998	87.24618	95.999109	83.822278	87.709707

*Note***:** Panel A: encompasses results with overall sample for the entire study period; Panel B: represents results using 2019 data as a validation set; Panel C: denotes results using 2018–2019 data as a validation set; Panel D: signifies results using 2017–2019 data as a validation set; Panel E: shows results using 20% random selection of the data automatically selected by the software; Panel F: highlights results before 2006 TASI collapse; and Panel G: presents results after 2006 TASI collapse. R^2: is the proportion of variance explained by the model; CV: is the coefficient of variation; NMSE: refers to the normalized mean square error; RMSE: refers to the root mean squared error; MSE: refers to the mean squared error; MAE: refers to the mean absolute error; and MAPE: refers to the mean absolute percentage error. The results obtained from the GRNN indicate that all six international stock markets exert an influence on the Saudi stock market. These results identify the SSE and NIK indices as exerting the most substantial impact among these markets. Furthermore, Panel F results show the relying of the Saudi market on the UK in consistency of the SVM model results; and finally, an intriguing observation from Panel G is the discernible increase in BRT influence on the Saudi market following the TASI collapse in 2006, highlighting a significant shift in market dynamics post-crisis.

Table 5
RBFNN results.

Stock Indices & Oil Prices	Panel A	Panel B		Panel C		Panel D		Panel E		Panel F	Panel G
	Importance of variables										
BRT	–	–		–		88.274		40.132		7.257	100.00
CAC	100.00	100.00		39.473		84.79		1.852		99.982	86.100
DAX	17.602	12.708		87.88		67.376		0.559		14.287	6.296
DOW	58.144	35.896		26.657		68.933		52.903		37.216	95.514
NIK	73.103	66.719		90.823		60.579		68.276		100.00	84.040
SSE	67.401	38.973		100.00		100.00		15.063		19.422	27.008
UK	26.211	23.162		28.198		20.099		100.00		88.635	10.165
WTI	17.423	19.475		–		86.46		43.481		28.823	63.914
Model Parameters											
Number of neurons	3	3		3		5		3		3	3
Minimum radius	2.40597	2.40597		6.91894		1.72602		5.58553		0.01	2.40597
Maximum radius	383.508	383.508		389.107		395.465		376.787		406.248	392.245
Minimum Lambda	1.74572	1.74572		1.74572		1.08473		0.37818		0.14297	1.56762
Maximum Lambda	9.55698	9.55698		2.1178		5.63195		4.46681		5.22204	9.55698
Regularization Lambda for final weights	5.0913e-005 after 4 iterations	5.3854e-005 after 4 iterations.		6.8294e-005 after 4 iterations.		6.7163e-005 after 4 iterations.		2.9616e-005 after 4 iterations.		1.8065e-005 after 4 iterations.	7.6960e-005 after 4 iterations.
Analysis of Variance	Training	Training	Validation	Training	Validation	Training	Validation	Training	Validation	Training	Training
Mean target value for input data	0.002002	0.002037	0.0013462	0.0020652	0.0014423	0.0021338	0.0012739	0.0020391	0.0018537	0.0073203	0.0006597
Mean target value for predicted values	0.002002	0.002037	0.0049253	0.0020652	0.0044667	0.0021338	0.0047689	0.0020391	0.0024791	0.0073203	0.0006597
Variance in input data	0.0011072	0.0011335	0.0006155	0.0011731	0.0005239	0.0012251	0.0004557	0.0010631	0.0012834	0.0006118	0.0010727
Residual (unexplained) variance after model fit	0.0010112	0.0010321	0.0006201	0.0010789	0.0004852	0.0010925	0.0004536	0.0009621	0.0012327	0.0005656	0.0009288
R^2	0.08677	0.08943	0.00000	0.08034	0.07383	0.10820	0.00466	0.09500	0.03953	0.07549	0.13413
CV	15.883786	15.771332	18.498992	15.904537	15.272306	15.490487	16.718425	15.211849	18.940530	3.248808	46.200322
NMSE	0.913232	0.910566	1.007536	0.919663	0.926173	0.891800	0.995338	0.904997	0.960470	0.924508	0.865873
Correlation between actual and predicted	0.294565	0.299056	0.121639	0.283437	0.307694	0.328937	0.198224	0.308226	0.201874	0.274757	0.366234
Maximum error	0.202625	0.2025719	0.0641558	0.1970203	0.062091	0.188017	0.0624889	0.1790914	0.2010963	0.1492048	0.1670608
RMSE	0.0317986	0.0321268	0.0249025	0.0328463	0.0220274	0.0330535	0.0212974	0.0310181	0.0351093	0.0237821	0.030477
MSE	0.0010112	0.0010321	0.0006201	0.0010789	0.0004852	0.0010925	0.0004536	0.0009621	0.0012327	0.0005656	0.0009288
MAE	0.0219563	0.0220855	0.0193931	0.0223443	0.0171814	0.0227742	0.0162766	0.0216362	0.0233438	0.0170735	0.0215067
MAPE	93.918158	93.902397	91.736524	93.163631	90.131558	94.125469	92.226327	93.696268	97.437315	89.5914	92.182067

Note: Panel A: encompasses results with overall sample for the entire study period; Panel B: represents results using 2019 data as a validation set; Panel C: denotes results using 2018–2019 data as a validation set; Panel D: signifies results using 2017–2019 data as a validation set; Panel E: shows results using 20% random selection of the data automatically selected by the software; Panel F: highlights results before 2006 TASI collapse; and Panel G: presents results after 2006 TASI collapse. R^2: is the proportion of variance explained by the model; CV: is the coefficient of variation; NMSE: refers to the normalized mean square error; RMSE: refers to the root mean squared error; MSE: refers to the mean squared error; MAE: refers to the mean absolute error; and MAPE: refers to the mean absolute percentage error. The results from the RBFNN demonstrate varied outcomes. Notably, these networks did not detect any significant influence of BRT in Panels A, B, and C. However, Panel D, which utilizes a three-year validation set, reveals a pronounced role for BRT and WTI, along with SSE. The divergent outcomes from this network suggest that employing a three-year validation set can enhance the predictive accuracy. This extended validation period seems better suited to capture the dynamic influences of BRT and WTI, as well as SSE, on the Saudi stock market, thereby offering a more comprehensive understanding of market influences over a longer time frame. Prior to the 2006 TASI collapse, the NIK, CAC, and UK indices were identified as key influencers of the Saudi stock market. In contrast, post-collapse in 2006, the DAX, SSE, and BRT emerged as the most influential indices on the Saudi stock market.

Table 6
Tree Boost results.

Stock Indices & Oil Prices	Panel A	Panel B	Panel C	Panel D	Panel E	Panel F	Panel G
	Importance of variables						
BRT	85.358	87.545	78.257	71.212	61.144	58.150	100
CAC	69.275	74.537	60.996	69.538	66.791	54.521	63.920
DAX	67.010	65.354	54.349	72.145	72.803	49.972	72.119
DOW	75.550	77.283	62.284	89.351	44.803	55.418	80.793
NIK	78.131	74.081	59.327	52.976	100	56.817	81.675
SSE	100	100	100	100	66.931	100	87.256
UK	68.880	47.829	51.928	39.350	60.857	55.346	69.001
WTI	80.198	76.63	70.252	43.141	65.536	60.134	90.969
Model Parameters							
Maximum trees in Decision Tree Forest	30,000	30,000	30,000	30,000	30,000	30,000	30,000
Maximum splitting levels	5	5	5	5	5	5	5
Minimum size node to split	10	10	10	10	10	10	10
Max. categories for continuous predictors	1000	1000	1000	1000	1000	1000	1000
Maximum depth of any tree in the forest	5	5	5	5	5	5	5
Average number of group splits in each tree	7.8	7.5	7	7.1	6.3	3.4	5.4.

Analysis of Variance	Training	Training	Validation	Training	Validation	Training	Validation	Training	Validation	Training	Training
Median target value for initial data sample	0	0	0	0	0	0	0	0	0	0.01	0
Mean target value for initial data sample	0.002002	0.002037	0.0013462	0.0020652	0.0014423	0.0021338	0.0012739	0.0020391	0.0018537	0.0048039	0.0006597
Mean target value for predicted values	0.0019583	0.0020205	0.0044383	0.0024701	0.004322	0.0002624	0.0005256	0.0007561	0.0007708	0.00479	0.0006238
Average absolute error for initial data sample	0.0225098	0.0226764	0.0194231	0.0230066	0.0180917	0.0236388	0.0162051	0.0223116	0.0233009	0.023341	0.0224792
Average absolute error after tree fitting	0.2026797	19.667062	1.0011493	16.910512	1.8044231	20.261854	2.5269671	17.551899	4.7533602	0.0455107	0.077277
Variance in initial data sample	0.0011072	0.0011335	0.0006155	0.0011731	0.0005239	0.0012251	0.0004557	17.551899	0.0012834	0.0012049	0.0010727
Residual (unexplained) variance after modelling	0.0000015	0.0008765	0.0006155	0.0007206	0.000503	0.0011977	0.0004527	0.0009691	0.001271	0.0000003	0.0000004
R^2	0.99863	0.22671	0.02055	0.38577	0.03982	0.02239	0.00664	0.08847	0.00966	0.99978	0.99965
CV	0.615814	14.533923	18.239291	12.997838	15.550133	16.218662	16.701814	15.266623	19.232808	0.107069	0.927742
NMSE	0.001373	0.773286	0.979446	0.614227	0.960177	0.977614	0.993361	0.911526	0.990342	0.000220	0.000349
Correlation between actual and predicted	0.999382	0.548733	0. 0.207245	0.685334	0.243056	0.432480	0.161720	0.518643	0.114867	0.999908	0.999842
Maximum error	0.0238938	0.1591657	0.0643359	0.1543385	0.0602533	0.2044509	0.0693443	0.1798361	0.2080557	0.0060966	0.0137122
RMSE	0.0012328	0.0296061	0.0245529	0.0268434	0.0224281	0.0346073	0.0212762	0.0311297	0.0356511	0.0005144	0.000612
MSE	0.0000015	0.0008765	0.0006028	0.0007206	0.000503	0.0011977	0.0004527	0.0009691	0.001271	0.0000003	0.0000004
MAE	0.0001979	0.0202336	0.0192529	0.018381	0.0173502	0.0233701	0.0160953	0.0214309	0.0231871	0.0001115	0.0001159
MAPE	0.6291531	87.278764	90.930954	79.97859	87.418428	98.534631	0.0160953	94.698572	97.715421	0.3472616	0.4612096

Note: Panel A: encompasses results with overall sample for the entire study period; Panel B: represents results using 2019 data as a validation set; Panel C: denotes results using 2018–2019 data as a validation set; Panel D: signifies results using 2017–2019 data as a validation set; Panel E: shows results using 20% random selection of the data automatically selected by the software; Panel F: highlights results before 2006 TASI collapse; and Panel G: presents results after 2006 TASI collapse. R^2: is the proportion of variance explained by the model; CV: is the coefficient of variation; NMSE: refers to the normalized mean square error; RMSE: refers to the root mean squared error; MSE: refers to the mean squared error; MAE: refers to the mean absolute error; and MAPE: refers to the mean absolute percentage error. The outcomes derived from the Tree Boost networks indicate that the SSE, BRT, and WTI are the predominant influencers on the Saudi stock market. Notably, the results from Panel G, which analyses the period post-TASI collapse in 2006, underscore that BRT and WTI have emerged as the most significant markets influencing the Saudi stock market. This finding aligns with the patterns observed in other network analyses, reinforcing the consistency of these influences across various modelling approaches.

Table 7
Decision Tree Forest results.

Stock Indices & Oil Prices	Panel A	Panel F	Panel G
	Importance of variables		
BRT	94.086	100	96.376
CAC	83.322	83.597	78.530
DAX	89.505	80.685	98.500
DOW	92.180	97.040	96.487
NIK	92.496	84.598	88.649
SSE	96.327	73.272	76.696
UK	86.014	92.167	83.035
WTI	100	96.380	100
Model Parameters			
Maximum trees in Decision Tree Forest	1000	1000	1000
Maximum splitting levels	500	500	500
Minimum size node to split	2	2	2
Max. categories for continuous predictors	1000	1000	1000
Maximum depth of any tree in the forest	42	26	44
Average number of group splits in each tree	503.4	146.2	330.3
Analysis of Variance: Out-of-bag validation data			
Median target value for initial data sample	0	0.01	0
Mean target value for initial data sample	0.002002	0.0073203	0.0006597
Mean target value for predicted values	0.0019583	0.0080148	0.0006005
Average absolute error for initial data sample	0.0224316	0.0176471	0.0224288
Average absolute error after tree fitting	22.956719	5.6070907	14.985445
Variance in initial data sample	0.0011072	0.0006118	0.0010727
Residual after modelling	0.0010651	0.0006498	0.001029
R^2	0.03802	0.00000	0.04074
CV	16.302247	3.482366	48.628077
NMSE	0.961984	1.062213	0.959264
Correlation between actual and predicted	0.213285	0.021659	0.226806
Maximum error	0.1923797	0.1552089	0.1816327
RMSE	0.0326363	0.0254918	0.0320785
MSE	0.0010651	0.0006498	0.001029
MAE	0.0224187	0.0183238	0.0224669
MAPE	96.701769	95.51372	96.459602

Note: Panel A: encompasses results with overall sample for the entire study period; Panel F: highlight results before 2006 TASI collapse; and Panel G: presents results after 2006 TASI collapse. R^2: is the proportion of variance explained by the model; CV: is the coefficient of variation; NMSE: refers to the normalized mean square error; RMSE: refers to the root mean squared error; MSE: refers to the mean squared error; MAE: refers to the mean absolute error; and MAPE: refers to the mean absolute percentage error. The results from the Decision Tree Forest model highlight the prominent role of BRT and WTI across all three panels. This consistent observation underscores the significant influence of these oil markets on the Saudi stock market, as evidenced in the model's findings.

market dynamics and for formulating effective investment strategies, particularly in the context of Saudi Arabia's evolving economic landscape. These findings hold substantial implications for investors and policymakers, underlining the importance of considering a wide range of international factors, including oil, in market analysis and decision-making processes. The variations in model outcomes also shed light on the behavioral shifts in the market pre- and post-2006 collapse, offering valuable insights for developing adaptive strategies in the face of market volatilities.

4.4. Robustness analysis

To enhance the accuracy of our findings, we employed the GMM model in our analysis. Tables 3, 6, 7, and 8, in conjunction with Fig. 10, collectively indicate a consensus among the results derived from SVM, TB, DTF, and GMM models. These findings suggest that BRT exerts the most pronounced influence on the Saudi stock market throughout the entire study duration. Similarly, these tables, along with Fig. 10, propose that WTI also holds a significant impact on the same market, albeit to a lesser degree compared to BRT. (Azar and Basmajian, 2013; Cevik et al., 2021; Finta et al., 2019; Hamdan and Hamdan, 2020; Jouini, 2013; Mensi et al., 2015).

Moreover, Tables 3, 5, and 8, alongside Fig. 10, highlight that SVM, RBFNN, and GMM models indicate the subsequent influence of SSE on the Saudi stock market. Additionally, these tables, along with Fig. 10, suggest that SVM, RBFNN, TB, and GMM models imply the subsequent effect of NIKKIE. Lastly, Tables 3, 4, 5, 6, 8, and Fig. 10 illustrate that SVM, GRNN, TB, RBFNN, and GMM models imply that DAX exerts subsequent impact.

These findings underscore a notable resemblance between the outcomes generated by the GMM model and those produced by machine learning models, thereby affirming the accuracy and consistency of our results across the entire study duration. Furthermore, these outcomes are consistent with the findings of Tissaoui and Azibi (2019), indicating a connection between the Saudi stock market and volatility indices of the German, Chinese, and British stock markets, alongside the influence of oil. Likewise, they align with the conclusions drawn by Arouri and Rault (2012), signifying a robust correlation between the Saudi stock market and the financial markets of the United States and Europe.

Preceding the 2006 collapse, Tables 3, 5, 6, 7, 8, and Fig. 10 collectively indicate that various models, SVM, RBFNN, TB, DTF, and GMM, suggest a noteworthy influence stemming from the British stock market on the Saudi stock market. The examination concerning the influence of oil and other markets displays an inconsistent ranking of impact across machine learning models. It is noteworthy that GMM model did not detect any significant association between these markets and the Saudi stock market. Conversely, following the collapse, an analysis of Tables 3, 4, 5, 8, and Fig. 10 reveals that SVM, TB, DTF, and GMM models point to BRT as the predominant driving force in the Saudi market. Additionally, Tables 3, 5, 8, and Fig. 10 propose that SVM, RBFNN, and GMM models indicate WTI trailing BRT in impacting the same market. These specific tables, along with Fig. 10, assert NIKKIE as the third impactful factor, succeeded by SSE in the fourth position and UK in the fifth.

The substantive coherence observed between the machine learning models and the GMM model reaffirms the precision of our findings, pinpointing SVM, RBFNN, and TB models as the most congruent with the GMM model. These outcomes delineate that the primary influencer on the Saudi stock market before the 2006 collapse is the British stock market, while after the collapse, it shifts to oil, the Japanese, and Chinese stock markets.

Notably, the GMM model indicates an inverse relationship between the Saudi and British stock markets across the study's duration. However, this inverse association extends post-2006 collapse to encompass the German and United States stock markets alongside the British market. This implies the potential for investors in these regions to consider investing in the Saudi stock market for diversification or hedging purposes. Simultaneously, it suggests the reciprocal potential for investors in the Saudi stock market to explore investments in these markets for similar diversification or hedging objectives. These findings bear significant relevance for policymakers, investors, and market participants seeking insights into the dynamics of the Saudi stock market and its interplay with global markets.

Our robustness analysis, employing the GMM model alongside ML models, has reinforced the validity and consistency of our findings. The concurrence between GMM and other models in identifying BRT and WTI as significant influencers aligns with prevailing theories on commodity market impacts and global inter-market dependencies. These findings offer practical insights for investors and policymakers, emphasizing the importance of oil in shaping market dynamics. Furthermore, the identified inverse relationships post-2006 collapse highlight strategic opportunities for international diversification and hedging, crucial for risk management in today's interconnected global

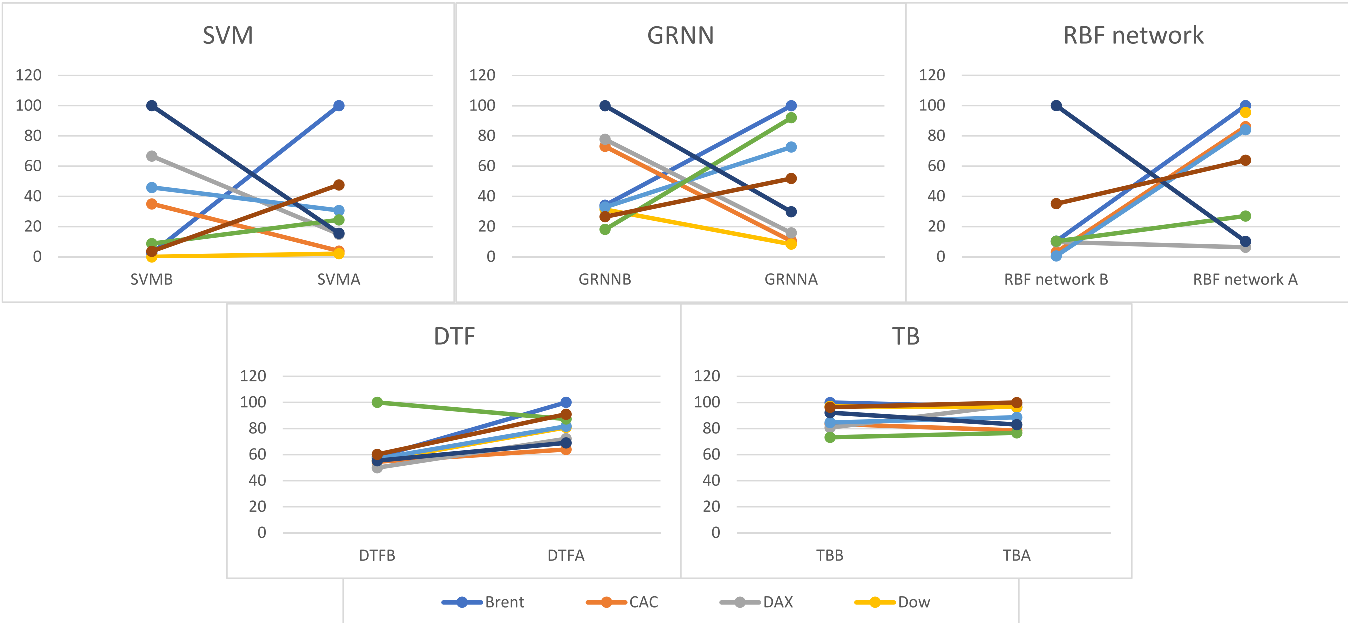

Fig. 8. The Importance of international stock indices and oil in predicting the Saudi stock index before and after the 2006 Saudi stock market collapse using SVM, GRNN, RBFNN (RBF network), DTF and TB models.
Note: SVMB: importance before 2006 Saudi stock market collapse using SVM, SVMA: importance after 2006 Saudi stock market collapse using SVM, GRNNB: importance before 2006 Saudi stock market collapse using GRNN, GRNNA: importance after 2006 Saudi stock market collapse using GRNN, RBFNN B: importance before 2006 Saudi stock market collapse using RBFNN, RBFNN A: importance after 2006 Saudi stock market collapse using RBFNN, DTFB: importance before 2006 Saudi stock market collapse using DTF, DTFA: importance after 2006 Saudi stock market collapse using DTF, TBB: importance before 2006 Saudi stock market collapse using TB and TBA: importance after 2006 Saudi stock market collapse using TB.

financial environment. This comprehensive analysis enriches the existing literature by offering nuanced insights into the evolving interplay between the Saudi stock market and global economic forces.

5. Conclusion and areas for future research

This study aimed to investigate the predictability power of oil prices and six international stock markets (China, France, UK, Germany, Japan, and the USA) on the Saudi stock market over the weekly period from January 2000 until December 2019, and to examine the co-movements that emerged due to the Saudi market crash in 2006. Our analysis used sophisticated machine learning techniques, namely SVM, GRNN, RBFNN, DSF and boost TB, and GMM to study the predictability power of oil and global stock markets on the Saudi stock market during pre-, post- 2006 and the whole study period.

Saudi Arabia launched Vision 2030 in 2016 to reduce its reliance on oil production, our study reveals that the Saudi stock market is still heavily influenced by oil. This finding is consistent with Jiang and Yoon's (2020) suggestion that there is a strong relationship between the Saudi stock market and oil, as Saudi Arabia is one of the largest oil-exporting countries. Additionally, our results support the findings of Mokni and Youssef (2019) that the Saudi market is the most closely related and dependent on oil prices among the Gulf Cooperation Countries (GCC). The Chinese stock market was found to have the second greatest influence, followed by the Japanese stock market, the British stock market, and the German stock market. The rankings of the French and US stock markets were swapped for seventh and eighth place, which supports Shen et al. (2015) assertion of contagion between stock markets of countries with significant trade exchange. For instance, Saudi Arabia's exports to China and imports from China in 2020 were valued at $8.18B and $26.51B, respectively. The study's results contradict Saâdaoui (2021) findings that the nexus between Saudi and UK stock markets is slightly less important than that between Saudi and US stock markets.

Moreover, a deeper analysis was carried out by accounting for the Saudi Arabian stock market collapse. We conducted five models before and after the collapse of the Saudi Arabian stock market. Our pre-collapse findings indicated that the British stock market was the most significant influencer on the Saudi stock market, followed by the German stock market, the Japanese stock market, the French stock market, the Chinese stock market, and oil, respectively. We also observed that there was no impact from the US stock market. In our post-collapse results, oil was found to be the most influential factor, followed by the Japanese stock market, the Chinese stock market in third place, and the British stock market in fourth place. The German stock market was ranked fifth, followed by the French stock market in sixth place, with the US stock market having the least influence.

To ensure the accuracy of our findings, we conducted our analysis using several machine learning models, namely SVM, GRNN, RBFNN, DTF, TB; and the GMM for robustness purposes. The results obtained were very similar, except for the results before the 2006 collapse. This could be attributed to the fact that during this time, stock prices reached inflated levels, exceeding their fair value, particularly when TASI peaked at 20,744 on February 26, 2006, its highest level ever recorded. Investors were more inclined to speculate rather than hold their investments (Benjelloun and Abdullah, 2009). These two factors could have contributed to the conflicting results of the three models used during that period.

Our study makes several contributions to the current literature. First, it sheds new light on the predictability power of international stock markets, oil prices on the Saudi stock market. Second, it examines the co-movement that emerged due to the Saudi market crash in 2006. Third, our results will be useful for individual investors in Saudi Arabia and investment funds, especially the Public Investment Fund in Saudi Arabia. Our results will help the Public Investment Fund to play its role in achieving Vision 2030 through two different aspects. First, it will help investment managers diversify the fund's portfolio of domestic and international investments. Second, it will improve the performance of

Fig. 9. TASI Japanese candlestick chart.
Note: The observed variation shown in this Figure could be ascribed to the potential overvaluation of stock prices exceeding their intrinsic worth, which coincided with TASI's apex on February 26, 2006. Moreover, investors may have displayed a greater preference towards speculative pursuits, as opposed to a long-term investment approach, during this time period (*Source*: TradingView[a]).
Available at: https://www.tradingview.com

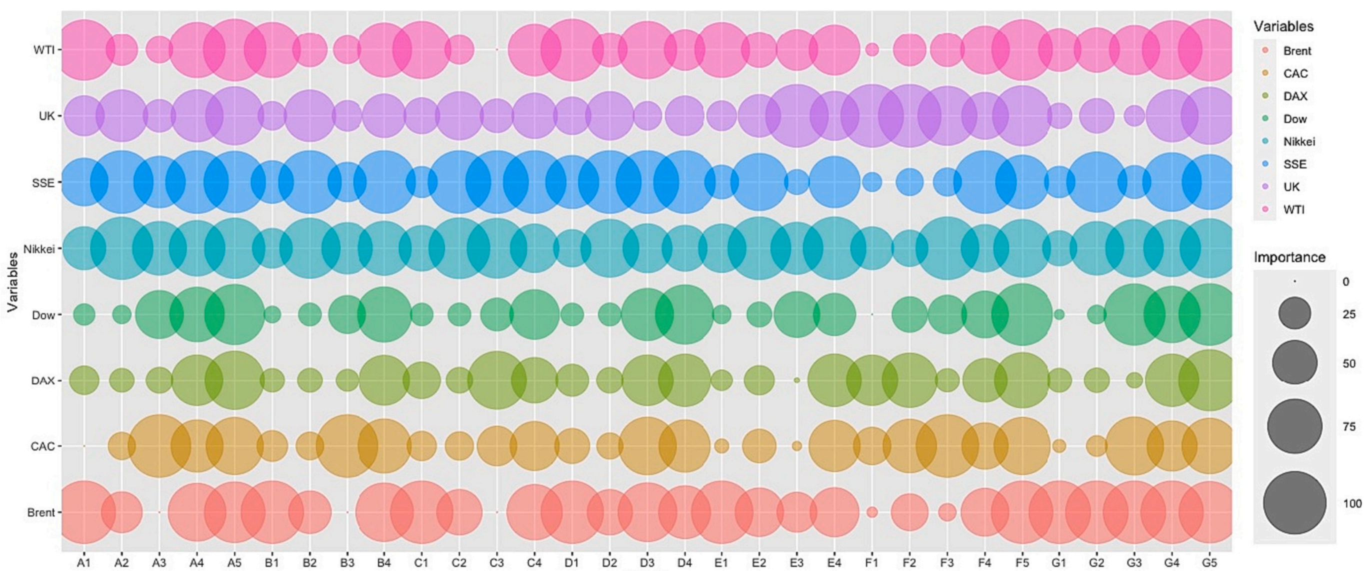

Fig. 10. The Importance of international stock indices and oil in predicting the Saudi stock using SVM, GRNN, RBFNN, DTF and TB models.
Note: A: encompasses results with overall sample for the entire study period; B: represents results using 2019 data as a validation set; Panel C: denotes results using 2018–2019 data as a validation set; Panel D: signifies results using 2017–2019 data as a validation set; Panel E: shows results using 20% random selection of the data automatically selected by the software; Panel F: highlights results before 2006 TASI collapse; and Panel G: presents results after 2006 TASI collapse; 1: denotes SVM; 2: denotes GRNN; 3: denotes RBFNN; 4: denotes TB; and 5: denotes DTF.

Table 8
The impact of oil and international stock markets on Saudi stock market using GMM.

Stock Indices & Oil Prices	Panel A	Panel F	Panel G
BRT	0.1837583*** 3.84	−0.0219021 −0.41	0.0784088*** 3.92
CAC	0.0088122 0.08	−0.1473876 −0.56	0.4481446*** 6.00
DAX	0.2173772** 2.35	−0.1827446 0.381	−0.2833378*** −3.18
DOW	−0.0483654 −0.44	0.0783486 0.47	−0.2500199** −2.52
NIK	0.2714937*** 7.16	0.0328616 0.31	0.5167581*** 12.93
SSE	0.0872269** 2.34	0.0934848 1.24	0.0886444*** 2.63
UK	−0.1135431 −0.88	0.3365779* 1.86	−0.1400919 −1.38
WTI	−0.2369505*** −9.78	0.0102557 0.19	−0.0869423** −2.21

Note: Panel A: encompasses results with overall sample for the entire study period; Panel F: highlight results before 2006 TASI collapse; and Panel G: presents results after 2006 TASI collapse. *, **, *** denotes significant relationship at 10%, 5%, and 1% threshold, respectively. This Table provides insights into the dynamic relationships between the Saudi stock market and several key global stock markets and commodity prices. Panel F indicates that the UK stock market had a positive and significant impact on the Saudi stock market before 2006. However, this effect was not observed in the subsequent years. In contrast, Panel G shows that several other markets, such as BRT, CAC, NIK, and SSE, had a significant and positive effect on the Saudi stock market. Conversely, DAX, DOW, UK, and WTI had a significant and negative effect. These findings suggest that the Saudi stock market is influenced by a complex set of domestic and global factors, and that the relationship between the Saudi market and other key markets is subject to change over time. Moreover, it is noteworthy that ML models, distinct from the GMM, were adept at identifying even the subtle influence of the UK market on the Saudi stock market in Panel G, post-TASI collapse in 2006. This highlights the nuanced capabilities of these models in detecting even minor but significant market roles across different time periods.

local investments, as our results will allow the fund to predict the future direction of the Saudi stock market using oil and six international markets.

Our findings hold significant implications for policymakers, particularly for the Saudi Capital Markets Authority. They can utilize these insights to implement preemptive measures aimed at mitigating the impact of major fluctuations in the global stock and oil markets on the Saudi stock market. This proactive approach is expected to reduce volatility in the Saudi market and subsequently lower investment risks. Simultaneously, it offers substantial support not only to the Public Investment Fund in Saudi Arabia but also to investors, investment funds, and hedging portfolios operating within the Saudi Arabia, United States, Germany, and Britain stock markets. These entities stand to gain significantly by adopting diversification or hedging strategies, effectively minimizing their investment risks. Our machine learning models reveal the considerable influence exerted by these international stock markets on the Saudi stock market. Notably, the GMM model not only confirms this influence but also indicates a contrary direction for this effect. Consequently, investors in these markets can optimize their use of the Saudi stock market for diversification or hedging purposes. Similarly, participants in the Saudi market can reciprocate by employing these international stock markets for similar risk management strategies.

In the short term, traders in the Saudi market can leverage our insights by meticulously monitoring the performance of international stock markets and oil during the Saudi weekend on Fridays, when these markets remain active. This proactive monitoring aids in predicting the potential performance of the Saudi stock market on the subsequent trading day, Sunday, when these markets are closed. Furthermore, this monitoring strategy can be implemented daily for the stock markets of Japan, China, and the United States. This is due to the trading sessions of Japan and China, starting 6 to 7 hours before the Saudi stock market, while the American stock market initiates and concludes trading prior to the opening of the Saudi market.

Our study makes significant strides in understanding the interplay between oil prices, international stock markets, and the Saudi stock market. We highlight the enduring impact of oil on the Saudi market, despite national diversification efforts. This aligns with existing theories on commodity-dependent economies and market interdependencies. Our analysis post the 2006 collapse underscores the increasing influence of oil, shifting relationships with global markets, and the evolving nature of investment strategies. However, our research is not without limitations. The reliance on weekly data may overlook finer market fluctuations, and our focus on selected international markets excludes other potential influencing factors.

Looking ahead, future research could broaden its scope by incorporating a wider range of international markets to further elucidate their influence on the Saudi stock market. Investigating the impacts using varied data frequencies, such as daily or monthly, could offer more granular insights into market dynamics. Additionally, exploring the role of other major commodities, socio-economic changes, and emerging market dynamics could provide a richer understanding of global financial interdependencies. The influence of technological advancements and digital assets, as well as the effects of pandemics and global crises, also present valuable avenues for deepening our comprehension of contemporary market behaviors.

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Hussein A. Abdou: Formal analysis, Conceptualization, Writing – review & editing, Visualization, Software, Methodology, Investigation, Supervision. **Ahmed A. Elamer:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Mohammad Zoynul Abedin:** Validation, Project administration, Investigation. **Bassam A. Ibrahim:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declared no potential conflicts of interest.

Data availability

Data available on request from the authors.

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