

Asset Pricing Movements Shaped by Investors' Behaviour: A DCC-GARCH Perspective on Saudi Arabia's TASI Index

Yassine Meliani ^{1*}, Lahcene Djediden ²

¹ University of Ain Temouchent, LMELSPM, Algeria, yassine.meliani@univ-temouchent.edu.dz



² University of Ain Temouchent, LMELSPM, Algeria, lahcene.djediden@univ-temouchent.edu.dz



Received: 11-10-2024

Accepted: 08-12-2024

Abstract

The study used a DCC-GARCH model to investigate the conditional association between the sentiment indexes and the TASI returns using weekly data from January 7, 2010, to August 1, 2024. The empirical analysis indicates that investor sentiment has a significant impact on the TASI index, with both positive and negative attitudes showing a strong correlation with changes in the market. The results also show how changes in oil and exchange rates have a knock-on effect on investor sentiment. The study provides valuable insights into the role investor attitude plays in asset pricing in the Saudi Arabian environment, particularly when accounting for external factors such as economic conditions and geopolitical threats.

Keywords:

Investors' behaviour;
Investors' sentiment;
Conditional correlation;
Financial market.

JEL Classification Codes: C61; D53 ;
G01

* Corresponding author

1. INTRODUCTION

The tenets of mainstream economic theory are that individuals make rational decisions based on all available information and that people behave rationally. This idea, known as rational actor theory (RAT), is the central tenet of the efficient market hypothesis (EMH). According to RAT, humans make perfectly reasonable decisions that result in outcomes that serve their own interests, or utility maximisation. According to RAT, when reasonable actors have constant access to correct and complete information, they base their decisions on computations that are error-free. Therefore, self-interested rational agents actively work to maximise their advantage in every given situation while continuously attempting to reduce their losses.(Hechter, 2001)

Behavioural finance emerged as a response to the neoclassical paradigm's inability to adequately explain financial occurrences. It argues that economic agents are not always rational and that investor decisions are influenced by human psychology. People might therefore make decisions based on psychological heuristics and biases. (Shiller, 1990). It implies that financial phenomena can be more thoroughly explained by models containing agents who exhibit some irrationality. Behavioural finance has application in a variety of financial disciplines, including asset pricing, corporate finance, and portfolio management. (Brooks & Byrne, 2008)

Both neoclassical and behavioural finance rely heavily on asset pricing to attempt to explain cross-sectional volatility in stock returns.(Nanayakkara, Nimal, & Weerakoon, 2020). The rational present value of anticipated future cash flows is always equal to capital market prices in neoclassical models because of the action of emotionless investors.(Baker & Wurgler, 2007). If a

stock is mispriced in these markets, the rational arbitrageurs will quickly correct the mispricing and bring the price down to its intrinsic value. The Markowitz portfolio theory gave rise to a robust body of knowledge known as neoclassical asset pricing.(Nanayakkara, Nimal, & Weerakoon, 2019)

Behavioural models in theory applied to asset pricing(Daniel, Hirshleifer, & Subrahmanyam, 1998) are based on particular heuristics or investor biases that explain stock returns. DHS (1998), one of the first models, uses two investor biases overconfidence and self-attribution to attempt to explain market underreaction and overreaction. DHS (1998) posits that overconfidence regarding private signals results in overreaction, whereas self-attribution sustains overconfidence and permits prices to overreact further, generating momentum. Two biases in judgement are the foundation of the BSV (1998) model: conservatism and representativeness bias. (Abeysekera & Nimal, 2017) BSV (1998) asserts that people tend to place more emphasis on current data trends than on the characteristics that lead to the creation of the data. Investors think that there are two regimes that the earning process stochastically alternates between: one with mean revert earnings and the other with predicted earning growths. These behavioural asset pricing models take into account investor overreaction and underreaction, which are visible in the markets, in contrast to neoclassical models. These theories present challenging empirical studies, even if they theoretically explain the actions of irrational stock market participants. (Barberis, Shleifer, & Vishny, 1998)

According to Baker and Wurgler (2007), theoretical behavioural models only attempt to address a small portion of the numerous psychological biases that influence an individual investor's behaviour in the markets. They contend that a few

chosen biases and trade frictions cannot adequately explain the complexity of real investors and marketplaces. As a result, they look at the top-down, macroeconomic investor sentiment method. It tracks the impact of reduced-form, aggregate sentiment on stock returns and focusses on measuring it. To represent the overall investor attitude in markets, they present the creation of a composite investor sentiment index.

The role of different sorts of investors and how they impact the stock market and corporate profitability is one of the most important issues in finance. Investor behaviour is an important factor that influences the performance of the stock market and businesses since different types of investors have distinct decision-making patterns. This is especially crucial in a developing stock market like the Saudi Arabian stock market, where a lot of individual investors with little experience and education in investing make up the market. Nonetheless, because of their significant exposure, high capital expenditure, and extensive investment knowledge, other categories of large investors, such as institutional and international investors, also play a significant and powerful role. (Phan, Bertrand, Phan, & Vo, 2023). This article aims to offer a more comprehensive understanding of the influence of various investor categories on stock market performance. By examining the relationship between investor behaviour and the benchmark index (TASI), we also look into the function of investor behaviour based on mood and its impact on the stock market in an emerging stock market.

This is the format for the remainder of the paper. We create a review of the literature in Section 2 to describe the studies and key findings. In Section 3, we look into how investor sentiment, as shown by the AII index, influences investment behaviour. The

primary findings and financial analysis are presented in Section 4. Some closing thoughts are finally provided in Section 5.

2. LITERATURE REVIEW

(Huber, Palan, & Zeisberger, 2019) The study challenges traditional finance by demonstrating that how investors perceive risk, rather than just its statistical measure, significantly influences asset prices and trading behavior. It reveals that assets perceived as less risky, even with identical volatility, command higher prices. Individual investors who share this perception tend to buy these assets more frequently, driving market prices upwards. (Ary, 2019) This study examines how investor confidence (measured by the Consumer Confidence Index) affects returns across different industries in Indonesia. The research suggests that high investor confidence leads to lower returns, particularly in property, real estate, construction, and finance. Furthermore, the findings indicate that investor sentiment can significantly impact traditional asset pricing models, suggesting potential mispricing of assets in the Indonesian stock market. (Hundal, Eskola, & Tuan, 2019) Using the CAPM model, this study examines the link between risk and return in the Finnish stock market. The results imply that, for Finnish enterprises, the conventional wisdom that increased risk translates into higher profits is accurate. Surprisingly, the study also finds that these businesses typically exhibit lower levels of volatility than the market as a whole. (Qasim, Hussain, Mehboob, & Arshad, 2019) This study looks into how Pakistani investors' decision-making is affected by herding and overconfidence biases. The research, which challenges the premise of rational investor behaviour at the heart of standard finance theories, shows compelling evidence that these

biases significantly influence investing choices by surveying 100 active investors. (Rupande, Muguto, & Muzindutsi, 2019) This study looks into the connection between South Africa's stock market volatility and investor sentiment. The research challenges conventional financial theories by demonstrating a high association between sentiment and volatility through the analysis of sentiment data and the use of econometric models. According to the research, investor sentiment has a big influence on stock returns and ought to be taken into account in asset pricing models in order to better understand how markets behave. (Hendershott, Livdan, & Rösch, 2020) Analyse the correlation between a stock's volatility (beta) and its performance during trading versus non-trading hours. According to the study, there is a typical relationship between beta and returns that is mostly valid during market closures, as described by the Capital Asset Pricing Model (CAPM). In a free market, this relationship is the opposite. This unanticipated trend holds true for many stock and beta types, indicating a nuanced interaction between investment risk and market dynamics. (Chauhan, Ahmad, Aggarwal, & Chandra, 2020) This study looks into whether or not herd mentality affects stock returns and whether or not investors in the Indian stock market mimic one other's actions. The researchers discovered that large-cap stocks have a higher prevalence of herding. Additionally, they found that this herding behaviour can forecast stock returns in the future, indicating that investors should take this into account. (Ortmann, Pelster, & Wengerek, 2020) During the COVID-19 pandemic, trading activity by retail investors increased considerably. Both the number and frequency of trades increased, with older and male investors experiencing a particularly strong uptick in activity. After a significant market decline, investor sentiment changed from initial enthusiasm to

decreased use of leverage. The influence of a worldwide crisis on an individual investor's behaviour is highlighted by this research. (Ángeles López-Cabarcos, M Pérez-Pico, & López Perez, 2020) This study examines the structure of investor sentiment research. It links sentiment to efficient markets and behavioral finance, identifying key research areas and influential works. The findings suggest that investor sentiment is a growing field with potential for further exploration using advanced methods. (Naseem, Mohsin, Hui, Liyan, & Penglai, 2021) This study examines how investor psychology impacted the Shanghai, Nikkei 225, and Dow Jones stock markets during the early stages of the COVID-19 pandemic. Using principal component analysis, the research found that negative investor sentiment, driven by fear and uncertainty, led to decreased stock market performance in all three markets. The study highlights the significant role of investor psychology in shaping market outcomes during crises. (Hu, Sui, & Ma, 2021) This research examines the dynamic relationship between investor sentiment, stock returns, and volatility. By constructing a sentiment index and employing a multivariate time series model, the study finds that investor sentiment significantly impacts stock returns, but the effect varies depending on market conditions. The results imply that investors must comprehend these intricate relationships and that conventional models may need to be modified to take sentiment-driven market swings into consideration. (Jiang, Liu, Peng, & Wang, 2022) Examine the relationship between a stock's financial success and investor interest in it. Researchers found that stocks garnering high investor attention tend to yield higher returns. This relationship holds true even after accounting for news and market regulations. Moreover, large investors appear to capitalize on these attention-driven price anomalies by trading more aggressively on such

stocks. The study offers potential explanations for these findings, including investor inattention and herd behavior. (Han, Hirshleifer, & Walden, 2022) This paper introduces a novel model of investment decision-making where social interaction plays a central role. Investors not only make their own investment choices but also influence others to adopt their strategies. The likelihood of convincing others increases with the strategy's past performance. Interestingly, riskier and more unconventional investment approaches tend to be more popular despite their inherent uncertainty. The model emphasizes the importance of social networks in determining the success and popularity of different investment strategies, challenging traditional financial models that primarily focus on individual rationality. (Bouteska, Sharif, & Abedin, 2024) The authors develop a new investor sentiment index (ISI) based on daily trading data and use it to explain stock market anomalies. They find that the ISI is a better predictor of market returns than existing sentiment measures. Moreover, the ISI helps explain the small-cap effect, a phenomenon that traditional asset pricing models struggle to capture. The study suggests that investor sentiment is a crucial factor in the Korean stock market and has implications for both investors and regulators. (Sakariyahu, Paterson, Chatzivgeri, & Lawal, 2024) The effect of investor attitude on asset price in the UK market is examined in this study. The study indicates that sentiment greatly enhances model performance when a new sentiment index is created and added to conventional asset pricing models. The findings imply that, in addition to more conventional factors, investor emotion is an important risk factor to take into account when assessing asset returns. This suggests that in order to properly represent market dynamics, a more thorough approach to asset pricing is required. (Yaakoubi, 2024) This study

integrates investor sentiment into its analysis of the relationship between market liquidity, liquidity risk, and stock returns. The study concludes that investor sentiment affects how market-wide liquidity affects stock performance. Illiquidity has less of an impact on returns during times of high sentiment, but there is a stronger correlation between returns and liquidity risk during times of low sentiment. This implies that conventional asset pricing models can fall short of capturing all of the market's intricacies, particularly when emotion is high.

Research gap

The analysis's findings will advance knowledge of the function of investor mood in financial markets, especially in an emerging market where fluctuations in foreign exchange rates and oil prices have a significant impact.

3. METHODOLOGY AND TOOLS

This empirical study uses a DCC GARCH (Dynamic Conditional Correlation Generalised Autoregressive Conditional Heteroskedasticity) model to examine how investor sentiment affects asset pricing in Saudi Arabia. The weekly data used in the investigation, which spans the years January 7, 2010, to August 1,

2024, includes 739 observations that were obtained from Thomson Reuters.

3.1 Data description

The study utilizes several key variables:

- **Independent variable**

AII sentiment index includes:

BL (Bullish Index Sentiment): Reflects optimistic investor sentiment.

BR (Bearish Index Sentiment): Reflects pessimistic investor sentiment.

- **Dependent variables**

RDYX (Returns of Dollar Index): Captures the fluctuations in the dollar index, which can impact asset prices.

ROIL (Returns of Oil Prices): Reflects changes in oil prices, crucial for oil-exporting economies like Saudi Arabia.

RTASI (Returns of TASI Index): represents the returns of the TASI Index, the primary stock market index in Saudi Arabia.

The DCC GARCH model is employed to capture the dynamic correlations between these variables, allowing for the examination of time-varying relationships and volatility spillovers. This approach is particularly well-suited to assess the conditional correlations between investor sentiment indices and asset prices in a volatile market environment. By focusing on these dynamics, the study aims to provide insights into how different types of

investor sentiment bullish, bearish, and neutral affect the pricing of assets in the context of Saudi Arabia's financial market.

Hypotheses

(H₀): Investor sentiment (as measured by AII index) has no significant effect on the asset prices (TASI index returns, oil price returns, and dollar index returns) in Saudi Arabia.

(H₁): Investor sentiment (as measured by Bullish, Bearish, and Neutral sentiment cases) has a significant effect on the asset prices (TASI index returns, oil price returns, and dollar index returns) in Saudi Arabia.

3.2 Econometric model

Engle and Sheppard (2001) introduced the DCC model, which is also referred to as the generalised version of the regular DCC. The models in this class are based on the assumption that a correlation matrix, R_t , and conditional standard deviations, D_t , can be obtained by breaking down the covariance matrix, H_t . Both D_t and R_t in the DCC-GARCH model are intended to fluctuate over time. (Engle III & Sheppard, 2001) The DCC model estimates the current correlation between series using data from the recent past. The estimation of a DCC model is often accomplished in two steps to simplify the estimation of the time-varying correlation matrix because correlation can be assessed in addition to volatility. (Engle, 2000) Shortly after, Christodoulakis and Satchell (2002) and Tse and Tsui (2002) created similar dynamic correlation models, dubbed the TVC (Time Varying Correlation) model. Aielli (2009) provided a different specification of the H_t in their corrected DCC (cDCC) model).

The DCC GARCH model

$$rt = \mu t + at$$

$$at = H_t^{1/2} z_t$$

$$H_t = D_t R_t D_t$$

where

rt: $n \times 1$ vector representing n assets' log returns at time t.

at: $n \times 1$ vector representing the n assets' mean-corrected returns at time t.

μt : $n \times 1$ vector representing the conditional rt's expected value.

Ht: $n \times n$ matrix of the CC.

$H_t^{1/2}$: Any matrix of size n by n at time t.

Dt: $n \times n$, diagonal matrix of the at-time t conditional sdv.

Rt: $n \times n$ CC matrix.

zt: $n \times 1$ the iid errors vector. (Orskaug, 2009)

Our research uses a modification of the standard DCC model first provided by Engle (2001) and takes into account the asset-specific correlation of news impact curves as well as the asymmetric dynamics in correlation. The stylised truth is that the conditional covariance matrix, Ht, and the asset returns, rt, are both conditionally normal with mean zero. (Acatrinei, Gorun, & Marcu, 2013).

4. EMPIRICAL RESULTS

Table 1. Descriptive statistics

	BL	BR	RDYX	ROIL	RTASI
Mean	0.35	0.32	0.002	0.004	-0.01
Median	0.35	0.30	0.005	0.003	0.00
Maximum	0.59	0.60	0.04	0.313	0.13
Minimum	0.15	0.15	-0.04	-0.290	-9.39
Std. Dev.	0.08	0.08	0.01	0.049	0.34
Skewness	0.12	0.74	0.05	-0.162	-26.91
Kurtosis	2.43	3.11	4.31	9.690	729.24
Jarque-Bera	11.64	69.24	53.95	1381.69	163.29
Probability	0.002	0.000	0.000	0.000	0.000

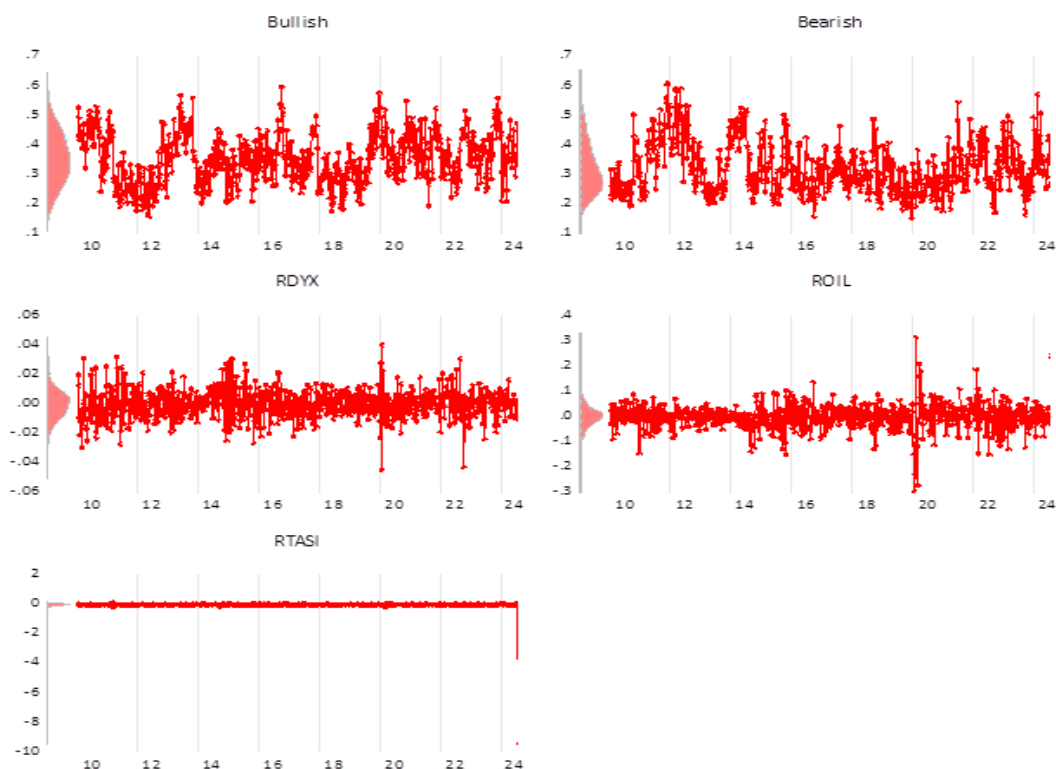
Source: author.

The descriptive statistics for the dataset showed in table 01 and figure 01 comprising (BL) (Bullish Index Sentiment), (BR) (Bearish Index Sentiment), (RDYX) (Returns of Dollar Index), (ROIL) (Returns of Oil Prices), and (RTASI) (Returns of TASI Index) provide key insights into the distribution and variability of these variables over 739 observations. The mean values indicate that, on average, (BL) is slightly higher than (BR), suggesting a more optimistic investor sentiment. The maximum and minimum values show considerable variation, particularly in (RTASI), which has extreme outliers as indicated by its high skewness and kurtosis. This is further supported by the Jarque-Bera test, where all variables reject the null hypothesis of normality at the 1% significance level. The standard deviations reveal that (RTASI) and (ROIL) have higher volatility compared to the sentiment

Asset Pricing Movements Shaped by Investors' Behaviour: A DCC-GARCH Perspective on Saudi Arabia's TASI Index

indices, indicating more variability in market returns and oil prices. Overall, the statistics reflect diverse distributions across the variables, with significant deviations from normality in most cases.

Fig.1. The movement of the variables



Source: author.

The graph illustrates weekly fluctuations in RDYX, ROIL, Bullish, Bearish and, RTASI index from 2010 to 2024. All variables exhibit varying degrees of volatility with no clear overall. Potential correlations between variables exist, which will be clear in our next analysis.

Table 2. The summary of stationary test

Group unit root test: Summary
Series: BL, BR, NEUT, RDYX, ROIL, RTASI

Method	Statistic	Prob.**	Cross- sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-25.94	0.00	6	4420
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-30.94	0.00	6	4420
ADF - Fisher Chi-square	444.89	0.00	6	4420
PP - Fisher Chi-square	614.67	0.00	6	4428

Source: author.

The results from all the unit root tests consistently reject the null hypothesis of non-stationarity (presence of a unit root) across the panel data. This suggests that all the series (BL, BR, RDYX, ROIL, RTASI) are stationary, meaning their statistical properties (mean, variance) do not change over time. While these stationary series could be considered white noise if they also exhibit no autocorrelation, the presence of ARCH effects in your data suggests they are not purely white noise but have some predictable structure. Stationarity is crucial for time series models, including DCC-GARCH, as it ensures that relationships between variables are stable and model assumptions are valid.

Table 3. Heteroscedasticity test using ARCH

Variable	Chi-squared	Degrees of freedom (df)	P-value
RTASI	50.911	12	0.000
ROIL	239.82	12	0.000
RDYX	79.519	12	0.000
BL	426.57	12	0.000
BR	420.35	12	0.000

Source: Authors

The ARCH LM-tests conducted on the variables rTASI, rOIL, rDYX, NEUT, BL, and BR reveal significant ARCH effects across all series, as evidenced by the very low p-values. These results indicate the presence of heteroskedasticity, meaning the variance of the series is not constant over time and exhibits volatility clustering. Consequently, it is necessary to model this time-varying volatility using a GARCH-type model to ensure that the econometric analysis accurately reflects the underlying dynamics of investor sentiment and asset prices within the Saudi Arabian market. This approach will help to obtain robust and reliable results by appropriately accounting for the changing variance in the data.

Table 4. Dynamic conditional correlation GARCH estimation (A-B)

Panel A			Panel B		
Parameters	Coef	P.V	Parameters	Coef	P.V
[BL].mu	0.34	0.00	[ROIL].mu	0.00	0.31
[BL].omega	0.00	0.00	[ROIL].omega	0.00	0.07
[BL].alpha1	0.49	0.02	[ROIL].alpha1	0.17	0.001
[BL].beta1	0.21	0.03	[ROIL].beta1	0.71	0.00
[RTASI].mu	0.00	0.02	[RDYX].mu	0.00	0.22
[RTASI].omega	0.00	0.00	[RDYX].omega	0.00	0.60
[RTASI].alpha1	0.25	0.02	[RDYX].alpha1	0.11	0.00
[RTASI].beta1	0.39	0.00	[RDYX].beta1	0.85	0.00
DCC					
		Coefficient	P-value		
Dcca1		0.005	0.00		
Dccb1		0.99	0.00		

Source: Author

The DCC-GARCH model results reveal that conditional correlations between variables are both dynamic and persistent, with the immediate response to shocks being positive and significant ('dcca1 = 0.0268'), while the correlations themselves are highly persistent ('dccb1 = 0.972'). The bullish sentiment index ('BL') shows a generally optimistic outlook with a significant mean ('BL.mu = 0.3460'), and its volatility components ('BL.alpha1' and 'BL.beta1') suggest that positive shocks lead to increased optimism that persists over time. For the TASI index returns, the moderate volatility and significant persistence imply that market returns are influenced by investor sentiment, particularly bullish sentiment. Additionally, the significant volatility in oil prices ('ROIL') and the dollar index ('RDYX') affects market sentiment and TASI returns, with oil prices having a notable impact due to Saudi Arabia's dependency

Asset Pricing Movements Shaped by Investors' Behaviour: A DCC-GARCH Perspective on Saudi Arabia's TASI Index

on oil. Overall, the results indicate that investor sentiment, especially bullish sentiment, has a significant and lasting effect on market returns, reflecting a period of sustained optimism.

Table 5. Dynamic conditional correlation GARCH estimation (C-D)

Panel C			Panel D		
Parameters	Coef	P.V	Parameters	Coef	P.V
[BL].mu	0.29	0.00	[ROIL].mu	0.00	0.29
[BL].omega	0.00	0.00	[ROIL].omega	0.00	0.07
[BL].alpha1	0.52	0.00	[ROIL].alpha1	0.17	0.00
[BL].beta1	0.25	0.03	[ROIL].beta1	0.71	0.00
[RTASI].mu	0.00	0.02	[RDYX].mu	0.00	0.22
[RTASI].omega	0.00	0.00	[RDYX].omega	0.00	0.60
[RTASI].alpha1	0.25	0.02	[RDYX].alpha1	0.11	0.00
[RTASI].beta1	0.39	0.00	[RDYX].beta1	0.85	0.00
DCC					
Coefficient		P-value			
Dcca1	0.005	0.00			
Dccb1	0.99	0.00			

Source: Author

The DCC-GARCH model results for the Bearish Index Sentiment (BR) reveal important insights into the impact of investor pessimism on key financial variables in Saudi Arabia. The conditional correlation dynamics show that 'dcca1' (0.0056) indicates a smaller immediate effect of bearish shocks on correlations compared to bullish shocks, while 'dccb1' (0.9943) reflects very high persistence in these correlations, suggesting that changes due to bearish sentiment remain for a long time. For the Bearish Index Sentiment ('BR'), the mean parameter ('BR.mu = 0.2969') indicates periods of notable pessimism,

though not constant. The significant GARCH parameters ('BR.alpha1 = 0.5212' and 'BR.beta1 = 0.2578') imply that bearish sentiment increases with negative shocks and persists moderately. This results in a negative impact on TASI returns, with heightened pessimism likely suppressing market performance and increasing volatility.

Oil price returns ('ROIL') and dollar index returns ('RDYX') also show significant volatility, impacting overall market sentiment. Persistent oil price volatility can amplify bearish sentiment, particularly if prices decline, affecting investor confidence and TASI returns.

In summary, the results suggest that periods of increased bearish sentiment lead to lower market returns and greater volatility. Understanding these dynamics is crucial for navigating market stress and making informed investment decisions.

5. DISCUSSION

The DCC-GARCH model results highlight that the correlations between the variables are both dynamic and persistent. Specifically, the immediate response to shocks is positive and significant ($dcca1 = 0.0268$), indicating that short-term changes in sentiment significantly affect market correlations. The high persistence in these correlations ($dccb1 = 0.972$) shows that these effects are sustained over time.

Bullish Sentiment (BL)

The bullish sentiment index (BL) displays a generally optimistic outlook with a significant mean ($BL.mu = 0.3460$). This suggests a prevailing positive sentiment in the market. The volatility components for the bullish sentiment index ($BL.alpha1$ and

BL.beta1) indicate that positive shocks lead to increased optimism that continues to affect the market for an extended period.

Financial Implications

- **Optimism and Market Returns:** The persistence of bullish sentiment, reflected by the high correlation persistence, suggests that periods of strong investor optimism lead to sustained positive returns on the TASI index. This indicates that a generally positive sentiment is likely to boost market performance over time.
- **Impact of Oil Prices:** Given Saudi Arabia's significant oil dependency, fluctuations in oil prices (ROIL) play a crucial role. Positive sentiment might be reinforced by rising oil prices, contributing to higher TASI returns. Conversely, oil price volatility could also affect sentiment, making it a key factor in market dynamics.

Bearish Sentiment (BR)

The bearish sentiment index (BR) shows that the immediate impact of bearish shocks on correlations is smaller ($dcca1 = 0.0056$) compared to bullish shocks, but the persistence of these correlations is very high ($dc cb1 = 0.9943$). This indicates that negative changes in sentiment have a lasting effect.

Financial Implications

- **Pessimism and Market Performance:** The mean parameter for bearish sentiment ($BR.mu = 0.2969$) suggests that while pessimism occurs, it is not constant. The significant GARCH parameters ($BR.alpha1 = 0.5212$ and $BR.beta1 = 0.2578$) indicate that negative shocks lead to increased pessimism, which persists and affects market returns negatively. Increased bearish sentiment tends to suppress market performance and heightens volatility.

- Impact of Oil Prices and Dollar Index: Similar to bullish sentiment, bearish sentiment is influenced by significant volatility in oil prices and the dollar index (RDYX). Persistent declines in oil prices can exacerbate bearish sentiment, reducing investor confidence and negatively impacting the TASI index.

The results underscore the significant and lasting impact of investor sentiment on market returns in Saudi Arabia. Bullish sentiment correlates with positive market performance and is influenced by oil prices, reflecting the role of optimism in boosting market returns. Conversely, bearish sentiment tends to suppress returns and increase volatility, especially during periods of adverse oil price movements. Understanding these dynamics is crucial for navigating market stress and making informed investment decisions, particularly in an environment sensitive to both global and regional economic factors.

6. CONCLUSION

In the Saudi Arabian context, various external factors contribute to spillover effects on investor sentiment and, consequently, investor behavior. Geopolitical risks in the Middle East significantly impact market confidence. Political instability, regional conflicts, and other geopolitical events can create uncertainty, influencing investor behavior both positively and negatively based on the nature of these events. Additionally, oil price fluctuations are vital due to Saudi Arabia's heavy reliance on oil exports. Rising oil prices tend to enhance market confidence and investor optimism, while falling prices can lead to pessimism and market instability. This volatility in oil prices is central in shaping investor sentiment and behavior, impacting asset prices. Exchange rate fluctuations also play a role by affecting trade

balances, inflation, and overall economic stability, thereby influencing investor behavior and market returns.

Our study, using the DCC-GARCH model, provides valuable insights into how investor sentiment affects asset prices and investor behavior in Saudi Arabia. The analysis indicates a generally optimistic investor outlook, as reflected in the bullish sentiment index ('BL'). With a significant mean ('BL.mu = 0.3460') and a positive, persistent response to shocks, bullish sentiment leads to favorable market conditions and increased investor buying behavior, enhancing market returns. Conversely, while bearish sentiment also impacts the market, its immediate effect on investor behavior is less pronounced compared to bullish sentiment. However, the persistence of bearish sentiment suggests that negative periods have a lasting impact on investor behavior, leading to increased market volatility and lower performance.

The volatility of oil prices and the dollar index further affects investor sentiment and behavior, influencing TASI returns. Given Saudi Arabia's dependence on oil, fluctuations in oil prices amplify both bullish and bearish sentiments, which in turn influence investor behavior and overall market conditions. Based on these findings, we accept the alternative hypothesis of a dynamic conditional correlation between investor sentiment and asset prices.

Overall, investor behavior in the Saudi Arabian market is predominantly influenced by optimistic sentiment, which significantly impacts market performance. Although bearish sentiment also affects investor behavior and market conditions, its impact is relatively smaller but persistent. External factors such as oil price volatility and geopolitical risks add complexity to investor sentiment dynamics, highlighting the importance of monitoring these influences for a comprehensive understanding of

market conditions. This study underscores the critical role of investor sentiment in shaping asset prices and investor behavior, offering valuable insights for navigating the Saudi Arabian financial market.

7. Bibliography List :

- Abeysekera, A. P., & Nimal, P. D. (2017). The four-factor model and stock returns: Evidence from Sri Lanka. *Afro-Asian Journal of Finance and Accounting*, 7(1), 1-15.
- Acatrinei, M., Gorun, A., & Marcu, N. (2013). A Dcc-Garch Model to Estimate. *Romanian Journal of Economic Forecasting*, 1(2013), 136-148.
- Ángeles López-Cabarcos, M., M Pérez-Pico, A., & López Perez, M. L. (2020). Investor sentiment in the theoretical field of behavioural finance. *Economic research-Ekonomska istraživanja*, 33(1), 2101-2228.
- Ary, W. W. (2019). Sentimen Investor Dan Three-Factor Asset Pricing Model (Studi Empirik Di Bursa Efek Indonesia). *Jurnal Manajemen Dan Keuangan*, 8(2), 221-237.
- Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of economic perspectives*, 21(2), 129-151.
- Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, 49(3), 307-343.
- Bouteska, A., Sharif, T., & Abedin, M. Z. (2024). Does investor sentiment create value for asset pricing? An empirical investigation of the KOSPI-listed firms. *International Journal of Finance & Economics*, 29(3), 3487-3509.
- Brooks, M., & Byrne, A. (2008). Behavioral finance: Theories and evidence. The Research Foundation of CFA Institute. University of Edinburgh.
- Chauhan, Y., Ahmad, N., Aggarwal, V., & Chandra, A. (2020). Herd behaviour and asset pricing in the Indian stock market. *IIMB Management Review*, 32(2), 143-152. doi:<https://doi.org/10.1016/j.iimb.2019.10.008>
- Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *The Journal of Finance*, 53(6), 1839-1885.

Asset Pricing Movements Shaped by Investors' Behaviour: A DCC-GARCH Perspective on Saudi Arabia's TASI Index

- Engle III, R. F., & Sheppard, K. (2001). Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH. In: National Bureau of Economic Research Cambridge, Mass., USA.
- Engle, R. F. (2000). Dynamic Conditional Correlation—A Simple Class of Multivariate GARCH Models, University of California at San Diego. Economics Working Paper Series, 9.
- Han, B., Hirshleifer, D., & Walden, J. (2022). Social transmission bias and investor behavior. *Journal of Financial and Quantitative Analysis*, 57(1), 390-412.
- Hechter, M. (2001). Solidarity, Sociology of. In N. J. Smelser & P. B. Baltes (Eds.), *International Encyclopedia of the Social & Behavioral Sciences* (pp. 14588-14591). Oxford: Pergamon.
- Hendershott, T., Livdan, D., & Rösch, D. (2020). Asset pricing: A tale of night and day. *Journal of Financial Economics*, 138(3), 635-662.
- Hu, J., Sui, Y., & Ma, F. (2021). The measurement method of investor sentiment and its relationship with stock market. *Computational Intelligence and Neuroscience*, 2021(1), 6672677.
- Huber, J., Palan, S., & Zeisberger, S. (2019). Does investor risk perception drive asset prices in markets? Experimental evidence. *Journal of Banking & Finance*, 108, 105635. doi:<https://doi.org/10.1016/j.jbankfin.2019.105635>
- Hundal, S., Eskola, A., & Tuan, D. (2019). Risk–return relationship in the Finnish stock market in the light of Capital Asset Pricing Model (CAPM). *Journal of Transnational Management*, 24(4), 305-322.
- Jiang, L., Liu, J., Peng, L., & Wang, B. (2022). Investor attention and asset pricing anomalies. *Review of Finance*, 26(3), 563-593.
- Nanayakkara, N., Nimal, P., & Weerakoon, Y. (2019). Behavioural asset pricing: a review.
- Nanayakkara, N., Nimal, P., & Weerakoon, Y. (2020). Neoclassical Asset Pricing Tests in Sri Lanka: A Structural Empirical Review.
- Naseem, S., Mohsin, M., Hui, W., Liyan, G., & Penglai, K. (2021). The investor psychology and stock market behavior during the initial era of COVID-19: a study of China, Japan, and the United States. *Frontiers in Psychology*, 12, 626934.
- Orskaug, E. (2009). Multivariate dcc-garch model:-with various error distributions. *Institutt for matematiske fag*,

- Ortmann, R., Pelster, M., & Wengerek, S. T. (2020). COVID-19 and investor behavior. *Financ Res Lett*, 37, 101717. doi:10.1016/j.frl.2020.101717
- Phan, T. N. T., Bertrand, P., Phan, H. H., & Vo, X. V. (2023). The role of investor behavior in emerging stock markets: Evidence from Vietnam. *The Quarterly Review of Economics and Finance*, 87, 367-376. doi:<https://doi.org/10.1016/j.qref.2021.07.001>
- Qasim, M., Hussain, R., Mehboob, I., & Arshad, M. (2019). Impact of herding behavior and overconfidence bias on investors' decision-making in Pakistan. *Accounting*, 5(2), 81-90.
- Rupande, L., Muguto, H. T., & Muzindutsi, P.-F. (2019). Investor sentiment and stock return volatility: Evidence from the Johannesburg Stock Exchange. *Cogent Economics & Finance*, 7(1), 1600233. doi:10.1080/23322039.2019.1600233
- Sakariyahu, R., Paterson, A., Chatzivgeri, E., & Lawal, R. (2024). Chasing noise in the stock market: an inquiry into the dynamics of investor sentiment and asset pricing. *Review of Quantitative Finance and Accounting*, 62(1), 135-169. doi:10.1007/s11156-023-01214-8
- Shiller, R. J. (1990). Market volatility and investor behavior. *The American Economic Review*, 80(2), 58-62.
- Yaakoubi, S. (2024). Investor sentiment and market-wide liquidity pricing. *Journal of Behavioral Finance*, 25(2), 229-243.