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Saudi Investor Sentiment, Stock Market Behavior and Pricing: New Evidences

Aloui Chaker[1], Besma Hkiri[2], Manel Alghamdi[3]

[1]Prince Sultan University
[2]Jeddah University
[3]Saudi Central Bank

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Abstract

This paper is a first attempt to check the relevance of investor sentiment to Saudi stock market behavior and pricing. In doing so, we use 'big data' from the web, searched using Google search volume (GSV), to design positive and negative sentiment metrics. We analyze the causal connectedness between sentiment and returns, volatility, and stock pricing, within a time-frequency approach, which enables us to account for high and low frequency investor behavior. We apply continuous wavelet coherence, discrete wavelet transformation and standard GJR-GARCH modelling to weekly data for the period January 2005 to March 2021. We produce several pieces of fresh and insightful evidence. We find a relevant impact of sentiment on stock returns, especially during the turbulent market episodes of the 2008 financial crisis and the ongoing COVID-19 pandemic. Negative sentiment intensifies market volatility with a time-investment horizon-varying impact. More importantly, sentiment is shown to have a significant scale-varying impact on stock pricing when included as an additional risk-loading factor in the market model. The explanatory power of the multiscale-sentiment model rises as time scale increases. Our results are consistent with theoretical expectations that Saudi investors have different perceptions of news and heterogeneous investment horizons, reflective of Saudi market dependency on individual investors. This paper contributes to the sentiment-return-risk nexus literature and offers new perceptions, implications and recommendations for portfolio managers, market regulators and policy designers.

Keywords: Investor sentiment, Google search volume, volatility, investment- horizon, wavelets, multi-scaling, GARCH modelling, sentiment-market pricing.

JEL Classifications : *C22, C58, G12, G41.*

* **Authors' contact**: Chaker Aloui, Email: caloui@psu.edu.sa, Besma Hkiri, Email: bhkiri@uj.edu.sa, Manel Alghamdi, Email: mmalghamdi@sama.gov.sa

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1. Introduction

Investor sentiment metrics can be extricated from many text sources, such as Twitter, Facebook, Wikipedia, Yelp, Flickr, Google, or other websites. Therefore, 'big data'[1] stock market-related searches can be used to track the emotions, moods and sentiments disclosed by the authors[2]. For instance, Google search trends offers a platform to search data across countries and languages. The intensive use of Google search and other social media to source financial and economic news may provide a real-time signal of investor sentiment, defined as *"belief about future cash flows and investment risks that is not justified by the facts at hand"* (Baker and Wurgler, 2007, p.127). Not only does Google search volume (GSV) mirror investors' attitudes in its accumulated data, but also it provides information about their expectations, beliefs and investment decisions (see, among others, Da et al. 2015; Gao et al., 2020).

The GSV time series of investor sentiment can be assessed for its ability to explain stock market return, price volatility and stock pricing. While the literature related to this line of research flourishes, the findings are still inconclusive regarding the explanatory power of sentiment metrics[3] (Kumar and Lee, 2006; Baker and Wurgler, 2006, 2007; Bu and Pi, 2014; D'Hondt and Roger, 2017; Steeves et al., 2021; Lu et al., 2012; Wang and Li, 2021; Lian et al., 2022). Recent research highlights the time and scale-varying patterns of the sentiment-market behavior nexus, the relevance of the heterogeneity of the investors' time horizons, and the prominence of the duration of such an effect. In this regard, Chakrabarty et al. (2015) state "*we conjecture that heterogeneous-horizon investors respond differently to relevant information supported by the evidence that empirical distribution of returns behaves in different ways across frequencies*" (Chakrabarty et al., 2015, p. 2). Because of their different risk profiles, beliefs and sentiments, investors make their investment decisions within various investment time horizons (long vs. short horizon investors). Long horizon investors are mainly concerned with stock price fundamentals

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[1] Here, big data refers to extremely large data sets that may be analyzed computationally to reveal patterns and trends, especially relating to human behavior and interactions.

[2] Hajiali (2020) gives a comprehensive literature review related to 'big data' and sentiment analysis, cited in the reference list.

[3] Here, we refer to only some new studies, other pioneering references are cited in the literature review.

leading trends, while short-term investors predominantly act in response to news arriving over the short-term horizon (Chakrabarty et al., 2015). This argument is supported by Müller et al. (1997) who present the heterogeneous market hypothesis. They state that long-term investors (low frequency investors), are concerned with lower frequencies, account more for systematic news than firm specific factors. In this way, relevant news is perceived differently. It drives lower frequency asset movements, which results in high dependence between sentiment and stock price. Conversely, high frequency movements are induced by short-term investors (high frequency investors) who account for firm specific factors when allocating assets and designing investment strategies. Based on these arguments, we presume that the investor sentiment, return and price volatility nexus varies across frequencies and over time. Another connected aspect relates to the explanatory power of the capital asset pricing model (CAPM). The model depends on a limited time scale, resulting in an inaccurate connectedness between risk and return (Gençay et al., 2002, 2005; Handa et al., 1989, Masih et al., 2010; In and Kim, 2013)[4]. The CAPM assumes that investors all have the same investment horizons. However, in practice, investors have different perceptions of news, various sentiments, various risk profiles and their investment decisions vary considerably over time horizons. Therefore, the 'true' connectedness between risk, return and sentiment is likely to vary over time scale space[5]. Following this line of research, many empirical works confirm that the estimated parameters of the CAPM change over investment horizons or frequencies (see, among others, Gençay et al., 2002; Gençay, 2003, 2005; In and Kim, 2013, Fernandez, 2006; Fernandez and Lucey, 2007; In et al., 2007; Masih al., 2010). As a result, the arbitrary choice of time scale used to estimate the CAPM with a standard OLS regression is inadequate, and a lot of information about the time scale-varying parameters is disregarded. To consider these two inadequacies, we resort, as in previous work, to a multiresolution analysis of the CAPM. Using wavelet filters, it is possible to decompose stock

[4] Chakrabarty et al. (2015) present asset pricing models in the presence of the heterogeneous market hypothesis and highlight the appropriate use of continuous and discrete wavelets. The paper is cited in the reference list.

[5] This issue was originally suggested by Levy (1972), who states, "*more attention should be devoted to the process of choosing the basic unit of time. An empirical study which is based on a yearly rate of return will yield different results from one which uses monthly rate-of-return data. This difference in findings is not a result of inconsistency or contradiction but is a result of selecting an inappropriate division of the period studied*" (Levy, 1972, p. 645).

returns into various time scales and examine the behavior of beta and the sentiment parameters across time scales without considering the main stylized facts of stock return behavior, including non-stationarity, seasonality, shifts in behavior and structural breaks. In the present study, a multiscale sentiment-pricing model is proposed.

We continue these interconnected lines of research, motivated by the aforementioned arguments, and revisit the sentiment-stock market behavior literature by asking the following research questions. To what extent can we use GSV data to design sentiment metrics? How does investor sentiment affect return and volatility across time scales and investment horizons (i.e., frequency bands)? Does sentiment matter as a relevant loading factor for asset pricing models? How does it act over time scales?

We are concerned with the Saudi market, and four main reasons influence our choice. Firstly, during the last decade, the Saudi market glimpsed substantial growth. For example, listed firms increased by 190 percent from 70 in 2004 to 203 in 2021, and the brokerages, asset managers and investment banks grew to 86. Secondly, the market activity is mostly dominated by individual investors. According to the Saudi Market Trading Report [6] (2021), individual transactions represent 96.51 percent of the total market capitalization, 89.07 percent of total buying activity and 90.90 percent of the selling activity, while foreign investors represent only 2.98 percent. Thus, the heterogeneity of investors' trading activity, how information influences decision-making, and the pre-eminence of individual investors requires a comprehensive analysis of the connectedness between Saudi investors sentiment and stock market dynamics. Thirdly, the increasing number of initial public offerings (IPO) (16 new listings in 2022, and more than 70 expected[7]), counting the partial IPO of ARAMCO, to reach the national economics goals outlined by the 2030 vision, points towards the rapid growth of the Saudi market. Fourthly, new regulations have been announced concerning market settlement and qualified foreign investors. The main objective is to create new investment opportunities and boost the role of the Saudi

[6] Monthly Report (August, 2021), available at: https://www.saudiexchange.sa/wps/wcm/connect/

[7] https://www.arabnews.com/node/2047826/business-economy

market in regional and global capital markets as a source of capital and an investment destination. Such reforms are intended to increase market depth, transparency and efficiency. To the best of our knowledge, and given the literature at hand, the sentiment-risk-return nexus has never been investigated with a multiscale approach in the Saudi market, and this is the first attempt to design positive and negative sentiment metrics based on GSV for Saudi investors.

Our contribution has at least five aspects. Firstly, we estimate Saudi investor sentiment metrics based on 'big data' related to Google. Following Da et al. (2015) and Gao et al. (2020), we estimate an investor sentiment index using GSV for a large sample of weekly data covering the January 2005-March 2021 period, which covers major extreme events, including the 2006 Saudi market collapse (Black February), 2008 global financial crisis (GFC), and the oil market collapse in 2014, and during 2020 when the COVID-19 health crisis. Our paper distinguishes itself from previous work by estimating two positive and negative sentiment metrics. Designing such sentiment metrics is useful as it gives a more profound understanding of the impact of sentiment on market behavior and pricing. Secondly, the resultant sentiment metrics are employed to assess their impact on the stock market. Thus, three aspects are considered: the aggregate return, price volatility and stock pricing. Our analysis is conducted within a time-frequency domain using both bivariate continuous wavelets and discrete multiresolution analysis. Thirdly, we investigate sentiment-volatility connectedness using the GJR-GARCH modelling approach in which positive and negative sentiment as well as other extreme events are included as control variables in the conditional variance. Once more, this is the first paper to account for sentiment and recent extreme events in Saudi market volatility modelling. Finally, we suggest and estimate a multiscale augmented market model in which sentiment is an additional risk-loading factor, allowing us to check its relevance in explaining stock pricing. The proposed model is estimated within a discrete multiresolution framework. Our underlying idea is to test the time scale-varying impact of sentiment on stock pricing. Finally, our paper is pioneering in this line of research since it uses a long and recent dataset and offers fresh insight for Saudi policymakers and regulators who wish to comprehensively understand the interactive linkages between investor sentiment, stock market behavior and asset pricing within a time-frequency framework. To the best of our knowledge, no previous work has tackled this subject in Saudi Arabia.

Operationally, the relationship between sentiment, return, price volatility and stock pricing are analyzed within a time-frequency domain. Thus, continuous and discrete wavelet methods are employed. Wavelets are an appropriate way to identify regions of high coherence between two time series in the time-frequency space. Moreover, these methods do not require any pre-treatment of the time series, easily decompose data into several time-frequency constituents and subsequently circumvent the loss of information and frequent irregularities in the data structure.

The paper continues as follows. Section 2 presents the theoretical arguments and previous research into sentiment-return-volatility-pricing interaction. Section 3 describes the data and the wavelet methods. Section 4 discusses the empirical outcomes and robustness checks. Section 5 concludes and offers the main policy implications and recommendations.

2. Underpinnings, literature review and research hypothesis

In this section, we present the main theoretical arguments, review the existing empirical studies and formulate our research hypothesis.

2.1. Sentiment, return, volatility interplay

Following the seminal papers of Fama (1970, 1991), the efficient market hypothesis (EMH) asserts that relevant information are quickly and simultaneously mirrored by stock prices. Consequently, for investors, it is impossible to *"beat the market"* as the market can neither be mispriced nor inflated. A rational investor, choosing from a set of contending viable investment alternatives, proceeds to select one from the set which maximizes the expected utility. From an investment point of view, the EMH highlights the assumed attitude of rationality in all investment decisions (Konstantinidis et al. 2012). However, it is presumed that investors possess the cognitive ability to acquire all accessible information and explore all profitable opportunities, thereby making optimal decisions to achieve their utility goal. Furthermore, the emergence of the 1987 crisis and speculative bubbles (the Internet bubble of the late 1990s) supports the dominance of behavioral finance over the EMH (Bris et al., 2007). Behavioral finance provides an alternative explanation for investors' decisions. This theory mixes insights from psychology and classical economic and financial theories. Behavioral finance rests on two major assumptions, specifically limited arbitrage and investor sentiment.

These arguments of behavioral finance are closely connected. For instance, De Long et al. (1990) and Barberis et al. (1998), among others, explain why arbitrage is limited and risky. They describe limited arbitrage as a situation where arbitrage opportunities exist but rapidly disappear. This limit to arbitrage can be understood based on behavior and social psychology, that is, investor sentiment. Changes in investor sentiment are, to some extent, random, and due to the short-term horizon of arbitrageurs, arbitrage remains risky. Therefore, the investor sentiment turns out to be extreme, and stock prices habitually do not converge to their intrinsic values (Barberis et al., 1998, p.307).

The sentiment theory concerns the question of what people believe, which affects their decision-making. Sentiment is a measure of the anticipations of an individual relative to an average. While a bullish investor expects the return to be greater than average, a bearish investor expects it to be less than average (Brown and Cliff, 2004). Specifically, investors' sentiments are associated with their levels of optimism or pessimism, which make them, to some extent, irrational investors (Kadilli, 2015). However, the literature deals with the proposition that investors are predisposed to exogenous sentiment waves, in contrast to the rationality hypothesis.

Using a wide range of investor sentiment proxies and standard and non-standard empirical methods, most behavioral finance research recognizes that investor sentiment affects both stock return and volatility. For instance, Baker and Wurgler (2007) suggest that sentiment's predictive content with respect to future market behavior is useful for portfolio managers allocating assets and designing investment strategies. Verma and Soydemir (2009) reveal the substantial effects of individual and institutional investor sentiment on DJIA and S&P500 stock returns. Baker et al. (2012) claim that, for some stocks that are simple to arbitrage, the expected return-sentiment nexus may be positive. To check the relevance of investor sentiment in predicting aggregate stock returns, Kadilli (2015) uses a consumer confidence index as a proxy. While, during normal times, investor sentiment negatively affects the aggregate stock returns of financial firms, turmoil periods are characterized by a positive and significant effect.

Kumari and Mahakud (2015) investigate the predictive power of investor sentiment in the Indian stock market using a sentiment index based on a set of sentiment proxies and variables related to Indian market characteristics, including firm performance and trading volume. They employed a non-linear GARCH process to capture the effect of institutional investor sentiment on market volatility. The inclusion of irrational investor sentiment in the mean and conditional variance equations shows that the index has a significant positive and negative effect on Indian stock market volatility[8]. The findings of Kumari and Mahakud (2015) are consistent with those of Liston (2016) regarding institutional investor sentiment's effect on stock returns. To assess the investor sentiment effect on sin stocks' conditional volatility, Liston (2016) suggests the sentiment-augmented asset pricing and GARCH models[9]. The results point to a substantial effect of both individual and institutional investor sentiment on conditional volatility. The GARCH model results reveal evidence of volatility clustering, the leverage effect, and variations in investor sentiment trailing changes in stock market volatility.

Ni et al. (2015) offer a pertinent analysis of the non-linear influence of investor sentiment on the Chinese stock market using quantile regressions. In terms of forecast horizons, the results show opposite impacts over long-term and short-term horizons. While investor sentiment positively affects Chinese stock returns in the short term (3 months), it negatively affects stock returns over 6 months and 12 months. These outcomes are in line with those of Lux (2011), who investigates the causality linkages between short-run and medium-run sentiments and stock returns in Germany. The empirical work is based on a VAR framework, and the results confirm the predictive power of the investor sentiments index on stock returns.

[8] The authors find that the effect of institutional investor sentiment on volatility is evidenced in emerging markets such as India for two reasons. Firstly, bullish sentiments increase market volatility. Secondly, institutional investors act as noise traders, increasing systematic risk via non-fundamental information (Kumari and Mahakud, 2015).

[9] For the sentiment-augmented asset pricing models, Liston (2016) implements several models, including the Sharpe-Linter Mossin CAPM model and Fama-French (1993) three-factor model. The effect of investor sentiment on sin stocks' conditional volatility is analyzed using a GARCH in the mean model.

The literature related to the sentiment-volatility nexus is extremely profuse. However, the results are still inconclusive and fail to provide comprehensive conclusions regarding the causality linkages and time-varying pattern. Recent research highlights the time and scale-varying pattern of the sentiments-market behavior nexus, the relevance of the heterogeneity of investors' time horizons, and the prominence of the duration of such an effect.

Dash and Maitra (2017) investigate the association between investor sentiment and stock returns in the Indian market, using wavelet filters to decompose stock returns and the sentiment proxy into various time scales. Their results point to a strong effect of investor sentiment on the aggregate return over short and long-time scales. Dash and Maitra (2018) examine the interactions between investor sentiment, global macroeconomic risk factors and sharia stock returns in India using wavelets and non-linear causality tests. The authors reveal that investor sentiment influences sharia stock returns only in high-frequency bands (short-term investment horizons). Lao et al. (2018) use a similar approach in the US stock market, decomposing stock returns and the Baker and Wurgler (2006) sentiment time series at various time scales using wavelet filters and testing the causal linkages over each time scale horizon. They reveal strong bilateral causality relationships. To investigate the lead-lag interactive linkages between investor sentiment and US stock returns, Marczak and Beissinger (2016) apply wavelet and phase analysis to monthly data and two alternative sentiment proxies. The authors show the presence of causalities when sentiment is used as a leading variable at the short-term investment horizon. Contrasting results are shown for longer investment time horizons. Based on these theoretical underpinnings and earlier empirical outcomes, we formulate our research hypothesis as follows: i. investor sentiment affects stock returns. ii. the sentiment effect varies across investment horizons and over time. iii. investor sentiment affects stock market volatility within a time scale-varying pattern.

2.2. The sentiment-pricing interplay over scales

The explanatory power of asset pricing models, including the CAPM and Fama-French multifactor models within time-frequency, has been intensively investigated over the last decade. However, the results are still inconclusive and fail to reach a consensus regarding their performance over time scales. For instance, McNevin and Nix (2018) use a multiscale analysis and a rolling 250-day window to estimate the Fama-French three-factor model for the US industry. They reveal that the use of wavelet methodology in the asset pricing models is "*worth it*", as wavelet analysis allows data to be decomposed into several time scales and thus permits the detection of time scale-varying risk factors over several scales. Bera et al. (2020) analyse the five-factor Fama-French model with a wavelet multi-scaling approach. The authors show that the five-factor model can detect fluctuations in average returns across investment horizons. The risk factor impact on average returns also varies over time scales. Based on the CAPM model, Mestre (2021) develops a time-frequency multi-beta model using wavelet decomposition. Non-standard model-based wavelets are able to capture the time-varying fluctuations of betas over various investment horizons. For this author, the time-frequency multi-beta model is more useful for long-term investors, and the effects of the Fama-French factors and other variables on equities are significant and increase as the time horizon increases. Gencay et al. (2005) use wavelet multiresolution analysis to test the Fama-French model and show that the explanatory power becomes stronger as the time scale increases. Inconsistent results are found by Handa et al. (1989), In and Faff (2010), Masih et al. (2010), Deo and Shah (2012, In and Kim (2013) and Bera et al. (2019). For these authors, the model performs substantially better for higher time scales, which is seen as a mispricing phenomenon and raises the question of information, primarily due to investment time horizon heterogeneity. Fernandez (2006) estimates the CAPM at various time scales for the Chilean stock market. The author finds evidence supporting the CAPM at a medium horizon scale. Masih et al. (2010) are concerned with GCC stock markets. They estimate the market model in a wavelet multiresolution analysis and find the beta parameter (i.e., systematic risk) exhibits a multi-scaling behavior for all selected markets. This result could be due to investors' heterogeneity and some specificities of the GCC in terms of liquidity, transaction costs, infrequent trading, and the predominance of individual traders (Masih et al., 2010, p.10).

Rua and Nunes (2012) estimate systematic risk using a one factor-model and the continuous wavelet transform (CWT) method for a large sample of emerging markets and find strong evidence of it varying across frequencies. Bortoluzzo et al. (2014) estimate the CAPM for the

Brazilian stock market. They show that the risk-return relationship is more evident at short-term investment horizons. These results are inconsistent with Gencay et al. (2005). In and Kim (2013) estimate the Fama-French three-factor model using multiscale wavelets and reveal that the three risk loading factors vary over time scales. Similar results are produced by Bera et al. (2019) using the five-factor model.

On the theoretical side, the low explanatory power of these pricing models over short scales is explained by the fact that short-time stock market movements are induced by short-term investors who are concerned with idiosyncratic risk and react to firm-specific news more than systematic risk. Therefore, for short-term traders, asset allocation decisions are dissociated from stock market trends (Gencay et al., 2003, 2005). This explains the low predictive power of the CAPM over short scales. Cooper et al. (2004) claim that stock prices tend to adjust over short scales, and their mispricing is corrected in the long run (long-time scales) as agents consider future news and revise their trading positions. Another theoretical argument relates to the existence of agents with heterogeneous investment horizons. Connor and Rossiter (2005) contend that investors are concerned with various investment horizons. Long-term horizon investors are more concerned with the fundamental factors governing overall stock price trends, while short-term investors adopt active portfolio management strategies, timing the market and tracking mispriced stocks, mostly reacting to relevant information within short time scales. Therefore, stock market behavior is governed by the interactions of agents having heterogeneous investment time horizons. For Chakrabarty et al. (2015), "*investors operating at various horizons consider different information or interpret the same news differently to breed their own expectations which results in a certain observable trend in the time-frequency domain*" (Chakrabarty et al., 2015, p.14).

On the other hand, the significance of investor sentiment highlights the explanatory power of asset pricing models. Baker and Wurgler (2006) show that investor sentiment has a stronger impact on stocks with prices that are highly subjective and difficult to arbitrage. Baker et al. (2012) design sentiment metrics for six major stock markets and reveal a strong ability to predict time series of cross-sectional returns within markets. Similar findings are presented by

Stambaugh et al. (2012) and Antoniou et al. (2016). For Stambaugh et al. (2012), investor sentiment has a stronger effect on cross-sectional stock pricing during periods of high sentiment. Antoniou et al. (2016) show that, when sentiments are high, short-term investors (low frequency) are relatively more confident and active in high beta stocks. Bathia and Bredin (2018) estimate a pricing model including various sentiment proxies in the US market. They show that the sentiment-augmented asset pricing model has the ability to capture the impacts of size, value, liquidity and momentum on risk-adjusted returns (Bathia and Bredin, 2018, p.2).

As stressed, our paper stands within these two interconnected lines of research but differentiates itself by proposing and estimating a multiscale sentiment-augmented asset pricing model for the Saudi market. Based on the theoretical arguments and previous empirical findings, we hypothesize that: i. sentiment enhances the explanatory power of the augmented pricing model. ii. the explanatory power of the sentiment-pricing model varies over time scales as individual investors have heterogeneous investment horizons.

3. Data and methodology

3.1. Data and variable specifications

In this paper, we employ relevant weekly data for the Saudi stock market. The sample period is from January 2005 to March 2021, yielding 834 observations. The data is gathered from Reuters DataStream. The sample period is large and accounts for at least three main extreme events (the market collapse of February 2006, the 2008 GFC and the COVID-19 pandemic from March 2020), as well as other exogenous shocks caused by global risk factors, including oil price drops and other geopolitical incidents. The weekly returns are computed as: $r_t = 100 * Ln(P_t/P_{t-1})$, where P_t, and P_{t-1} refer, respectively, to prices at time (t) and $(t-1)$.

3.1.1. The investor sentiment measure

Following the related literature, investor sentiment is estimated via survey-based feedback from individual investors, market-implicit sentiment measures or indirect sentiment indicators. Here, we use GSV, following Da et al. (2015) and Gao et al. (2020), and construct a sentiment metric for Saudi investors. Formally, we start by selecting 149 keywords associated with ‘good’ and ‘bad’ sentiments, such as “gold”, “crash”, “profit”, “earning”, “dividends”, “political risk”, “failure”,” stocks”, “IPOs”, etc. Secondly, we translate the 149 keywords into Arabic. Here, we assume that individual investors are making their searches using the Arabic language. Then we download the GSVs related to each selected key work using the link (https://www.google.com/trends/) and keep only words with relevant search volume. We download the GSV at a weekly frequency over the whole sample period. Thirdly, we compute the weekly change (ΔGSV) for each selected keyword, eliminate outliers corresponding to insignificant words unrelated to finance or economics, and remove the seasonality effects in the time series to come up with weekly adjusted variations ($A\Delta GSV$). Fourthly, we check the relevance of the selected keywords and their connectedness to Saudi stock. Following Gao et al. (2020), we run a backward rolling regression on stock market returns. Here, the underlying idea is to let the stock returns speak and select only relevant keywords having either positive or negative effects. We retain the keywords with significant estimated parameters, as measured by a t-student test. It is worth noting that we can check the robustness of our keyword selection by employing principal component analysis (PCA) to isolate the common relevant keywords and their corresponding GSVs. Da et al. (2015) consider only negative effects since their main objective is to construct a “*fear index*”. However, in the present study, we consider both positive and negative effects (i.e., positive and negative estimated parameters) for two foremost reasons. Firstly, the use of weekly data allows us to gather many data related to optimistic and pessimistic investors’ sentiments. The weekly frequency may reduce the noise effect compared to the daily data used by Da et al. (2015). Secondly, because of the short-selling restrictions in the Saudi market, we conjecture that traders with positive sentiments have a more relevant role in explaining stock returns, as traders with pessimistic sentiments suspend their trading because of the short-selling restrictions. Following Gao et al. (2020), we consider only the top 30 positive and top 30 negative keywords to construct the GSV metric. Then, we have[10]:

$$Sent_t = \sum_{i=1}^{30} R_i^{+} \Delta AGSV_i - \sum_{i=1}^{30} R_i^{-} \Delta AGSV_i \quad (1)$$

[10] For more technical details, the readers can refer to Da et al. (2015), Gao et al. (2020) and Gao et al. (2019), cited in the reference list.

where $\sum_{i=1}^{30} R_i^{\pm} \Delta AGR_i$ designates the weighted average of the t-statistics inherent to the top 30 positive (negative) keywords. Using this approach, we get a sentiment metric that assesses the aggregate net sentiment in the market.

3.2. Methodology

3.2.1. Investors' fears and aggregate returns in the time-frequency domain

The continuous wavelet transform (CWT) method requires instantaneous localization over time and frequencies. With reference Aloui and Hkiri (2014), and Nunes and Rua (2009), the CWT is provided by the equation:

$$W_x(u,s) \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \overline{\psi(\frac{t-u}{s})} dt. \quad (2)$$

Explicitly, $W_x(u,s)$ is obtained by sticking out the specific wavelet $\psi(.)$ on the used variables. The CWT method has three variants that permit to explore a signal conjointly in the time and frequency bands: the wavelet power spectrum, cross-wavelet power, and wavelet coherence (WC).

The wavelet coherence plot permits to outline the connectedness between variables over frequency bands and time scales. Given its ability to picture the timing and scale of shocks, the WC method offers insight into the lead-lag interactions among the used time series simultaneously over frequency bands and time scales.

Traders are heterogeneous, and the various investment horizons confirm the presence of various scale bands. Therefore, traders can make asset allocations' decisions differently in various frequencies. Specifically, short-term traders are involved with short-term time series coherence, focused primarily on low scales, while long-term traders are concerned with high scales. Mathematically, the cross-wavelet tool has the ability to decompose, then restructure the $X(t)$ function, resulting in the equation:

$$x(t) = \frac{1}{C_{\Psi}} \int_{0}^{\infty} \left[\int_{-0}^{\infty} w_x(u,s) \Psi_{u,s}(t) du \right] \frac{ds}{s^2}, s > 0 \quad (3)$$

The WC approach is an appropriate method for running the coefficients of local correlation between two-time series, $X(t)$ and $Y(t)$. Given these two time series, with wavelet transforms given as $Wx(u,s)$ and $Wy(u,s)$ one can express the cross-wavelet spectrum as $Wxy(u,s) = Wx(u,s)W_x^*(u,s)$.

Like Fourier analysis, the wavelet squared coherence (WSC) is the absolute value of the smoothed cross-wavelet spectrum squared, normalized by the smoothed wavelet power spectra:

$$R^2(u,s) = \frac{|S(s^{-1}\, W_{xy}(u,s))|^2}{S(s^{-1}|W_x(u,s)|^2(s^{-1}|W_y(u,s)|^2)} \tag{4}$$

The WC offers the localized correlation coefficient between two signals through time and frequencies. Evidently, WC can faithfully identify co-evolution among signals across various investment horizons. In equation (4), S gives the smoothing coefficient, and $R^2(u,s)$ is the correlation coefficient which meets the ensuing dissimilarity $0 \leq R^2(u,s) \leq 1$. When the WSC value is close to zero, the correlation between the two-time signals is low, while a correlation coefficient close to one signifies the presence of high dependence (coherence).

The phase difference offers a picture of the unpunctuality of the oscillations among the used variables as a function of frequencies. The direction of the arrows indicates the phase difference. Specifically, in the WC plots, the lead-lag interactions among two variables is captured by the direction of the arrows. The variables are in a positive relationship (in phase) when the arrows are directing to the right, while they are in a negative relationship (anti-phase) when they are directing to the left.

3.2.2. Aggregate return and investor sentiments: The spectral causality approach

The Granger causality test is one frequently used causality tests. However, this linear test remains unsatisfactory because it only explores the reciprocal interactions among the relevant variables in a static manner. Hence, Breitung and Candelon (2006) develop a Granger test that can inspect the causal linkage among variables in a dynamic context. Their Granger causality test operates in the frequency space to account for the spillover behaviour across variables at different frequencies. Bozoklu and Yilanci (2013) show that the causality can be estimated at all points in the frequency distribution. It is worth noting that the principle of the spectral tool involves decomposing the causality between two variables, *y* and *x*, at several frequencies (short, medium and long term). According to Breitung and Candelon (2006), the variables *y* and *x* denote two-time series that are stationary.

Let V_t = (Y_t,X_t) be a two-dimensional vector of time series achieved at $t = 1 \ldots, T$ with a finite-order VAR derived framework, illustrated as:

$$\theta(L)Z_t = \varepsilon_t \quad (5)$$

Based on Bozoklu and Yilanci's (2013) definition, the model given in Eq. (5) can be written as:

$$\begin{aligned} Y_t &= \theta_{11,1}Y_{t-1} + \theta_{11,2}Y_{t-2} + \ldots + \theta_{11,p}Y_{t-p} + \theta_{12,1}X_{t-1} + \theta_{12,2}X_{t-2} +, \ldots, + \theta_{12,p}X_{t-p} \\ X_t &= \theta_{21,1}X_{t-1} + \theta_{21,2}X_{t-2} + \ldots + \theta_{21,p}X_{t-p} + \theta_{22,1}Y_{t-1} + \theta_{22,2}Y_{t-2} +, \ldots, + \theta_{22,p}Y_{t-p} \end{aligned} \quad (6)$$

The model presented in Eq. (5) can be drawn as a matrix representation by means of the lag operator (L):

$$\theta(L)\begin{pmatrix} Y_t \\ X_t \end{pmatrix} = \begin{pmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{pmatrix}\begin{pmatrix} Y_t \\ X_t \end{pmatrix} = \varepsilon_t \quad (7)$$

where $\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - \cdots - \theta_p L^p$ is a 2×2 lag polynomial, and $\theta_1 - \theta_2 - \cdots - \theta_p$ are 2×2 autoregressive coefficient matrices. The error vector ε_t designates white noise with zero mean and covariance matrix $E(\varepsilon_t, \varepsilon'_t) = \sum$ where $\sum$ is presumed positive and symmetric. Given these characteristics, Breitung and Candelon (2006) employ the Cholesky decomposition method to decompose matrix $\sum$ as $G'G = \sum^{-1}$ where G and G' are, respectively, the lower and upper triangular matrices. Consequently, the moving average representation of the system is expressed as:

$$\begin{pmatrix} Y_t \\ X_t \end{pmatrix} = \psi(L)\eta_t = \begin{pmatrix} \psi_{11}(L) & \psi_{12}(L) \\ \psi_{21}(L) & \psi_{22}(L) \end{pmatrix}\begin{pmatrix} \eta_{1t} \\ \eta_{2t} \end{pmatrix} \quad (8)$$

where $\psi(L) = \theta(L)^{-1}G^{-1}$. The predictive power of X_t can be computed by comparing the predictive part of the spectrum to the intrinsic part corresponding to each frequency. Referring to Geweke (1982), the causality measure (CM) is plotted as expressed in Eq. (5):

$$CM_{X\rightarrow Y(\omega)} = log\left[1 + \frac{|\psi_{12}(e^{-i\omega})|^2}{|\psi_{11}(e^{-i\omega})|^2}\right] \quad (9)$$

If $\left|\psi_{12}(e^{-i\omega})\right|^2$=0, X does not cause Y at frequency (ω). Therefore, we test H (0) indicating no causality at frequency $\omega$by referring to the standard F test. The frequency (ω) is equal to 2Π/cycle duration (T); for ω ∈ (0, π), where *T* and *p* denote the size sample and the optimal lag order of the VAR model, respectively. Gomez-Gonzalez et al. (2015) state that if the values of (ω) are near zero, this is synonymous with long-term causality. However, if the values of (ω) are near to Π, this suggests a short-term causality between *x* and *y*.

3.2.3. Market volatility and sentiment: GJR-GARCH modelling

The univariate GJR-GARCH model of Glosten, Jagannathan and Runkle (1993) is employed to model the time-varying volatility. The investor sentiment metrics are included as control variables in the conditional variance of the GJR-GARCH model. Therefore, the statistical significance of estimated sentiment parameters indicates an impact of sentiment on market volatility, while the sign of the parameter shows a sense of causality. We include dummy variables corresponding to extreme local and global events (2006 market collapse, 2008 GFC and COVID-19 pandemic) in the conditional variance. Our main goal is to check whether these extreme incidents affect stock volatility.

It is worth noting that at least two main features of the GJR-GARCH model motivate our choice. Firstly, empirically, the model accounts for the asymmetrical behavior of the time-varying volatility. The conditional variance accounts for responses to past positive and negative stock returns. From a behavioral finance perspective, the model is suitable to account for investors' heterogeneous expectations, risk profiles, and responses in terms of investment decisions during bull and boom market conditions. Secondly, the GJR-GARCH model includes the main observed facts of financial time series, which is the stronger effect of lagged negative shocks on the variance than positive shocks, known as the ‘leverage effect’. The increased risk is assumed to emerge from the increased leverage induced by negative shocks. In this regard, numerous studies show the methodical preference of the GJR-GARCH over alternative models. For instance, Nugroho et al. (2019) show, using the Markov chain Monte Carlo method, the superiority of the GJR-GARCH-model over other standard GARCH-class models, including GARCH, GARCH-M and Log-GARCH in terms of data fitting. Similar outcomes are evidenced by Naimy et al. (2021), who show the superior performance of the GJR-model compared to GARCH-type models including the IGARCH, EGARCH, SGARCH, APARCH, TGARCH and CGARCH. Formally, our GJR-GARCH (1,1) model is written as:

$$r_t = \sigma_t \varepsilon_t \,, \varepsilon_t \sim N(0,1) \tag{10}$$

Eq. (10) describes the mean return process, while the conditional variance equation is expressed as:

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1}) r_{t-1}^2 + \beta \sigma_{t-1}^2 + \vartheta s_{t-1}^{+} + \delta s_{t-1}^{-} + \sum_{k=1}^{M} \tau_k dum_{k,t} \tag{11}$$

where the positivity of the conditional variance is assured by $\omega > 0, \alpha \geq 0, \beta \geq 0, and\ \alpha + \gamma \geq 0$, while $\alpha + \beta + 0.5\gamma < 1$ assures the stationarity of the conditional variance. I is an indicator function expressed as:

$$I_{t-1} = \begin{cases} 0\ if\ r_{t-1} \geq 0, (positive\ shock) \\ 1\ if\ r_{t-1} < 0, (negative\ shock) \end{cases} \tag{12}$$

s_{t-1}^{+} and s_{t-1}^{-} refer, respectively, to the lagged changes of positive and negative investor sentiments. The positivity of the estimated coefficients ϑ and δ indicates that positive (negative) investor sentiment intensifies Saudi market volatility, while a significant negative coefficient implies a negative effect on the volatility.

3.2.4. Pricing and sentiment

We investigate the connectedness between sentiment and stock pricing over time scales using the Haar wavelet transformation and a sentiment multiscale pricing model. Here, we progress in two steps. We briefly expose the orthogonal wavelet data decomposition as suggested by Gençay et al. (2002), then describe our proposed sentiment-multiscale pricing model.

3.3. The orthogonal wavelet transformation

We employ the orthogonal Haar transformation (Mallat, 1998; Gençay et al., 2002) to decompose weekly returns into scales. The transformed time series of returns are represented as a linear combination of wavelet functions:

$$r_t = \sum_k s_{j,k}\phi_{j,k}(t) + \sum_k d_{j,k}\psi_{j,k}(t) + \sum_k d_{j-1,k}\psi_{j-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t) \quad (13)$$

where (j) refers to the number of scale crystals (or frequency), while (k) designates the number of coefficients in the specified component. $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$ denote, respectively, the father and mother orthogonal wavelets, expressed as:

$$\phi_{j,k}(t) = 2^{-j/2}\phi\left(\frac{t-2^j k}{2^j}\right), for\ j = 1, \ldots J \quad (14)$$

$$\psi_{j,k}(t) \ = 2^{-j/2}\psi\left(\frac{t-2^j k}{2^j}\right), for\ j = 1, \ldots J \quad (15)$$

The father wavelets designate the low-frequency (smooth) part of the time series, while the mother wavelets represent the high-frequency (detailed) part of the time series. $s_{j,k}$ and $d_{j,k}$ represent the wavelet parameters. They are generated by the functions:

$$s_{j,k} \approx \int \phi_{j,k}(t) f(t) dt \quad (16a)$$

$$d_{j,k} \approx \int \psi_{j,k}(t) f(t) dt \quad (16b)$$

where $s_{j,k}$ refers to the ‘smooth’ component of the time series, and $d_{j,k}$ refers to ‘detail’, which represents the scale deviations from the ‘smooth’ component. Following Gençay et al. (2005), Fernandez (2006), Fernandez et al. (2007), Masih et al. (2010) and McNevin and Nix (2018), we decompose the time series into (j) crystals (d_j). Then the crystals are decomposed into a time domain, taking a multiresolution approach:

$$\hat{r}^J = D_1 + \cdots + D_J + S_J \quad (17)$$

where d_j designates the recomposed time series in the time domain from the crystal, while S_j is the recomposition of the residual terms. As a result, the return series $\hat{r}^J$ contains separate components of each series at each frequency (j), and d_j designates the contribution of the frequency to the original time series. The approximation in Eq. (17) is called a multiresolution decomposition (Fernandez, 2006, p.208).

3.4. The sentiment-multiscale pricing model

At this point, we use the recomposed time series obtained for each scale and run some exploratory OLS regressions to investigate the relationship between the weekly returns of each stock, the market return, and positive and negative sentiments over each recomposed crystal. We use weekly data for all listed Saudi firms, starting from January 2005, the inception of our sample period. We find 32[11] firms operating in various industries. As a first step, we use the orthogonal Haar wavelet transformation to decompose the time series into scales[12]. We consider the following five scales: scale 1 is 2-4 weeks, scale 2 is 4-8 weeks, scale 3 is 8-16 weeks, scale 4 is 16-32 weeks, and scale 5 is 32-64 weeks. In the next step, we estimate the following three-factor market pricing model regression:

$$\begin{aligned} R_i &= \alpha_i^j + \beta_i^j R_m^j + \gamma_i^j Sent^{+,j} + \delta_i^j Sent^{-,j} + \varepsilon_i^j \\ &= \alpha_i^j + \beta_i^j D_m^j + \gamma_i^j Sent^{+,j} + \delta_i^j Sent^{-,j} + \varepsilon_i^j, for\ j = 1, \dots 5 \end{aligned} \tag{18}$$

The key parameters we are concerned with are γ_i^j and δ_i^j measuring the impact of positive and negative sentiment on pricing. If these parameters are stable over the selected scales, there is no multi-scaling effect of investor sentiment. Put another way, there is no reason to accept the research hypothesis that the sentiment-pricing nexus varies across investment horizons. Conversely, if the sentiment parameters vary over time scales, the multi-scaling phenomenon is evidenced. Correspondingly, the variability of the β_i^j parameter across scales (j) indicates that it

[11] We note that we consider only firms having data available from January 2005, as listed in Reuters DataStream.

[12] It is worth noting that the number of j crystals that can be used has to fulfill the relation $N \geq 2^j$ where N denoted the number of observations. As we use weekly data, we have 52 observations. Thus, the maximum number of crystals that can be generated is 5.

depends on time scales and, therefore the return interval has an effect on market model outcomes.

Using the same approach as Gençay et al. (2003), we derive the wavelet variance (σ_x^2) for $x_1, x_2, \ldots x_n$ time series. If we consider $v_x^2(\tau_j)$ the wavelet variance for scale $\tau_j = 2^{j-1}$, the variance can be written as:

$$\sigma_x^2 = \sum_{j=1}^{\infty} v_x^2(\tau_j) \tag{19}$$

Using the spectral density function, the variance is given by $\sigma_x^2 = \int_{-\frac{1}{2}}^{\frac{1}{2}} S_x(f)df$, where $S_x(f)$ denotes the spectral density function for the frequency $f\left[-\frac{1}{2};\frac{1}{2}\right]$. Gençay et al. (2003) define the unbiased variance estimator as:

$$\hat{V}_x^2(\tau_j) = \frac{1}{(n'_j - L'_j)2^j} \sum_{t=L'_j}^{n'_j-1} d_{j,t}^2, \tag{20}$$

where $n'_j = (n/2^j)$ refers to the number of discrete wavelet transforms at level (j) and (n) represents the size of the sample. The number of discrete wavelet transform boundary parameters at level (j) is given by $L'_j = (L-2)(1-\frac{1}{2^j})$, where L is the width of the wavelet filter used.

In the same way, the unbiased wavelet covariance is derived as:

$$\hat{V}_{xy}^2(\tau_j) = \frac{1}{(n'_j - L'_j)2^j} \sum_{t=L'_j}^{n'_j-1} d_{j,t}^{(x)} d_{j,t}^{(y)} \tag{21}$$

Using the unbiased variance and covariance, we derive the beta coefficient for stock (i) for time scale (j) as:

$$\hat{\beta}_i^2(\tau_j) = \frac{\hat{V}_{R_{m,R_i}}^2(\tau_j)}{\hat{V}_{R_m}^2(\tau_j)} \tag{22}$$

where $\hat{V}_{R_{m,R_i}}^2(\tau_j)$ denotes the covariance between the market and stock return for each stock (i) at time scale (j), while $\hat{V}_{R_m}^2(\tau_j)$ gives the variance of the market return at time scale (j).

Based on the abovementioned unbiased wavelet estimators, the wavelet R^2 can be computed as (Gencay, 2003):

$$\hat{R}_i^2(\tau_j) = \hat{\beta}_i^2(\tau_j)\frac{\hat{V}_{R_m}^2(\tau_j)}{\hat{V}_{R_i}^2(\tau_j)} \tag{23}$$

The wavelet R^2 is another key estimator for our study since it shows how the explanatory power of sentiment evolves over time scales. The expected outcomes allow us to add to the debate regarding the explanatory power of the sentiment-scaled pricing model (Norsworthly et al., 2000; Gençay et al., 2003; Fernandez, 2006; Masih et al., 2010).

4. Empirical findings and discussion

In this section, we present our wavelets coherence analysis and the spectral causality tests of the sentiment-return nexus. We report the outcome of the GJR-GARCH modelling of the sentiment-volatility relationship. Finally, we give the estimation results of the sentiment-pricing model within a multiresolution framework.

4.1. Sentiment metrics time path

Figures 1a and 1b show the time movements of negative and positive sentiments, respectively, while the aggregate time return movements are plotted in Figure 1c. As we see, the three-time series are extremely volatile over the whole sample period and exhibit some clustering volatility. They appear to be correlated, as the volatility clustering in the sentiment metrics corresponds to high levels of aggregate market volatility. This high dependence turns out to be more evident during turbulent market periods such as the Saudi market collapse (beginning of 2006), GFC (2008), and the ongoing COVID-19 pandemic (beginning of 2021).

Figure 1:

Sentiments and aggregate stock return time movement

Figure 1a:

Negative sentiment metrics time movements

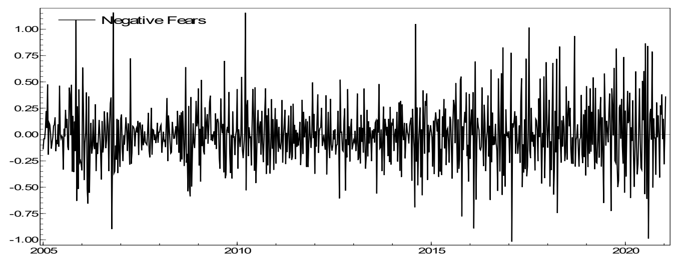


Figure 1b:

Positive sentiment metrics time movements

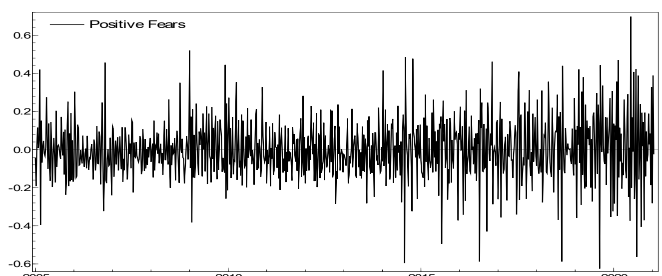
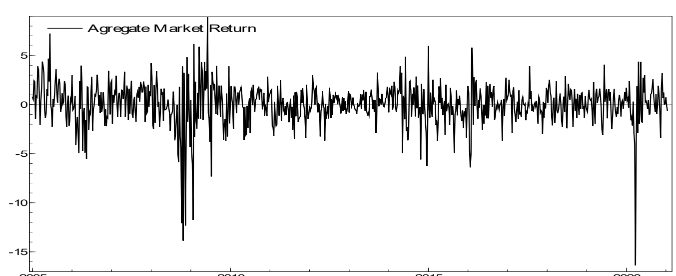


Figure. 1c:

Aggregate stock return time movements



Notes:

The time series are at weekly frequency, covering the period January 2005 to March 2021. Data for the market weekly returns are gathered from Reuters DataStream and expressed as logarithmic returns.

4.2. Investor sentiment-returns nexus

Here, we assess the impact of Saudi investor sentiment on aggregate stock return. Specifically, we analyse the impact of changes in positive and negative sentiment on the behavior of the Saudi market over time scales and investment horizons (i.e., frequency bands). For a more comprehensive wavelet analysis, we consider three major extreme events: the recent COVID-19 health crisis (March 2020), the 2008 GFC (October 2008), and the 2006 Saudi market collapse (Black February). Our main goal is to examine how investor sentiment impacts the Saudi market during turbulent market conditions. Figures 2a and 2b plot the wavelet coherence between investors' positive sentiments (Figure 2b.), negative sentiments (Figure 2a), and the aggregate return. The color bar gauges the power of the co-movement between the two variables. Red refers to strong coherence between the variables. The direction of the arrows shows the phase differences between the two-time series. Visual inspection of Figure 2b reveals the existence of some significant red islands of high coherence over the whole sample period. There is a particularly distinctive behavior of the co-movement in the (16-64) week frequency band. Two large islands of high coherence are located in the period 2006-2008 at the medium (16 week) frequency and low (32-64 week) frequency, which may be attributed to the two extreme events of the 2006 Saudi market collapse and the start of the GFC, indicating that Saudi positive sentiments and returns reach their maximal co-movement during turbulent market conditions. Similarly, another island of high coherence can be seen starting from March 2020, which corresponds to the COVID-19 outbreak in Saudi Arabia. The phase difference points to some appealing findings. Most of the arrows are turned up to the right, signifying that the two-time series are in phase with investor sentiment as a leading variable (i.e. aggregate return as a lagging variable). In other words, the causality linkage goes from investor sentiment to aggregate return, specifically during periods of high coherence (medium- and long-term investment horizons). Figure 2a shows the negative sentiment and aggregate return coherences over time and across frequency bands. Again, investor sentiment drives a positive (in phase) relationship with the aggregate return at the medium- and long-term horizons. Specifically, high coherence, localized at the medium and low frequencies (16-32 and 32-64 weeks), is especially scattered over the sub-period 2006 to 2010, which includes the Saudi market turmoil and GFC. Interestingly, a large island of high coherence is seen at the short and medium scales (8-16 and 16-32 weeks) and spreads from the beginning of 2020, coinciding with the first announcements of COVID-19 infections in Saudi Arabia. Our findings indicate that investor sentiment can drive the stock market during extreme events.

Figure 1:

Wavelet coherence between sentiment and aggregate return

The whole sample period

Figure 2a:
Negative sent. vs. aggregate return: whole sample

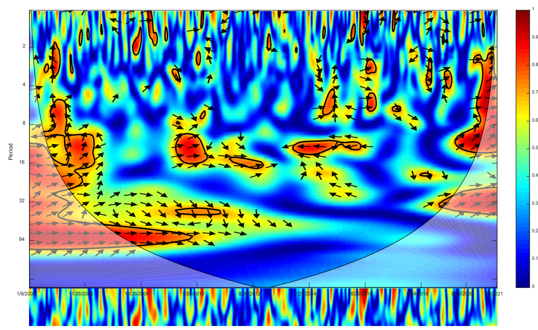
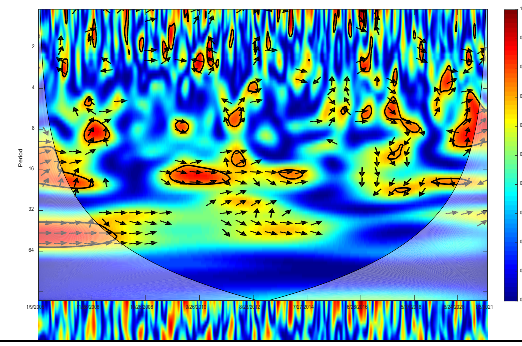


Figure 2b:
Positive sent. vs. aggregate return: whole sample



The COVID-19 health crisis

Figure 2c:
Negative sent. vs. aggregate return: pre- COVID-19

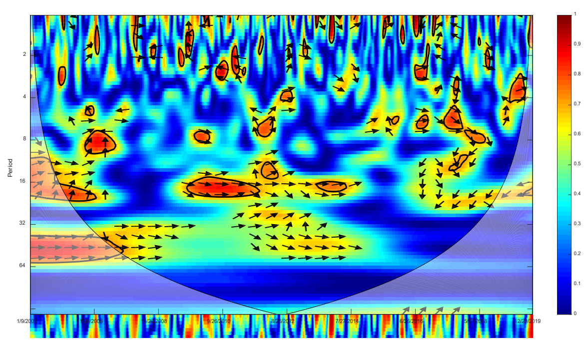


Figure 2d:
Positive sent. vs. aggregate return: pre- COVID-19

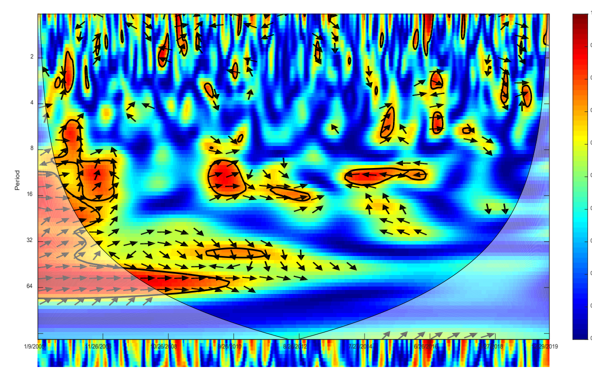


Figure 2e:
Negative sent. vs. aggregate return: post COVID-19

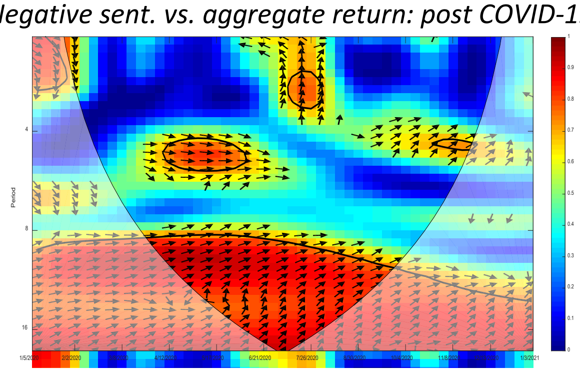
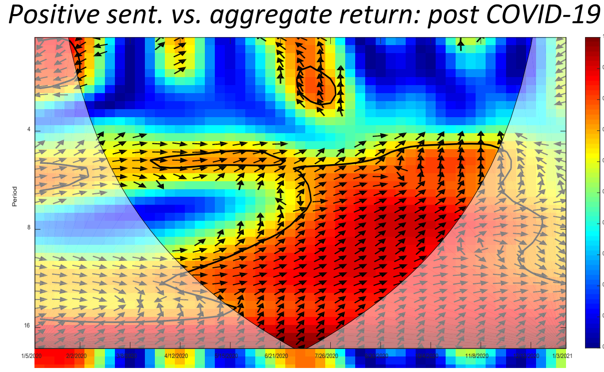


Figure 2f:
Positive sent. vs. aggregate return: post COVID-19



The 2008 GFC

Figure 2g:
***N**egative sent. vs aggregate return: pre- GFC*

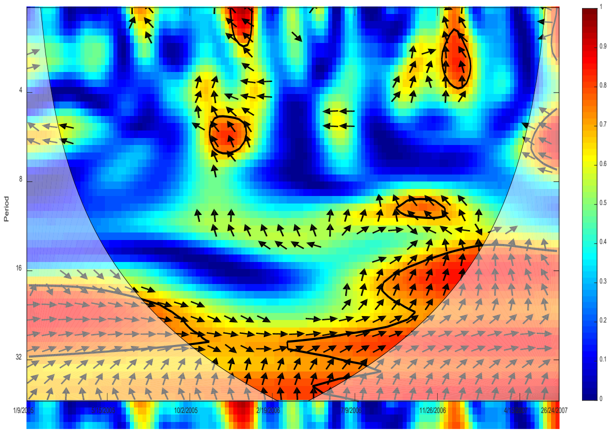


Figure 2h:
Positive sent. vs. aggregate return: pre- GFC

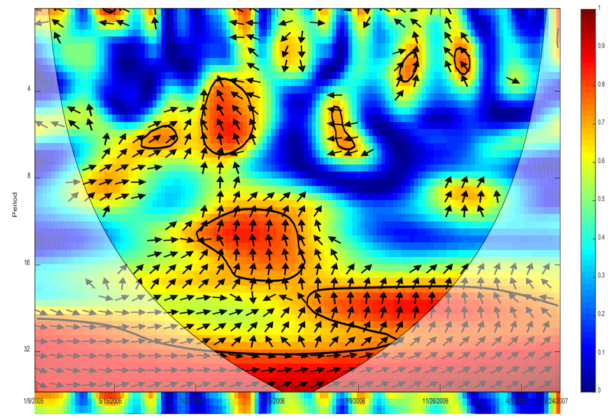


Figure 2i:
***N**egative sent. vs. aggregate return: post- GFC*

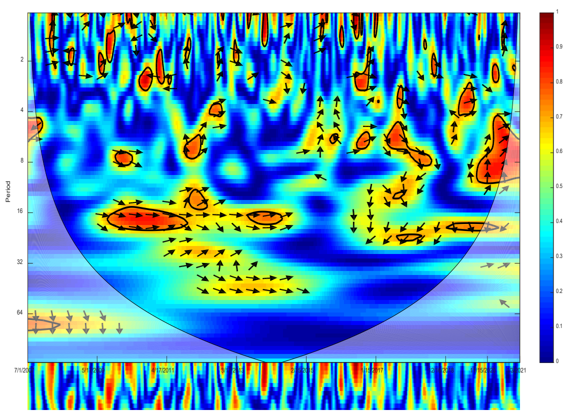
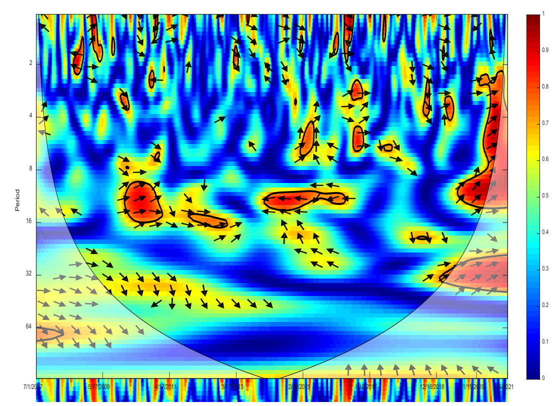


Figure 2j:
Positive sent. vs. aggregate return: post- GFC



The 2006 Saudi market collapse

Figure 2k:
Negative sent. vs. aggregate return: pre- 2006 collapse

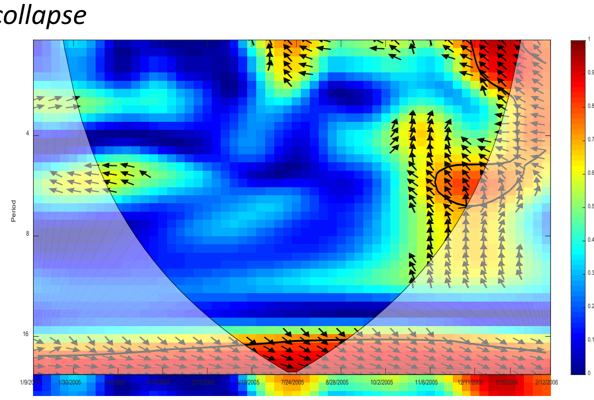


Figure 2l:
Positive sent. vs. aggregate return: pre- 2006 collapse

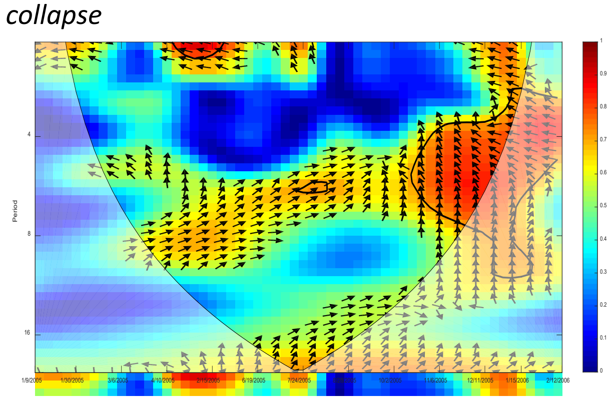


Figure 2m:
Negative sent. vs. aggregate return: post- 2006 collapse

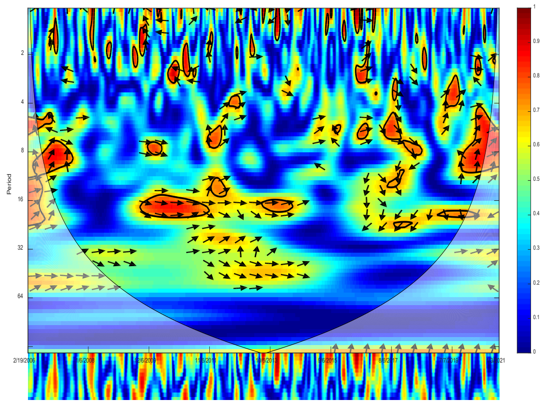
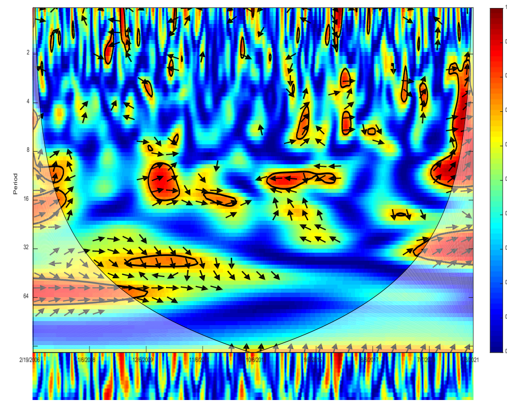


Figure 2n:
Positive sent. vs. aggregate return: post- 2006 collapse



Notes:
The inspection of the directions of the arrows shows the phase difference among the used time series. When arrows are pointed to the right (left) this means that that the time series are in phase (anti-phase), to the right and up (down), the first time series is leading variable (lagging variable), and to the left and up (down), the first time series is a lagging variable (leading variable). The time is reported on the horizontal axe while the frequencies (weeks) are reported on vertical axe. The color bars show the degree of correlation between the time series. Red refers to a very strong coherence between the time series. Sent. Designates that the investor sentiment. The frequency bands in wavelets are viewed as short and long-term investment horizons and are given in terms of weeks. High and medium frequency bands correspond to 1-52 band-weeks, while low-frequency bands are higher than 64 weeks' frequency bands (more than one-year investment horizon).

4.2.1. Impact of exogenous shocks: The COVID-19 outbreak

As noted, we explore the impact of the COVID-19 outbreak on the sentiment-return interplay in the time-frequency domain. We implement wavelet coherence for the periods before and after the health crisis. Here, we consider the date 02 March 2020, when the Saudi Ministry of Health announced the first case of COVID-19 in Saudi Arabia, as a cut-off date. It is worth noting that the Saudi government reacted confidently and expeditiously to the pandemic. It set up innumerable support systems and made very stringent restrictions to contain the spread of the virus (partial and complete curfew, travel restrictions, suspending government and private employee attendance at workplaces). Therefore, we presume that, during the most rampant conditions of the COVID-19 pandemic, investors intensified their Google searches to get access to information to help them with investment decisions. Traders took investment decisions and reallocated their portfolios based on market-pandemic-related information, which, in turn, affected stock returns and market volatility. Figure 2d shows the wavelet coherence between positive investor sentiment and aggregate returns before the COVID-19 pandemic. As we can see, the two years pre-COVID-19 (2018-2020) seem to be calm since no significant islands of high coherence are seen in the wavelet plot, except a few small islands of red in high-frequency bands (4-8 weeks), implying that positive investor sentiment only marginally affects aggregate returns over short-term investment horizons.

In the post-COVID-19 sub-period (Figure 2f), we can clearly perceive a huge island of high dependence covering the whole sample period between positive sentiment and market return over the short and medium terms (4–16-week frequency bands), indicating that positive sentiment and returns reach their maximum level of coherence during this period. The correlation ranges between 0.8 and 1. Moreover, we can discern other small areas of red at the short-term horizon (less than four-week frequency) at the beginning of the COVID-19 outbreak in Saudi Arabia (March 2020). The arrows are horizontal and predominantly pointed to the right and up, which indicates that the two-time series are in phase with positive sentiment as the driver variable. From a financial standpoint, during turbulent market conditions, investors' attention to market-related information increases, and traders tend to rebalance their portfolios to avoid risk, which may explain positive sentiments causing aggregate returns. This result corroborates the main findings of recent work related to COVID-19's impact on the Saudi market. For instance, Sayed et al. (2021) reveal, using a nine-day event window, that the Saudi market was negatively affected by the announcement of the first cases. The announcement's impact varied across industrial sectors. Analogous outcomes are presented by Tissaoui et al. (2021), who implement multivariate and partial wavelet methods and the autoregressive distributed lagged (ARDL) model to show significant connectedness between market return, infectious disease-confirmed cases and market illiquidity.

The wavelet coherence between negative sentiment and returns for the pre-COVID-19 period (Figure 2c), is typically similar to its positive counterpart wavelet. Only a few small areas of high coherence are detected over short- and mid-term investment horizons. The arrows are mostly turned to the left during the two years pre-COVID-19, revealing that the two-time series are out of phase, with aggregate return as the leading variable. Figure 2e shows that the wavelet coherence between negative investor sentiment and aggregate return is highly pronounced over the whole post-COVID-19 sub-sample period. A large area of high coherence is visible in the 8-16’ week frequency band. The phase analysis shows that the arrows are turned to the right, showing that the two time series are in phase, with negative investor sentiment as a directing time series. This outcome is similar to Figure 2d (positive sentiment vs. aggregate return). To sum up, investor sentiment metrics are strongly connected to aggregate returns. The causalities mostly go from sentiment to stock return. These results support our research hypothesis.

4.2.2. Impact of the 2008 GFC

Figures 2g and 2h show wavelet plots between negative (positive) investor sentiment and aggregate return during the 2008 GFC. It is worth noting that the two plots are quite similar, with a huge area of high coherence over the 16-32’ week frequency band (mid-term investment horizon). Other small areas of relevant dependencies are located in the high-frequency bands (2-8 weeks). The arrows mostly point up and to the left, showing that causality through the time-frequency domain goes from sentiment to aggregate returns. Likewise, the two variables are in phase, suggesting that traders make their investment decisions based on the flows of relevant information from their Google searches and react in a timely manner. To sum up, the Saudi aggregate return seems to be most affected by investor sentiment, while the causality linkage varies substantially across investment horizons.

4.2.3. Impact of the 2006 market collapse

Figures 2k, 2l, 2m, and 2n plot the wavelet coherence between the investor sentiment metrics and the Saudi aggregate return before and after the Saudi stock market collapse, commonly known as Black February, where we consider 26 February 2006 as the cut-off date sub-dividing the sample. On 25 February 2006, the Saudi market reached its highest level at 20,634 points. The next day witnessed a massive selling wave in the first minute of trading, initiating an enormous panic for small and medium investors, with the closure of more than 60 listed firms on a sharp decline, as 1.5 million stocks were sold in the first minute of trading. The market index lost around 980 points in February 2006, representing 4.75percent of the total market. During these extreme market conditions, we presume that the sentiments of individual investors played a key role. Thus, assessing the connectedness between sentiment, news, and stock returns is helpful to understand how the Saudi market is driven by sentiment rather than firm fundamentals during tempestuous times.

The wavelet coherence plots reveal that investor sentiment is strongly connected to aggregate return in the pre-collapse period. Figure 2k shows the coherence between negative sentiment and aggregate return, with a big area of high co-movement covering the end of 2005 in the (8-16) week frequency band, which means that negative sentiment and panic strongly drive aggregate return. This may be due to the fact that Saudi traders had poor expectations of the eventual market recovery and endured selling their stocks. At this frequency band, the arrows are turned to the right, indicating that the two-time series are in phase, with the aggregate stock market as a lagging variable, which suggests that causality goes from sentiment to stock return. Moreover, we see an even bigger island of high dependence between negative sentiment and return at the high frequency (1-8 week) bands. The arrows are turned to the left and up, suggesting that the causality goes from aggregate returns to investor sentiment, meaning that bad news related to Saudi market performance notably impacts investor sentiment. A different configuration is seen for the positive sentiment (Figure 2l), where only one large area of high coherence is found at the 2-8’ week investment horizon. The arrows are mostly turned to the left and up, showing that the two variables are in anti-phase, with investor sentiment as the lagging variable. In the post-collapse sub-period (Figures 2m and 2n), we see a relatively low coherence between investor sentiment and aggregate return. Indeed, a few areas of significant coherence are located at the long-term investment horizons (higher than 16’ week frequency). Taken as a whole, the average returns seem to be largely affected by investor sentiment, specifically during the chaos of the market collapse. Because of their fears, individual investors intensified their Google searches, looking for relevant information to make the appropriate decisions to avoid risk, reallocate their assets and seek safer investments. Furthermore, we perceive that the sentiment metrics are closely associated with market conditions, and their effect increases during turbulent market conditions. These findings are in line with Baker and Wurgler (2006), who claim that investor sentiment depends on market conditions, which leads to waves of positive and negative sentiment.

4.3. Robustness checks

4.3.1. The spectral causality test

To ensure the robustness of the wavelet-based outcomes, we take the frequency domain causal approach, built on Breitung and Candelon's (2006) spectral Granger causality test, for two main reasons. Firstly, this spectral test outperforms other traditional causality tests since it allows for the estimation of the causal nexus over three investment horizons: the short, medium, and long run (see, among others, Tastan, 2015; Khan et al., 2019; Xie et al., 2022). Specifically, the test uses three frequencies to estimate the causal connection within these three investment horizons. Secondly, the frequency domain causal approach has the ability to account for seasonality in the times series. The spectral Granger causality test results are shown in Figure 3. For an easier interpretation of the plots, the frequencies ($\omega_i = 0.5{,}1.5$ and 2.5) are shown on the x-axis while the y-axis shows the F statistics testing the null hypothesis of no Granger spectral causality. The red and green horizontal lines indicate the 5percent and 10percent critical values. When the black line exceeds the red (green) horizontal line, the calculated F statistic is higher than its critical value, which means that we reject the null hypothesis of no causal nexus going from investor sentiment to aggregate return. The spectral causality plots for the whole sample period (Figures 3a and 3b) show that positive sentiment causes aggregate returns over the long and short terms ($i.e.\ \omega_i = 0.5\ and\ 2.5$). This finding is supported by the significance of the F-statistics (Table 1), rejecting the null hypothesis of no causality for these investment horizons. Conversely, negative sentiment has no causal effect on return over the three-time horizons. This outcome supports the bivariate wavelet analysis for the whole sample period.

For the COVID-19 health crisis, the causality tests show that positive sentiment causes return over the short and long horizons during the pre-health crisis period. This result corroborates the wavelet plots since high coherence is detected for very high (4-8 week) and very low (more than 128 week) frequencies. Contrariwise, the causal effect of negative sentiment is only identified for the short term. For the post-health crisis period, while the two variables are strongly correlated over time scales and frequencies, no causal relationship is shown. From a financial perspective, this may be due to the fact that investor sentiment and returns are mutually impacted by the same exogenous risk factors. In this regard, it is worth noting that the Saudi economy faced dual external shocks from COVID-19 and the collapse of oil prices. The breakdown of negotiations among OPEC+ led to what is likely to be a persistent oil price collapse, with an outstanding drop in prices of more than 30percent. As for the other two shocks (2008 GFC and Saudi market collapse), the spectral causality tests are comparable. The causality mostly runs from sentiment to stock returns for the post-period but varies across frequencies. For the post-2006 market collapse (Figures 3m and 3n), positive sentiment causes aggregate return over the long-term and short-term investment horizons, while negative sentiment causality is limited to the short-term.From the spectral causal plots (Figures 3i and 3j) for the post-2008 GFC, we note that positive sentiment causes aggregate returns over the short-term $(\omega_i = 0.5)$ and long-term $(\omega_i = 2.5)$ investment horizons.

Figure 2:

Breitung and Candelon (2006) spectral Granger causality plots

The whole sample period

Figure 3a:

Negative sent. vs. aggregate return

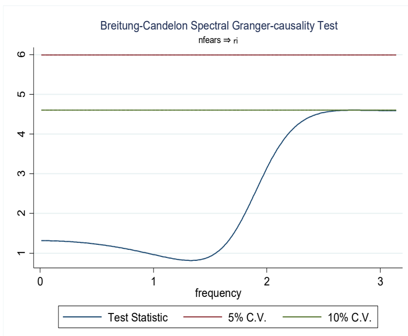
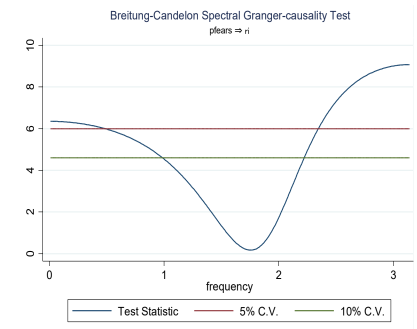


Figure 3b:

Positive sent. vs. aggregate return



The COVID-19 health crisis

Figure 3c:

Negative sent. vs. aggregate return: pre COVID-19

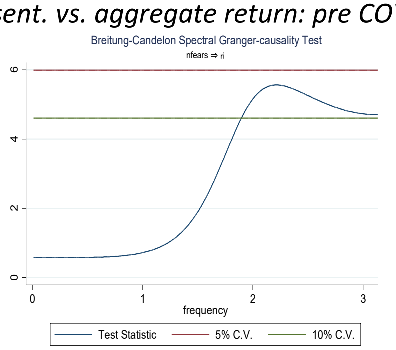


Figure 3d:

Positive sent. vs. aggregate return: pre COVID-19

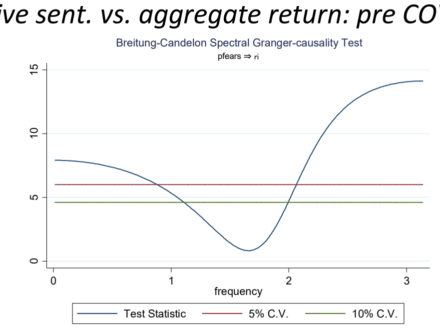


Figure 3e:

Negative sent. vs. aggregate return: post COVID-19

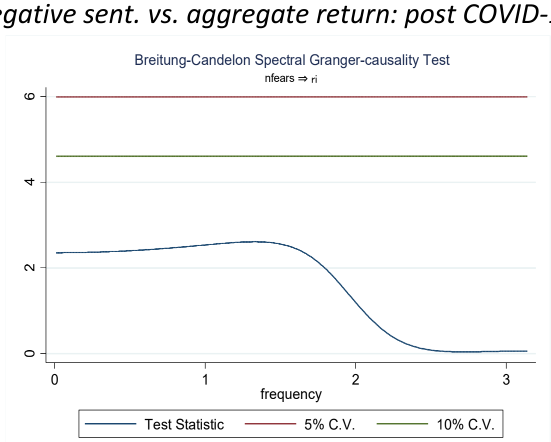
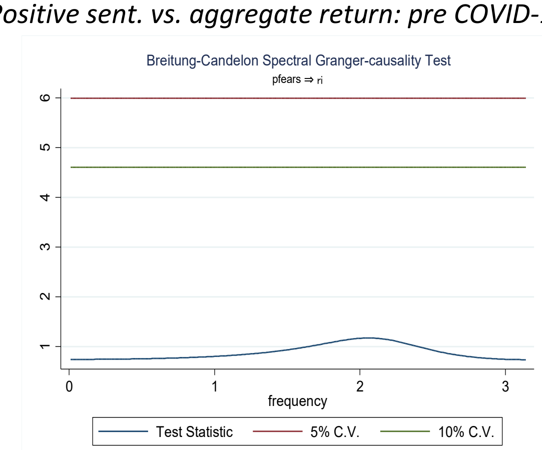


Figure 3f:

Positive sent. vs. aggregate return: pre COVID-19



The 2008 GFC

Figure 3g:

Negative sent. vs. aggregate return: pre-GFC

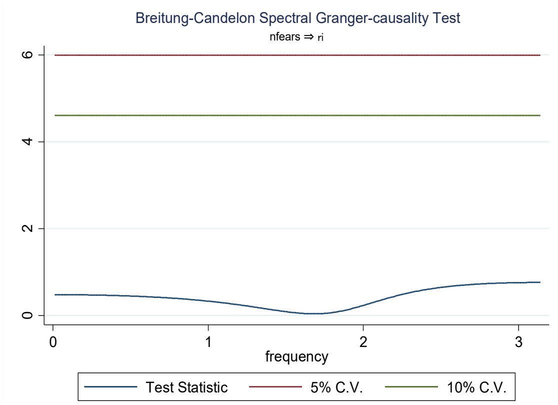


Figure 3h:

Positive sent. vs. aggregate return: pre GFC

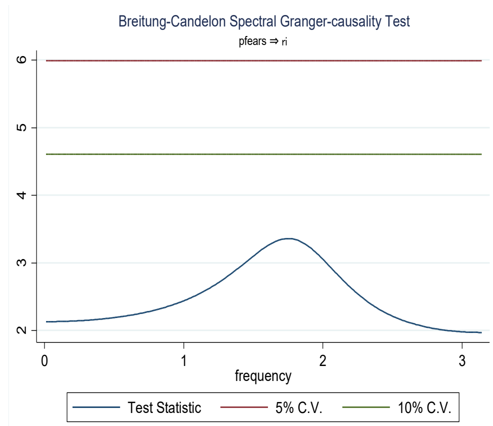


Figure 3i:

Negative sent. vs. aggregate return: post GFC

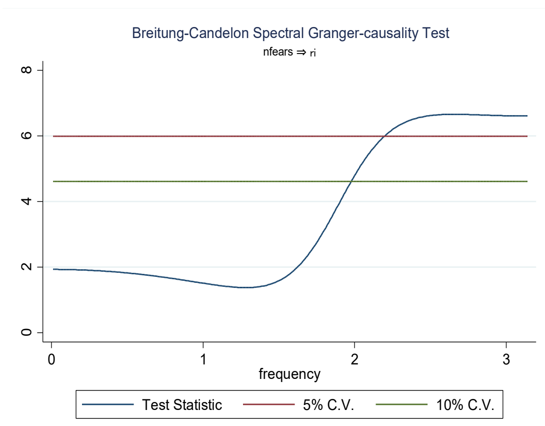
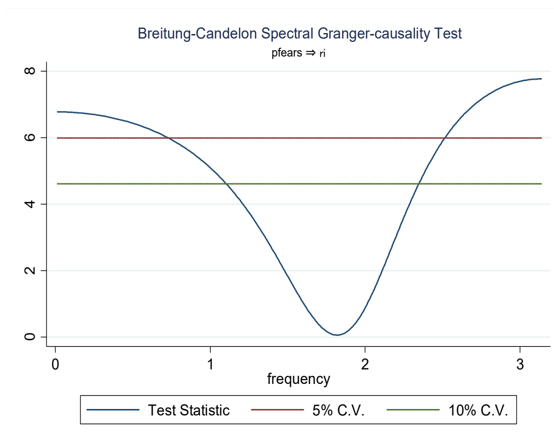


Figure 3j:

Positive sent. vs. aggregate return: post GFC



The 2006 market collapse

Figure 3k:
Negative sent. vs. aggregate return: pre 2006 collapse

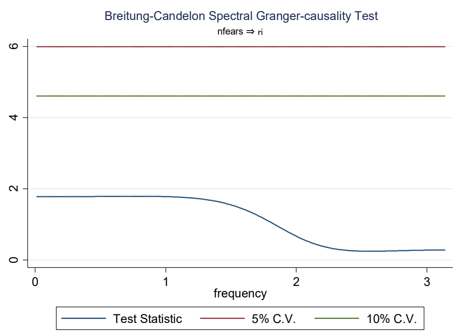


Figure 3l:
Positive sent. vs. Aggregate return: pre 2006 collapse

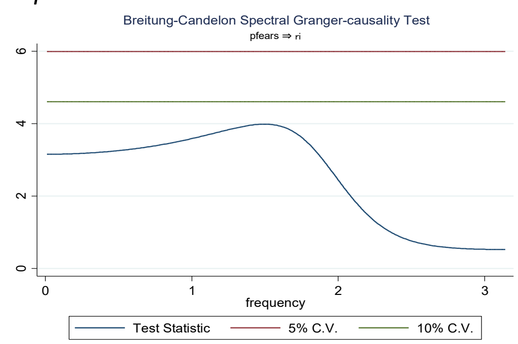


Figure 3m:
Negative sent. vs. Aggregate return: post-2006 collapse

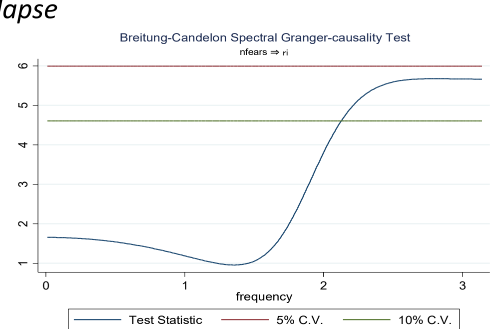
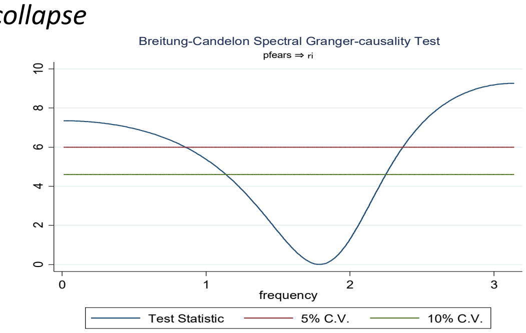


Figure 3n:
Positive sent. vs. Aggregate return: post-2006 collapse



Notes: The frequencies ($\omega_i = 0.5, 1.5\ and\ 2.5$) are shown on the x-axis, while the y-axis reports the F statistics relative to Granger causality null hypothesis. These frequencies are used to assess the causality linkage over short, medium and long run, respectively. The red and green horizontal lines indicate the 5% and 10% critical values. Sent. is investor sentiment.

Table 1:

Breitung and Candelon (2006) spectral Granger causality test results

Causality	Long-term	Medium-term	Short-term
	$\omega = 0.5$ *(p-value)*	$\omega = 1.5$ *(p-value)*	$\omega = 2.5$ *(p-value)*
		Whole period	
Positive sent.→ return	5.9753425*	1.337742	7.2981812**
	(.05040468)	(.51228662)	(.02601478)
Negative sent → return	1.2267369	.91859088	4.5433219
	(.54152369)	(.63172858)	(.10314072)
		Pre- 2006 market collapse	
Positive fears→ return	3.2538143	3.9862297	.75871085
	(.19653649)	(.1362703)	(.68430235)
Negative sent→ return	1.7818835	1.5441314	.24434291
	(.4102692)	(.46205761)	(.88499662)
		Post- 2006 market collapse	
Positive sent. → return	6.9474358**	1.679929	7.2131697**
	(.03100155)	(.43172586)	(.02714439)
Negative sent. → return	1.5405446	1.0529828	5.5914843***
	(.462887)	(.59067379)	(.06106953)
		Pre-2008 GFC	
Positive sent. → return	2.1908712	3.1008744	2.2123904
	(.33439391)	(.2121552)	(.33081525)
Negative sent.→ return	.44290772	.08322478	.64259518
	(.8013529)	(.95924152)	(.7252074)
		Post-2008 GFC	
Positive sent.→ return	6.4335817**	1.828473	5.8866851*
	(.04008349)	(.40082253)	(.05268932)
Negative sent.→ return	1.817589	1.5798003	6.6201901
	(.40300976)	(.45389011)	(.0365127)**
		Pre-COVID-19	
Positive sent.→ return	7.3561411**	1.4246317	12.211685***
	(.02527169)	(.49050694)	(.0022298)
Negative sent.→ return	.57978074	1.8927024	5.257902*
	(.7483456)	(.38815474)	(.07215411)
		Post- COVID-19	
Positive sent.→ return	.75387792	.93235025	.92444624
	(.68595795)	(.6273974)	(.62988178)
Negative sent.→ return	2.4003576	2.5570667	.07844257
	(.30114037)	(.27844539)	(.96153791)

Notes: Table 1 reports the Breitung and Candelon (2006) spectral Granger causality test results between positive and negative investor sentiments and assets returns during exogenous shocks (2006 Saudi market collapse, 2008 GFC, COVID-19 outbreak) and over different horizons (short, medium, and long term). Figures in parentheses are the p values related to the F statistic, while ω_i refers to the selected frequency band. Sent. is investor sentiment.

4.4. Sentiment and market volatility: GJR-GARCH modelling

As highlighted, we use a GJR-GARCH[13] model to investigate the impact of investor sentiment on market volatility. We estimate various specifications in which we include positive and negative sentiment metrics as control variables. We include other dummy variables corresponding to extreme events (2006 market collapse, 2008 GFC and COVID-19 pandemic) to test the impact of extreme events on the conditional variance. The GJR-GARCH estimations are given in Table 2, panel A, while the diagnostic tests are given in panel B. From the reported outcomes, we note that the autoregressive component in the mean equation is positively signed and significant, while the constant is insignificant. From the conditional variance equation, we perceive that the estimated ARCH, GARCH and GJR-GARCH components are significant for all the estimated specifications. More importantly, the GJR estimated parameters are significant and positively signed for all specifications, which implies that the impact of shocks on volatility is asymmetric and negative shocks increase volatility. This reinforces our choice of the GJR-GARCH model to account for asymmetry and the leverage effect in the time series. Diagnostic tests support the appropriateness of the GJR specification since the hypothesis of serial correlation of the squared standardized residuals is rejected by the Ljung-Box statistic, and the LM ARCH test rejects any ARCH effects remaining in the residuals. For the first three specifications, the estimated parameters relative to positive and negative sentiment are positively signed and significant when included in the GJR conditional variance equation. This means that both negative and positive sentiments have positive and significant impacts on aggregate volatility. Such a finding supports our research hypothesis regarding the response of the volatility to investor sentiment.

Furthermore, when including three dummy variables corresponding to the Saudi market collapse, 2008 GFC and COVID-19 pandemic, their estimated parameters turn out to be positive and significant, meaning that volatility increases during unsettled market conditions. This result is reinforced by the time movement of the GJR-GARCH conditional volatility shown in Figure 5. This

[13] We estimate various univariate GARCH-class models, including, among others, GARCH, CGARCH, FIGARCH, EGARCH and TGARCH. The diagnostic tests show the superiority of GJR-GARCH in terms of data fitting. To conserve space, the estimations of the selected models are not reported here but are available upon request addressed to the corresponding author.

time path clearly shows a sizeable surge of aggregate market volatility during tumultuous market circumstances, and we can incontestably see a volatility upsurge, specifically during the GFC and recent COVID-19 pandemic. From a behavioral perspective, investor attention increases during tumultuous market conditions as investors tend to intensify their Google searches for pertinent information to help them make appropriate investment decisions to sidestep downside risk and suboptimal portfolio diversification. These outcomes are consistent with recent findings in the sentiment-volatility nexus literature (see, among others, Badshah et al., 2018; Yen et al., 2021; Long et al., 2021; Mahmudul et al., 2022; Xue et al., 2022; Alshammari and Goto, 2022). For instance, Badshah et al. (2018) employ copula and quantile regressions and find a positive and asymmetric interaction between sentiment and stock volatility for a large sample of emerging markets. Their findings are supported by Mahmudul et al. (2022), who take a wavelet causality approach to show that conventional stock volatility reacts asymmetrically to positive and negative sentiments, and the response varies across time scales and frequencies. Xue et al. (2022) and Long et al. (2021) reveal a resilient ability of sentiment to predict volatility. Our results of the GJR-GARCH modelling approach are in line with Yen et al. (2021), who, using a GJR-GARCH model including several firm-specific factors and macroeconomic incidents in the GJR-GARCH conditional variance, show a strong effect of sentiment during the 2008 GFC. In the Saudi market, our findings corroborate the recent conclusions of Alshammari and Goto (2022), who find that over the short term, the Saudi market is mainly driven by retail investor attention posing risk and providing profitable opportunities at the same time.

Table 2:

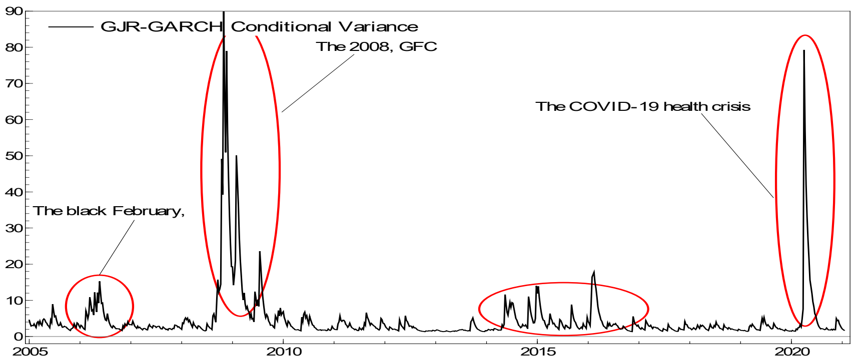
Estimation results of the univariate GJR GARCH model for the fear volatility nexus

Panel A: GJR-GARCH(1,1) estimates				
$Mean\ Eq.: \ r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t \sim N(0,1)$				
$Cst.(m).$	0.065	0.063	0.061	0.062
	(0.98)	(0.88)	(0.73)	(0.66)
$AR(1)$	0.149***	0.149***	0.148***	0.133***
	(3.90)	(3.88)	(4.01)	(3.82)
$Variance\ Eq.: \ \sigma_t^2 = \omega + (\alpha + \gamma I_{t-1}) r_{t-1}^2 + \beta\sigma_{t-1}^2 + \vartheta s_{t-1}^+ + \delta s_{t-1}^- + \sum_{k=1}^{M} \tau_k dum_{k,t}$				
$ARCH(1)$	0.124***	0.131***	0.129***	0.113***
	(4.05)	(3.99)	(4.11)	(4.31)
$GARCH(1)$	0.711***	0.702***	0.721***	0.732***
	(7.57)	(6.66)	(4.44)	(3.55)
$GJR\ (\gamma)$	0.149**	0.131*	0.156**	0.144**
	(2.42)	(1.94)	(2.21)	(3.01)
$\vartheta\ (s_{t-1}^-)$	0.436***	-	0.442***	-
	(3.13)		(3.06)	
$\delta\ (s_{t-1}^+)$		1.72**	0.154**	-
	-	(2.21)	(1.92)	
$\tau_{1\ (dum\ 1)}$	-	-	-	0.541**
				(2.05)
$\tau_{2\ (dum\ 2)}$	-	-	-	0.111**
				(2.47)
$\tau_{3\ (dum\ 3)}$	-	-	-	0.263
				(0.99)
Panel B: Test diagnostics				
$Q(20)$	10.12	11.03	10.09	11.06
	[0.92]	[0.94]	[0.91]	[0.96]
$LM - Arch\ test$	0.69	0.58	0.55	0.62
	[0.50]	[0.71]	[0.85]	[0.92]

Notes: Table 2 reports the univariate GJR-GARCH model outcomes for the fear-volatility nexus. *Panel A* reports the GJR-GARCH (1,1) estimates, whereas *Panel B* represents the test diagnostics. s_{t-1}^+ refers to lagged positive fear, while s_{t-1}^- is lagged negative fear. $dum_{k,t}$ is the dummy variable representing the extreme event. $Q(20)$ is the Ljung-Box test statistic of the squared residuals. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Figures in parentheses refer to the t-student statistics and those reported in square brackets designate the p-values.

Figure 3:

GJR-GARCH conditional variance, time varying



4.5. Multiscale sentiment-pricing model results

As stated in Section 3, we estimate a multiscale sentiment-pricing model with five-time scales. Scale 1 is 2-4 weeks, scale 2 is 4-8 weeks, scale 3 is 8-16 weeks, scale 4 is 16-32 weeks, and scale 5 is 32-64 weeks. We are concerned with the parameters γ_i^j and δ_i^j to assess the impact of positive and negative sentiment on the stock pricing for each time scale (j). We consider 32 firms that have weekly data available from January 2005 and perform 160 OLS regressions $(5\ time\ scales * \ 32\ stocks)$. The regression model is given by:

$$\begin{aligned} R_i &= \alpha_i^j + \beta_i^j R_m^j + \gamma_i^j Sent^{+,j} + \delta_i^j Sent^{-,j} + \varepsilon_i^j \\ &= \alpha_i^j + \beta_i^j D_m^j + \gamma_i^j Sent^{+,j} + \delta_i^j Sent^{-,j} + \varepsilon_i^j, \qquad for\ j = 1, \dots 5 \end{aligned} \tag{24}$$

The estimated parameters of the sentiment-pricing model from each time scale of the individual stocks are shown in Table 3. Several remarks can be made about the estimated parameters of sentiment. For positive sentiments, the parameters are mostly negatively signed and vary over scales with no clear trend. The parameters tend to be relatively high for the long-term compared to the short-term horizons. For negative sentiments, the estimated scaled parameters are negative and vary non-monotonically over the time scales. Another interesting result appears in Table 3. The parameters inherent to the scaled beta change non-monotonically with time scales. However, there is no clear trend in the behavior of beta over the time scales. From a financial viewpoint, the scale-varying beta is explained by the scale relationship between stock return and systematic risk. Short-term and long-term investors have various perceptions of risk. Long-term investors are more concerned with the permanent component of risk (systematic risk) than the short-term risk component (specific risk). Our results confirm that the stock-return beta connectedness has a multiscale nature and the time scales are more relevant in explaining the relationship over the time scales. Our results corroborate those of Gençay et al. (2005). Observing the behavior of R^2 over the time scales, we perceive that it increases monotonically as we move to higher time scales (longer intervals). This result implies that the explanatory power of the market returns and investor sentiment metrics increases when moving to higher scales. Put another way, the systemic risk and sentiment effects are better captured over long-time horizons than short-term horizons. This result shows that the explanatory power of the sentiment-pricing model increases substantially over long-term investment horizons. However, our findings are inconsistent with Norsworthy et al. (2000), Fernandez (2006) and Masih et al. (2010) but in line with Gençay et al. (2005). Masih et al. (2010) estimate a multiscale standard market model for GCC countries and report a substantial decrease of R^2 moving to higher time scales, as individual investors are mainly driven by short-termism. However, Masih et al.'s (2010) estimated multiscale model does not account for sentiments and covers a very short period and only a few firms. Gençay et al. (2005) report opposite conclusions, stating that "*the predictions of the CAPM are more relevant at medium- to long-run horizons as compared to short-time horizons*" (Gençay et al., 2005, p.68). For the Saudi market, where individual investors dominate the trading activity, our results point to the relevance of retail investor sentiment in explaining individual stock pricing.

Table 3:

Estimated parameters of the sentiment-pricing model for each time scale of individual stocks

	Total				$\beta_i^j R_m^j$					$\gamma_i^j Sent^{+,j}$				
	$\beta_i^j R_m^j$	$\gamma_i^j Sent^{+,}$	$\delta_i^j Sent^{-}$	R^2	D_1	D_2	D_3	D_4	D_5	D_1	D_2	D_3	D_4	D_5
ALRAJHI	0.0040	-0.0231	0.0006	0.0386	0.0002	0.0077	0.0039	0.0127	0.0090	-0.0160	-0.0328	-0.0679	0.0024	0.0131
ALGASIM	0.0040	0.0139	0.0072	0.0181	-0.0007	0.0087	0.0012	0.0150	0.0021	0.0199	0.0189	0.0726	-0.0754	-0.2127
ALJAIRA	0.0050	-0.0211	0.0044	0.0410	0.0030	0.0047	0.0029	0.0096	0.0161	-0.0224	0.0093	-0.0499	-0.0959	0.0724
ALUJAIN	0.0082	-0.0090	0.0054	0.0548	0.0042	0.0108	0.0004	0.0080	0.0195	-0.0083	-0.0244	0.0880	-0.0003	0.0510
ARABNB	0.0042	-0.0125	-0.0016	0.0382	0.0028	0.0057	0.0003	0.0095	0.0144	-0.0109	-0.0165	-0.0224	-0.0053	0.0611
ARBN	0.0084	-0.0176	0.0176	0.0720	0.0047	0.0123	0.0053	0.0165	0.0154	-0.0104	-0.0091	-0.0129	-0.1685	-0.0356
AUTO	0.0053	-0.0169	0.0212	0.0362	0.0027	0.0044	0.0073	0.0138	0.0061	-0.0091	-0.0239	0.0523	0.0973	-0.2134
BASICIN	0.0045	-0.0121	-0.0007	0.0353	-0.0009	0.0090	0.0010	0.0131	0.0131	-0.0100	-0.0119	-0.0134	0.0600	0.1123
BATIC	0.0049	0.0102	0.0089	0.0222	0.0023	0.0071	0.0020	0.0186	0.0113	0.0087	0.0013	0.1058	0.0166	-0.0215
BSF	0.0025	-0.0108	-0.0079	0.0175	0.0001	0.0051	0.0008	0.0043	0.0143	-0.0086	-0.0070	-0.0493	-0.0177	0.0890
CABLESUP	0.0065	-0.0085	0.0092	0.0418	0.0026	0.0106	0.0007	0.0164	0.0125	0.0015	0.0138	-0.0132	-0.1908	-0.1045
CHEMICAL	0.0022	-0.0032	-0.0016	0.0094	-0.0006	0.0028	0.0030	0.0131	0.0015	0.0084	-0.0310	0.0089	-0.0791	-0.0165
ELECTRICITY	0.0018	-0.0103	0.0048	0.0094	0.0010	0.0041	0.0026	0.0074	0.0008	-0.0173	-0.0011	0.0115	0.0006	-0.0341
FITAIHI	0.0058	-0.0090	0.0092	0.0364	0.0047	0.0077	0.0013	0.0124	0.0068	-0.0091	-0.0047	0.0720	-0.1717	-0.2227

Notes: Table 3 reports the estimated parameters of the sentiment-pricing model for each time scale of individual stocks. The first column reports the selected firms, while the remaining columns report the estimated parameters. β_i^j is the parameter of the market return for stock (i) at time scale (j). γ_i^j and δ_i^j are the parameters of the positive (negative) sentiment metrics for stock (i) at time scale (j). The reported parameters are estimated for the scaled sentiment-pricing model.

Table 3 (Continued)

	Total				$\beta_i^j R_m^j$t					$\gamma_i^j Sent^{+,j}$				
	$\beta_i^j R_m^j$	$\gamma_i^j Sent^{+,j}$	$\delta_i^j Sent^{-,j}$	R^2	D_1	D_2	D_3	D_4	D_5	D_1	D_2	D_3	D_4	D_5
GAZINDU	0.0034	-0.0149	0.0060	0.0197	0.0023	0.0049	-0.0030	0.0091	0.0088	-0.027	0.0208	0.0039	-0.0204	-0.0336
GYPSUM	0.0041	-0.0280	0.0111	0.0257	0.0011	0.0049	0.0038	0.0087	0.0088	-0.022	-0.048	0.0341	-0.0708	-0.0670
INDL	0.0061	-0.0192	0.0248	0.0401	0.0044	0.0068	0.0018	0.0157	0.0141	-0.031	0.0011	0.0600	-0.0162	-0.0600
INDUSTINV	0.0055	-0.0147	0.0096	0.0356	0.0022	0.0079	0.0014	0.0136	0.0151	-0.020	0.0087	0.1118	-0.0838	-0.0722
INDZT	0.0054	-0.0249	0.0171	0.0375	0.0014	0.0082	0.0008	0.0110	0.0138	-0.041	0.0156	0.0577	0.0423	0.0089
INVESTBANK	0.0040	-0.0136	0.0001	0.0408	0.0015	0.0059	0.0027	0.0077	0.0097	-0.005	-0.025	-0.0182	-0.0406	-0.0042
MAKKAH	0.0046	-0.0099	0.0055	0.0327	0.0041	0.0044	0.0018	0.0081	0.0113	-0.012	0.0014	0.0303	-0.0589	-0.1334
METAL	0.0069	0.0027	0.0125	0.0408	0.0039	0.0090	0.0041	0.0199	0.0039	0.013	-0.023	0.0394	-0.0786	-0.0306
NAMA	0.0067	-0.0120	0.0132	0.0363	0.0042	0.0101	-0.0005	0.0161	0.0094	-0.019	0.0008	0.0580	-0.0091	-0.1719
PIPES	0.0088	0.0045	0.0022	0.0703	0.0061	0.0091	0.0082	0.0159	0.0039	0.0250	-0.027	-0.0515	-0.0651	0.0405
RIYADBANK	0.0024	-0.0107	0.0023	0.0160	0.0001	0.0033	0.0008	0.0074	0.0120	-0.011	0.0015	-0.0002	-0.0365	0.0217
SABIC	0.0029	-0.0153	0.0041	0.0151	-0.0017	0.0055	0.0003	0.0092	0.0162	-0.001	-0.033	-0.0146	-0.0666	0.0584
SAUDBBK	0.0023	-0.0080	-0.0071	0.0144	-0.0008	0.0067	-0.0003	0.0026	0.0123	-0.006	-0.024	-0.0008	0.0651	0.0341
SAVOLA	0.0040	-0.0171	-0.0029	0.0247	0.0010	0.0087	-0.0020	0.0137	0.0078	-0.014	-0.018	-0.052	-0.1052	0.0912
SINAD	0.0067	-0.0259	0.0136	0.0555	0.0046	0.0073	0.0043	0.0157	0.0100	-0.024	-0.026	-0.023	-0.0111	0.0109
TAIBA	0.0038	-0.0090	0.0031	0.0226	0.0023	0.0006	0.0039	0.0138	0.0086	-0.007	0.0008	0.0194	0.0135	-0.0654
THIMAR	.00534	-.0279	.0201321	0.0192	0.0022	0.0077	0.0002	.01849	0.0083	-0.023	-0.037	-0.039	0.0521	0.0834
ZAMIL	.00621	-.0141	.0111359	0.0502	0.0027	0.0086	0.0061	.01377	0.0064	-0.009	-0.025	.03497	-0.0739	-0.0221

Notes: Table 3 reports the estimated parameters of the sentiment-pricing model for each time scale of individual stocks. The first column reports the selected firms, while the remaining columns report the estimated parameters. β_i^j is the parameter of the market return for stock (i) at time scale (j). γ_i^j and δ_i^j are the parameters of the positive (negative) sentiment metrics for stock (i) at time scale (j). The reported parameters are estimated for the scaled sentiment-pricing model.

Table 3 (Continued)

	$\delta_i^j Sent^{-,j}$					R^2				
	D_1	D_3	D_4	D_5	D_5	D_1	D_3	D_4	D_5	D_5
ALRAJHI	0.0015	-0.0200	0.0439	-0.0382	-0.0345	0.0044	0.1179	0.0692	0.2781	0.3393
ALGASIM	0.0011	-0.0018	0.0220	0.1088	0.1305	0.0039	0.0722	0.0196	0.2108	0.1156
ALJAZIRA	0.0078	-0.0265	0.0351	0.0247	-0.1704	0.0169	0.0448	0.0311	0.1021	0.1829
ALUJAIN	0.0077	-0.0164	0.0006	0.0649	0.0998	0.0135	0.0949	0.0150	0.0517	0.6398
ARABNB	-0.0024	-0.0011	-0.0109	-0.0275	-0.0396	0.0157	0.0721	0.0080	0.2062	0.5622
ARBN	0.0112	0.0100	0.0414	0.0817	0.0367	0.0211	0.1212	0.0542	0.2702	0.3663
AUTO	0.0181	0.0147	-0.0439	-0.0024	0.0877	0.0146	0.0197	0.0884	0.1479	0.1474
BASICIN	-0.0029	-0.0141	0.0231	-0.0008	-0.0244	0.0041	0.1225	0.0110	0.3522	0.6102
BATIC	0.0128	-0.0141	0.0281	0.0276	0.0197	0.0081	0.0497	0.0429	0.2348	0.1645
BSF	-0.0090	-0.0101	-0.0083	-0.0425	-0.0768	0.0067	0.0554	0.0235	0.0929	0.5325
CABLESUP	0.0069	-0.0081	0.0239	0.0591	0.0828	0.0079	0.0069	0.0029	0.2603	0.3425
CHEMICAL	-0.0003	-0.0194	0.0174	0.0158	0.0462	0.0016	0.0430	0.0433	0.2618	0.0420
ELECTRICITY	0.0107	-0.0100	-0.0091	-0.0069	0.0818	0.0069	0.0473	0.0169	0.1436	0.2433
FITAIHI	0.0100	-0.0089	0.0149	0.1133	0.1248	0.0225	0.0551	0.0238	0.2373	0.2214
GAZINDU	0.0179	-0.0340	0.0099	0.0508	0.0412	0.0153	0.0653	0.0180	0.1601	0.4529
GYPSUM	0.0076	-0.0484	-0.0046	0.1114	0.0489	0.0042	0.0386	0.0333	0.2504	0.2232
INDL	0.0341	-0.0059	0.0164	0.0966	0.0243	0.0308	0.0336	0.0202	0.2576	0.5337
INDUSTINV	0.0161	-0.0248	-0.0280	0.0205	0.1000	0.0077	0.0675	0.0468	0.2195	0.5881
INDZT	0.0248	-0.0152	0.0127	-0.0264	0.0966	0.0133	0.0869	0.0186	0.1763	0.5302
INVESTBANK	-0.0061	0.0025	0.0266	-0.0019	0.0092	0.0091	0.0712	0.0384	0.1587	0.3531
MAKKAH	0.0128	-0.0264	0.0294	0.0186	0.0520	0.0240	0.0487	0.0290	0.1215	0.5250
METAL	0.0126	0.0057	0.0216	0.0116	0.0058	0.0180	0.0520	0.0273	0.3213	0.0170
NAMA	0.0265	-0.0187	-0.0313	0.0045	0.1675	0.0219	0.0762	0.0057	0.1674	0.3490
PIPES	-0.0030	-0.0047	0.0859	0.0008	0.0082	0.0337	0.0893	0.1031	0.2240	0.0394
RIYADBANK	-0.0007	-0.0011	0.0108	-0.0022	-0.0416	0.0028	0.0340	0.0056	0.1660	0.5637
SABIC	-0.0042	0.0003	0.0231	0.0680	-0.0136	0.0046	0.0630	0.0081	0.3890	0.5825
SAUDBBK	-0.0033	-0.0210	-0.0058	-0.0293	-0.0533	0.0033	0.1133	0.0008	0.0350	0.3128
SAVOLA	0.0027	-0.0283	0.0175	0.0683	-0.1245	0.0026	0.1220	0.0155	0.3083	0.2765
SINAD	0.0150	-0.0095	0.0386	0.0809	0.0589	0.0242	0.0733	0.0433	0.3323	0.4002
TAIBA	0.0053	-0.0166	0.0117	0.0159	0.0204	0.0073	0.0091	0.0381	0.2673	0.3411
THIMAR	0.0219	-0.0019	0.0488	0.0698	0.1560	0.0072	0.0395	0.0059	0.2005	0.3835
ZAMIL	0.0122	-0.0025	0.0176	0.0409	0.0381	0.0107	0.0757	0.0918	0.2910	0.1761

Notes: Table 3 reports the estimated parameters of the sentiment-pricing model for each time scale of individual stocks. The first column reports the selected firms, while the remaining columns report the estimated parameters. β_i^j is the parameter of the market return for stock (i) at time scale (j). γ_i^j and δ_i^j are the parameters of the positive (negative) sentiment metrics for stock (i) at time scale (j). The reported parameters are estimated for the scaled sentiment-pricing model.

5. Discussion, policy implications and research avenues

Here, we discuss our findings and their main policy implications, highlighting suggestions for further research.

5.1. Discussion

In this paper, we investigate the investor sentiment-market behavior nexus in Saudi Arabia with a wavelet-based approach. We use information technology and 'big data' to construct sentiment metrics based on the GSV using weekly data for a relatively large sample period (January 2005 to March 2021), which allows us to see changing patterns of the sentiment-market behavior interplay around turbulent market conditions over time scales and investment horizons. We conjecture that the intensive use of Google search and other social media to track financial and economic news may convey a real-time signal for investor sentiment analysis. The GSV not only reflects the attitudes of market operators and accumulated data related to the volume of Internet searches but offers ideas about market operators' expectations, fears, and moods.

Broadly speaking, our study presents many interesting breakthroughs and fresh empirical outcomes. From the first point of view, we show how the use of information technology and market-related 'big data' is a key driver of investor sentiment relevance in the stock market. The impressive growth in the use of the Internet over the last decade has made substantial changes to stock markets, pointing to the crucial role of investor sentiment. Therefore, investor sentiment may be perceived as a powerful source of information that can be exploited by market operators to better understand market behavior, make predictions and evaluate assets. The investor sentiment metrics capture real-time market expectations, as investor beliefs are instantaneously coupled to the market for implied volatility.

From an empirical perspective, our study implements various standard and non-standard methods, including continuous bivariate wavelets, multiresolution analysis, wavelet causality tests, and the univariate GJR-GARCH time series model. Our goal is to account for the main stylized facts of stock market behavior such as asymmetry, leverage effect, non-stationarity and nonlinearity of the financial data. The continuous and discrete wavelet methods have the benefit of analysing the sentiment-market behavior nexus within time scales and investment horizons. It is worth mentioning that this is the first empirical research to estimate positive and negative sentiment metrics for Saudi investors and explore their interplay with returns, volatility and asset pricing.

Looking at the sentiment-return interplay, our findings show a key role of sentiment in explaining stock market return over investment horizons. Our bivariate wavelet coherence analysis points to strong time and scale-varying dependence among the two variables. Accounting for unsettled market conditions (2006 market collapse, 2008 GFC and COVID-19 health crisis), we reveal that the aggregate returns are significantly affected by sentiment. Because of their fears, Saudi investors tend to intensify their Google searches to get relevant information to make appropriate decisions to avoid risk, reallocate assets and seek safer investments. These outcomes corroborate the conclusions of Baker and Wurgler (2006) who claim that investor sentiment depends on the market conditions, which leads to waves of positive and negative sentiment. Our results are consistent with the spectral Granger causality test outcomes. Concerning the sentiment-volatility nexus, the univariate GJR-GARCH outcomes reveal that both negative and positive investor sentiments have a positive and significant impact on volatility which is strengthened during unsettled market conditions. We presume that investor attention increases during tumultuous market conditions as they intensify their Google searches for news to help them make sound investment decisions to sidestep downside risk and suboptimal portfolio diversification.

To explore pricing-sentiment connectedness, we use multiresolution analysis. For the first time, we suggest and estimate a multiscale sentiment model in which positive and negative sentiments are counted as risk-loading factors. Our findings point to some first-hand insightful outcomes. We show that the explanatory power of the market returns and investor sentiment metrics increases monotonically when moving to higher scales. This means that sentiment effects are better captured over long-term horizons than short-term horizons. In addition, the parameters inherent to the scaled beta vary non-monotonically with time scales. There is no clear trend in the behavior of betas over the time scales. In financial terms, this result implies that short-term and long-term investors have different perceptions of risk. Long-term investors are more concerned with the permanent component of risk (systematic risk) than the short-term risk component (specific risk), while short-term traders are more concerned with the 'noise' component. Our results are consistent with Gencay et al. (2005).

5.2. Policy implications

Our findings lead to several prominent implications for portfolio managers, market regulators and policy designers, pointing to the influence of investor sentiment on stock returns, volatility and asset pricing.

5.2.1. For portfolio managers

Portfolio managers are invited to benefit from the information content of investor sentiment. In doing so, they can, for instance, take advantage of the investor sentiment metrics to sort stocks into various portfolios with respect to their sentiment sensitivity. The degree of stock exposure to sentiment can be considered a novel parameter when portfolio managers allocate assets and design investment strategies. Putting up a sentiment-based portfolio management strategy may be beneficial in terms of expected return and risk. In other words, portfolio managers are invited to adopt sentiment-sparked dynamic portfolio management by rebalancing portfolios with respect to the intensity of exposure to sentiment. A comparative analysis between a non-sentiment strategy and a sentiment strategy in terms of portfolio management performance would be very enlightening. Furthermore, the investor sentiment metrics can be integrated into the portfolio optimization process as an input variable combined with other tools. At this point, it could be interesting to account for the time scale-varying sentiment-return-risk-pricing interplay and create a multiscale sentiment-based portfolio optimization. Moreover, it can be fruitful to consider the investor sentiment metrics as criteria for portfolio optimization rather than input variables. Finally, portfolio managers are invited to consider 'beta sentiments' to evaluate stocks when they adopt an active management strategy to track mispriced stocks and time the market.

5.2.2. For market regulators

Market regulators are invited to focus their attention on the pivotal role of sentiment in explaining stock market behavior. Furthermore, given the relevance of investor sentiment and the prevalent weight of individual investors, the Saudi stock market authorities are invited to increase the weight of institutional investors in the trading activity and popularize the stock market culture, investment theories and risk assessment methods, especially for individual investors.

5.2.3. For policy designers

For policy designers, it is very useful to recognize the financial and economic relevance of investor sentiment as it is persuasively connected to economic uncertainty and financial stability. The sentiment-economic uncertainty nexus could be discussed at the micro and macro levels. At the micro level, investors with negative sentiment tend to have pessimistic expectations of the future and may cause firms to delay or bring down investments, thereby making economic policies less effective. At the macroeconomic level, policy designers are asked to consider the connectedness between economic policy uncertainty and investor sentiment. Investor sentiment may accentuate economic policy uncertainty as an increased degree of risk aversion that may have a negative impact on investment intent. Therefore, we believe that the Saudi authorities should fully consider the impact of economic uncertainty and financial instability on individual investors' sentiment, moods and beliefs when designing economic policies.

5.3. Limitations and further study directions

Our research has a few limitations, which would pave the way for several future research avenues. Firstly, the investor sentiment metrics are designed based on GSV, which is not a direct sentiment measure and may be biased as it is mostly reflecting population search trends[14]. Thus, it can be fruitful to include other social media and websites, such as Twitter, Facebook, Wikipedia, Yelp, Flickr and_others to extract market-related information. For instance, Saudis are more

[14] The authors are grateful to one anonymous reviewer for highlighting this point.

familiar with Twitter as the Kingdom has the highest number of active users in the Arab region, 2.4 million, representing around 40percent of Arab active users (Arab Social Media Report, 2022)[15]. Twitter, therefore, may have the potential to provide a real-time proxy for investor sentiment. We believe that Saudi individuals have no longer become passive investors, as they communicate, 'retweet', comment, analyse, react and express their sentiments and moods, which may influence their investment decisions over time scales. Another GSV connected concern is inherent to the use of Arabic language and the eventual clues in related keywords, which may affect the accuracy of the sentiment data.

Secondly, it would be useful to explore other data frequencies, including intraday data, to assess the impact of sentiment on stock return or volatility. This may help confirm the robustness of the results to the frequency of the data used. The use of firm-level data may be helpful in explaining how firms respond to sentiment. Thirdly, the application of deep learning, data mining or neural network methods to social media or Google trends 'big data' could enhance the performance analysis of investor sentiment. Fourthly, the inclusion of further loading risk factors in the sentiment-pricing model would increase the explanatory power of sentiment in pricing within multiscale behavior. Finally, our paper could be extended, for comparative purposes, to other countries in the GCC region where stock markets are highly dominated by individuals.

6. Conclusion

In this paper, we make an initial attempt to design investor sentiment metrics and connect them to stock return, volatility, and pricing within a time-frequency framework. We use Google search 'big data' to construct positive and negative sentiment metrics for Saudi investors. We investigate the Saudi investor sentiment-return-volatility-pricing nexus between 2005 and 2021. This period covers several extreme events, including the 2006 Saudi market collapse, 2008 GFC, recent oil market collapse and COVID-19 outbreak. We make several new and fresh insights into the sentiment-return-volatility nexus within the time-frequency domain. Our finding shows that high levels of coherence between sentiment and aggregate returns mainly occur during turbulent

[15] https://arabsocialmediareport.com/Twitter/

events when sentiment leads aggregate returns at the medium- and long-term scales. The results of the spectral causality test robustness check corroborate our findings, revealing the driving role of sentiment during major extreme events. Interestingly, the inclusion of sentiment variables in the GJR conditional variance equation allows us to visualize the significant impact of investor sentiment on aggregate volatility. This aggregate volatility is intensified during turbulent periods. Further, we propose and estimate a first-hand multiscale sentiment-pricing model. Our findings show the multiscale tendency of systematic risk and the investor sentiment coefficients over investment horizons. The predictive power of sentiment is revealed to be stronger at higher scales (long-term horizons). Sentiment turns out to enhance the explanatory power of the market pricing model with a substantial time scale nature, mainly attributed to the heterogeneity of the investment horizons of individual Saudi investors. We suggest that there are several operational inferences for portfolio managers, market regulators and financial policy designers. Investors and portfolio managers should take into consideration the information contained in investor sentiment as well as the time scale variation of the 'sentiment beta', which would guide decision makers to make better investment decisions. Therefore, sentiment analysis could play a substantial role in portfolio selection. It is worth noting that a pricing model incorporating sentiment variables is demonstrated to have better reliability for expected return than a model with one aggregate value, indicating that sentiment contributes to explaining the expected return. Regulatory authorities should focus on exploring the crucial role of sentiment in explaining Saudi stock market behavior and stock performance. Policy engineers should pay attention to the relevant relationships between economic uncertainty, financial stability and investor sentiment by developing the financial regulation and relative laws to support market's agents redeem confidence and grant financial stability.

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