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Causality between market return and sentiment: New evidence from Saudi stock exchange using wavelet analysis

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Abstract: In this paper we investigate the causality between stock return and sentiment in Saudi stock market. we apply the wavelet-based method to explore the different time horizons of this relationship. The maximum overlap discrete wavelet transform (MODWT) is employed to decompose the series up to five timescales. We used the wavelet spectrum and the wavelet coherence to study the relationship between sentiment and return of different time horizons of investors. Finally, the granger causality test show the strong causality between return and sentiment in all time frequencies except from 2 to 4 months

Keywords: Causality; return; sentiment; trading volume; wavelet

JEL classification : C22 ; C32 ; G10;G12

1- Introduction

Sentiment may influence investor decisions in several manners and as a result has an impact on stock prices. So, the consideration of psychological factors extends the approach to explain the movements of stock returns and the process of decision-making.

Large number of studies in literature focus on the relationship between stock returns and investor sentiment. Brown and Cliff (2004), Solt and Statman (1988), Jansen and Nahuis (2003), Wang et al. (2006) and Bekiros et al. (2016) find that returns cause sentiment rather than vice versa.Baker and Wurgler (2006, 2007) studied the effect of high and low sentiment (optimism and pessimism) on stock returns and they find that investor sentiment affects stock prices in two main cases: the limit of arbitrage and the unclear firm valuation.

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Brzeszczy ´nski et al. (2015) studied the impact of public information arrival in emerging markets. Chu et al. (2016) find that the influence of investment horizon or time-frequency is expected to have economic and statistical significance for the sentiment and stock return causal relationship. This conclusion is confirmed by Marczak and Beissinger, 2016).

Bekiros et al. (2016) concluded that investor sentiment could forecast stock returns, and the results showed the projecting power stemmed from investors' biased ideas on future cash flows. Kling and Gao (2008) employed survey data to maintain that there was no strong bilateral long-term Granger causality between stock prices and investor sentiment.

Aloui et al. (2016) investigate the co-movement between investors' sentiment and the Islamic and conventional equity returns over diverse time-scales and frequencies in the US market. Using squared wavelet coherence methodology, they show that the time-varying nature of co-movement exists for both the Islamic and conventional indexes. They conclude that the Sharia rules have no influence on the connectedness between sentiment and Islamic equity returns.

Loa et al. (2018) investigate the nonlinear asymmetric Granger causality between investor sentiment and stock returns for US economy while considering different time-scales. The wavelet method is utilized to decompose time series of investor sentiment and stock returns at different time-scales to focus on the local analysis of different time horizons of investors. They find evidence of strong bilateral linear and nonlinear asymmetric Granger causality between longer-term investor sentiment and stock returns.

Dash and Maitra (2018) investigate the relationship using a broad set of implicit sentiment proxies and value-weighted market indices. The wavelet method has been used to decompose sentiment variables and stock returns into different timescale frequencies. they find a strong effect of sentiment on return both in the short-and long-run by employing decomposed returns and sentiment proxies at different time-scale frequencies.

In this paper we examine the causality between investor sentiment and stock markets on Saudi stock exchange using wavelet analysis. We extend the existing literature in several ways. First, our study focuses on Saudi market which is an emerging market where the low level of market integration and a huge investors' behaviors can lead to new conclusions. Second, we took into consideration different Granger causality time horizons on investor sentiment to investigate the relationship on short and long periods.

Third, we apply the wavelet-based method to investigate the different time horizons of relationship investor sentiment and stock returns.

The remainder of the paper proceeds as follows. Section 2 presents methodology. Section 3 elaborates data and results. Section 4 concludes the paper.

2- Methodology

As its name suggests, a wavelet is a small wave. In the present context, the term "small" essentially means that the wave raises and declines in a limited time frame. In order to clarify the notion of small wave, we start by introducing a function, which is called the mother wavelet and is denoted by $\psi(t)$. This function is defined on the real axis and must satisfy two conditions (Masset (2015)):

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \tag{1}$$

$$\int_{-\infty}^{\infty} |\psi(t)|^2 dt = 1 \tag{2}$$

Considered together, these conditions suggest at first that at least some coefficients of the wavelet function must be different from zero and secondly that these leavings from zero must cancel out. A vast variety of functions meets conditions (1) and (2). Nevertheless, these conditions are very general and not sufficient for many practical purposes. Therefore, one has to impose additional conditions in order to run a specific analysis with wavelets. One of these conditions is the so-called admissibility condition, which states that a wavelet function is admissible if its Fourier transform.

$$\psi(f) = \int_{-\infty}^{\infty} \psi(t) e^{-i2\pi f t} dt, \tag{3}$$

Is such that

$$C_{\psi} = \int_{0}^{\infty} \frac{|\psi(f)|^2}{f} df \; satisfies \; 0 < C_{\psi} < \infty \tag{4}$$

These conditions allow reconstructing a function from its continuous wavelet transform (see Percival and Walden (2000) for more details).

In this paper we will apply the maximal overlap discrete wavelet transform (MODWT) because the

MODWT keeps at each frequency a complete resolution of the series. Whatever the scale considered, the length of the wavelet and scaling coefficient vectors will be equal to the length of the original series. The wavelet and scaling coefficients at the first level of decomposition are obtained as follows:

$$\tilde{w}_1(t) = \sum_{l=0}^{L-1} \tilde{h}_l x(\acute{t}) \; and \; \tilde{v}_1(t) = \sum_{l=0}^{L-1} \tilde{g}_l x(\acute{t}), \tag{5}$$

Where t=0, 1, ...T and t'=t-l mod T.The MODWT coefficients for scales $j > 1$ can be obtained using pyramid algorithm (Masset, 2015).

$\tilde{w}_j$ and $\tilde{v}_j$ are calculated as:

$$\tilde{w}_j(t) = \sum_{l=0}^{L-1} \tilde{h}_l \tilde{v}_{j-1}(\acute{t}) \; and \; \tilde{v}_j(t) = \sum_{l=0}^{L-1} \tilde{g}_l \tilde{v}_{j-1}(\acute{t}), \tag{6}$$

Where $\acute{t} = 2^{j-1} l$ mod T.

Using matrix notation, we can conveniently calculate the wavelet and scaling coefficients up to scale J. we first define a matrix $\widetilde{W}$ that is composed of J+1 sub-matrix, each of them $T \times T$:

$$\widetilde{W} = \begin{bmatrix} \widetilde{W}_1 \\ \widetilde{W}_2 \\ \vdots \\ \widetilde{W}_J \\ \widetilde{V}_J \end{bmatrix} \tag{7}$$

Each $\widetilde{W}_J$ has the following structure:

$$\widetilde{W}_J = \begin{bmatrix} \tilde{h}_0/2^{j/2} & 0 & 0 & \cdots & 0 & \tilde{h}_{L-1}/2^{j/2} & \cdots & \tilde{h}_1/2^{j/2} \\ \tilde{h}_1/2^{j/2} & \tilde{h}_0/2^{j/2} & 0 & \cdots & 0 & 0 & \cdots & \vdots \\ \vdots & \tilde{h}_1/2^{j/2} & \tilde{h}_0/2^{j/2} & \cdots & 0 & 0 & \cdots & \tilde{h}_{L-1}/2^{j/2} \\ \tilde{h}_{L-1}/2^{j/2} & \vdots & \tilde{h}_1/2^{j/2} & \cdots & 0 & 0 & \cdots & 0 \\ 0 & \tilde{h}_{L-1}/2^{j/2} & \vdots & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \tilde{h}_{L-1}/2^{j/2} & \ddots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & 0 & \cdots & \tilde{h}_0/2^{j/2} & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & \tilde{h}_1/2^{j/2} & \tilde{h}_0/2^{j/2} & \cdots & 0 \\ 0 & 0 & 0 & \cdots & \vdots & \vdots & \cdots & 0 \\ 0 & 0 & 0 & & \tilde{h}_{L-1}/2^{j/2} & \tilde{h}_{L-2}/2^{j/2} & & \tilde{h}_0/2^{j/2} \end{bmatrix} \tag{8}$$

$\widetilde{V}_J$ has a similar structure as $\widetilde{W}_J$ but it contains associated to the father wavelet instead of the mother wavelet.

After that we can calculate all wavelet and scaling coefficients as follow:

$$\widetilde{w} = \widetilde{W}x, \tag{9}$$

Where $\widetilde{w}$ is a vector made up of *J + 1* length *T* vectors of wavelet and scaling coefficients, $\widetilde{w}$, …, $\widetilde{w}_j$ and $\tilde{v}_j$.

Then, Multiresolution analysis can be used to reconstruct the original time series x(t) from the wavelet and scaling coefficients, $\tilde{v}_j$ and $\widetilde{w}_j$. Given all the coefficients, the time series *x(t)* can be described briefly:

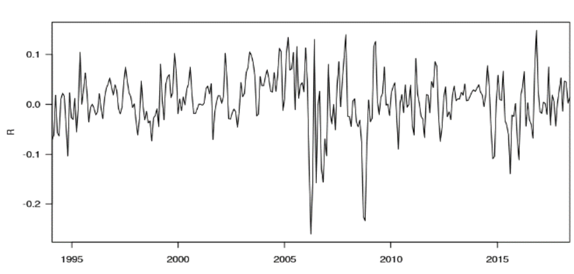
$$x(t) = D_1(t) + \cdots + D_J(t) + S_J(t) \tag{10}$$

Where $D_J(t)$ is the recomposed series and $S_J(t)$ is the residue.

3- Empirical results

3-1- Data

In this paper, we use monthly changes of Saudi stock market index "TASI" over the periods 1994:2 to 2018:6 as stock returns (R) which is 293 observations. The data are taken from the official web site of the Saudi stock exchange (www.tadawul.com.sa) while stock returns are calculated by taking the natural logarithm of the ratio of two successive prices. For investor sentiment (S) we use the trading volume as proxy according to Lee and Swaminathan(2000) and Chuang et al. (2010). The fluctuations of marketreturn and sentiment are shown in figure 1 and 2 respectively.



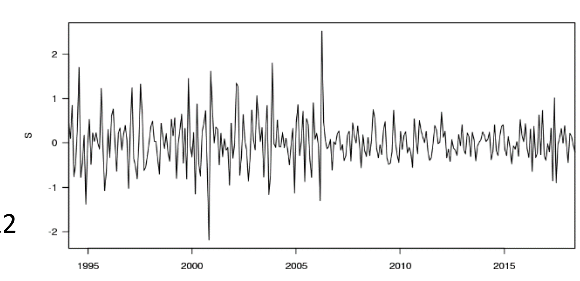


Fig. 1. Market returns **Fig. 2.** Sentiment Index

The market index and the sentiment index show a strong positive relationship. At the tops of the market, the sentiment reaches its highest levels. And around the troughs of the market, it gets the lowest levels. The descriptive statistics of all these data are reported in table 1.

Table 1. Descriptive Statistics

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
R	0.0219	0.021355	2.784122	-2.54349	0.725049	0.340441	5.362703	73.81118**
S	0.005313	0.010659	0.178952	-0.29775	0.066874	-0.74977	5.329709	93.71298**

(**) Represents the significance level of null hypothesis rejected at 5%

From table 1, we can see that the mean for market return and sentiment indicator is near to zero. The standard deviation shows that market return present higher volatility compared with sentiment index. According to Jarque-Bera, both indexes are not following normality. For market return skewness is positive which means that the distribution has a long right tail. For sentiment index, skewness is negative indicating that the distribution has a long-left tail. Kurtosis for both indexes exceeds 3 implying that the distributions are peaked relative to the normal.

3-2- Wavelet Decomposition

The maximum overlap discrete wavelet transform (MODWT) is employed using the software R. Time series for market return and sentiment index are decomposed up to five timescales. The time-scale frequencies are D1 (2-4 months), D2 (4-8 months), D3 (8-16 months), D4 (16-32 months), and D5 (32-64 months). The decomposition results are shown in figure 3.

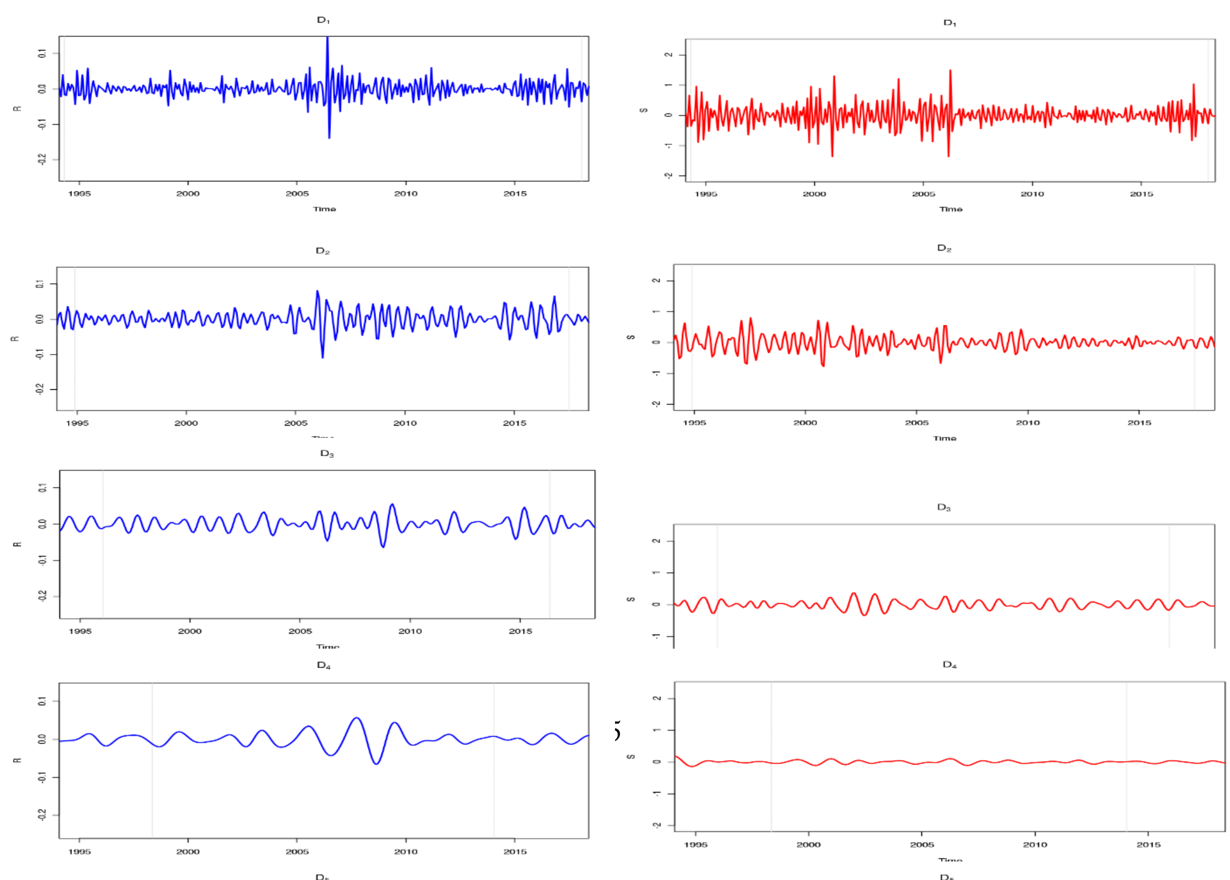


Fig. 3. Decomposition results of market return (R) and sentiment index (S) (D1 to D5)

3-3- Wavelet spectrum

Figures 3 and 4 illustrate the continuous wavelet spectrum using the Continuous Wavelet Transform (CWT) for market return and sentiment index. In the wavelet spectrum, the black contour shows 5% significance level. The color code ranges from blue (low power) to red (high power).

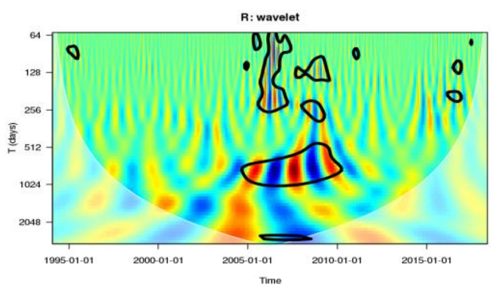


Fig. 4. Wavelet power spectrum of market index

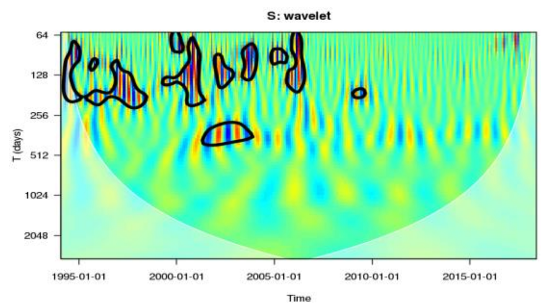
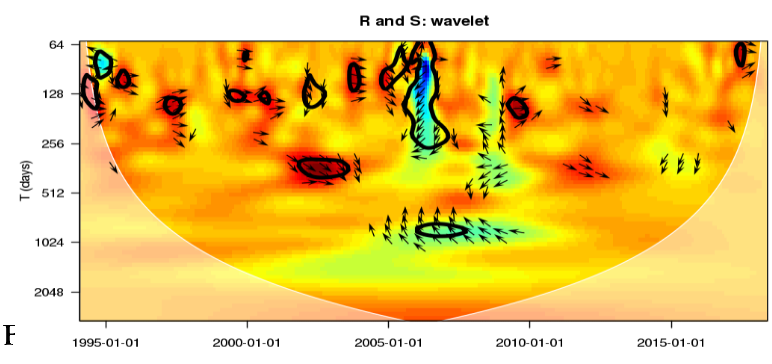


Fig. 5. Wavelet power spectrum of sentiment Index

In figures 4 and 5, the x-axis is the wavelet location in time. The y-axis is the wavelet period in years. The black contours are the 10% significance regions, using a red-noise background spectrum. In figure 4, we can see thatsignificant disturbance during years 2007 for time scales (64 to 256 days) which can be explained by the financial crisis 2007-2008. Also, we have significant area during year 2009 for time scales 128 and 256. This disturbance is due to the global financial crisis 2009. We can see a significant trouble in long times scales (between 412 and 1024 days) from 2005 to 2010. This can be explained by the contagion of crisis from 2006 to 2010. In figure 5, we can see the wavelet power spectrum for sentiment where significant areas lie in short time scales (from 64 to 256) during years 1995 to 1998 and from 2000 to 2007.



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From the given plot, we conclude that the series we are analyzing are highly volatile from short to long timescales. As the spectrum gets hotter, more is the volatility.

3-4- Causality tests

Before performing the causality test, we will test the stationarity of time series using the Augmented Ducky-Fuller test (ADF). The results are shown in table (2). The tested results by the ADF show that original and decomposed series are stationary.

Table 2. Augmented Ducky-Fuller tests (Unit root tests)

	Original series	Decomposed series				
		D1	D2	D3	D4	D5
Return	-33.655***	-60.769***	-45.492***	-33.542***	-44.906***	-22.313***
Sentiment	-16.489***	-61.725***	-47.247***	-37.884***	-45.177***	-21.265***

Notes: The lag-length of ADF is chosen by the Schwarz information criterion. D1–D5 represents the time horizons with timescales of 2 to 4, 4 to 8, 8 to 16, 16 to 32 and 32 to 64 months, respectively.
(***)significance at 1% level

After that, the linear Granger causality test is performed for original and decomposed series (table 3)

Table 3. Granger Causality test

Series	H0: Return does not Granger cause Sentiment		H0: Sentiment does not Granger cause Return	
	F- statistics	Prob	F- statistics	Prob
Original series	14.638***	0.000	3.695**	0.024
D1	2.564*	0.077	2.002	0.135
D2	3.53**	0.029	12.234***	0.000
D3	34.144***	0.000	16.142***	0.000
D4	10.085***	0.000	13.986***	0.000
D5	12.403***	0.000	9.618***	0.000

Notes: D1–D5 represents the time horizons with timescales of 2 to 4, 4 to 8, 8 to 16, 16 to 32 and 32 to 64 months, respectively
(***)significance at 1% level
(**)significance at 5% level
(*)significance at 10% level

According to the results in table (3), the null hypothesis that return does not granger cause sentiment is rejected. However, the null hypothesis that sentiment does not granger cause return is rejected except for the first decomposed series D1 (p=0.135). That means that return has a significant impact on sentiment, and, sentiment has also impact on return except for D1 which represents time scale from 2-4 months. This means that sentiment has impact on return for longer-term investors more than shorter-term investors.

4- Conclusion

This paper aims to examine the causality between investor sentiment and stock returns for the Saudi market by using a wavelet analysis and Granger causality test. We find that there is two-directional linear causality from stock returns to investor sentiment and from investor sentiment to stock returns. Given the different time-scales, sentiment cause return in long term more than shorter terms.

Wavelet decomposition lets us to analyze the different frequencies of financial data to find the multi-scale relationship of time series. Using the wavelet spectrum for return and sentiment we detect the same periods of disturbance.

The results of our paper give an important insight to decision makers and policy makers. They have to take into consideration investor sentiment especially in long term.

Declarations

Availability of data and material

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests

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Authors' contributions

AA has collected data, prepared literature review and methodology. MZ has analysed and interpreted data. Both authors read and approved final manuscript.

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