Time-varying coherence of investor sentiment in US Islamic and Non-Islamic returns

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Abstract:
Investor sentiment is a systematic risk factor that may cause additional risk and return by deviating stock prices away from their fundamentals. The study aims to investigate the search-based investor sentiment index relationship with Islamic and non-Islamic stock returns at multiple periods and frequency, in which discrete wavelet transformation, continuous wavelet transforms, cross-wavelet transform, and Granger causality was used. Continuous wavelet transformation displayed investor sentiment as having a higher correlation of multiple episodes across the short-term investment horizon. In comparison, stock returns presented a higher correlation in the medium- to long-term during the crisis period. Cross-wavelet findings suggested a negative (out-phase) coherency of investor sentiment toward stock returns, in which investor sentiment was the leading variable. Further, non-Islamic stock returns exhibited greater sensitivity toward investor sentiment compared to their counterparts, thereby iv demonstrating a unidirectional causal relationship toward stock returns in the original series and short-term. However, a mixed causal relationship at the medium-term was demonstrated while bi-directional for the long-term and smoothing component.

Keywords: Investor Sentiment; Google Trends; Islamic and Non-Islamic Stocks Returns; US Market; Wavelet Analysis

Introduction

An investor's ultimate objective is to earn a justified yield using various investment/trading strategies that consider different risk-return combinations. Arbitrage pricing theory suggests that investors observe dynamics in the market’s fundamentals and act accordingly to make their investments more profitable and can hedge against systematic risk factors. Whereas, in the real world, the financial securities market does 8 not serve only according to rational investors' decisions based on fundamentals (Shiller, 1991, 2000). For instance, traditional asset pricing models have neglected to explain various shocking events that have occurred in the financial market such as the Great Crash of 1929, the Nifty Fifty bubble of the early 1970s, the Black Monday crash of October 1987, the Dot.com bubble of the 1990s, the more recent GFC in 2008, and the Coronavirus (COVID-19) pandemic which caused an abnormal variation in the stock prices. These variations in market prices caused mispricing, which unsupported by the fundamental values of the underlying assets.

However, mispricing is not merely limited to conventional stock market boundaries; instead, it has somehow equal effect on the Islamic stock market (Merdad et al., 2015; Narayan

& Phan, 2017, among others). The existing literature in this field has well-documented both the theoretical arguments and empirical evidence concerning the effect of investor sentiment on mispricing, which depends on the limit to arbitrage (Baker & Wurgler, 2006; Birru, 2018, among others). Moreover, they revealed that the magnitude of investor sentiment is subject to the limit to arbitrage, where the stocks with a higher limit to arbitrage tend to be more sensitive to investor sentiment and vice versa. Having said that, there are two different views of arguments concerning the limit to arbitrage in the Islamic stock market. First, the camp of arguments suggests a higher limit to arbitrage, while the opponent camp suggests a lower limit to arbitrage in the Islamic stock market.

Since Muslim investors have fewer shares to choose from, they consequently have fewer opportunities to diversify their investment portfolios or counter to noise traders by aggressively adopting the opposite position. Second, Islamic stocks have one additional 'Islamic risk' factor that creates an idiosyncratic risk of Islamic stocks compared to non-Islamic stocks, which has tied arbitrage from wagering against noise traders' in the Islamic stock market. Third, short selling is Haram in the Islamic stock market that forbids arbitrageurs from adopting an opposing position to counter mispricing caused aside from the fundamentals of the underlying stock. Similarly, E. M. Miller (1977) reported that short selling impediment could limit arbitragers to exploit mispricing. However, the opponent's camp contends that non-Islamic stock firms have higher financial leverage ratios, which cause a higher probability of bankruptcy, unlike Islamic stocks containing the threshold value of 33%. Second, Islamic stocks are filtered through a sharia screening process, eliminating sin stocks and highly speculative stocks and encourage investors to trade on the fundamentals of the underlying stock.

Investor sentiment acts in a wave shape, subject to market situations and their response over a period (Baker & Wurgler, 2006). Moreover, market information is perceived differently by different participant groups, which causes heterogeneity in the market. Supportably, stocks have market condition dependency where they are more vulnerable to investor sentiment during periods of high turmoil and vice versa (Dash & Maitra, 2018). However, the relationship between investor sentiment and stock market movement is not static but quite dynamic, altering with different times and frequencies (durations). The finance literature has recently shifted to focus on the time and frequency relationship of investor sentiment in the conventional stock market such as by (Khan, Hernandez, & Shahzad, 2020; Maitra & Dash, 2017, among others). However, limited studies have focused on the time-frequency relationship of investor sentiment in the Islamic stock market employing different investor sentiment measures. Following the FEARS sentiment index methodology, Trichilli, Abdelhedi, and Abbes (2020) examine investor sentiment in Islamic and non-Islamic stocks, demonstrating that their relationship depends on the different states and time horizons. Similarly, Trichilli et al. (2020) reveal that bearish investor sentiment is more persistent, whereas bullish sentiment is more favorable to invest in the GCC Islamic stocks markets. Aloui et al. (2016) examined investor sentiment's time-varying effect in Islamic and non-Islamic stock returns. Using Baker and Wurgler's (2006) composite sentiment index, the authors demonstrate a significant correlation between investor sentiment and Islamic stock returns. Following the financial stress index as a proxy for investor sentiment, Ftiti and Hadhri (2019) report the time-varying relationship of investor sentiment with Islamic stock returns.

The existing literature indicates the gap in examining whether the search-based investor sentiment index is equally sensitive to Islamic and non-Islamic stocks at a different time and frequency. Also, to investigate the lead-lag relationship between investor sentiment and Islamic and non-Islamic stock returns. Furthermore, the literature evidences the gap in this area to examine the causal relationship between investor sentiment and Islamic and non-Islamic stock returns at different times and frequencies.

Methodology

Data Description

This study used two different sets of data for the period between January 2004 and December 2018. The study extracted weekly data of 20 sentiment-induced keywords from Google Trends for the period of study, while the second set of data represented the daily stock indices prices for the seven US Islamic stock indices.

The study used GSV in gauging household investors sentiments, with SVI data retrieved from Google Trends. GSV is commonly used in searching vast volumes of data for entity names, symbols, or using various other available sentiment keywords, worldwide or related to specific countries, with specific intervals or distribution, such as 93 monthly, weekly, or daily intervals. Google trends provide search series data from January 2004 and beyond. Also, normalized GSV data are accessible between 0 and 100 in search occurrences for particular words and specific periods. Relative GSV data are also accessible and quantified as the number of searchers carried out for a specific keyword used divided by the sum of searches for all keywords for the respective period.

Table 1: Index Code Index Name Index Tickers DataStream

Index code	Index Name	Index Datastream codes
D1	DJ ISLAMIC US	PRICE INDEX DJIMUS$(PI)
D2	DJ ISLAMIC US MID CAP	PRICE INDEX DJIUMC$(PI)
D3	DJ ISLAMIC US LARGE CAP	PRICE INDEX DJIULC$(PI)
D4	DJ ISLAMIC US SMALL CAP	PRICE INDEX DJIUSM$(PI)
D5	FTSE SHARIA USA $	PRICE INDEX FTSUSA$(PI)
D6	MSCI AC AMERICAS IS U$	PRICE INDEX MSAMFI$(PI)
D7	S&P 500 SHARIA $	PRICE INDEX SP500S$(PI)

The Table posits the lists of codes used in the study, names and tickers symbols used in Datastream for US Islamic stocks indices from 2004 to 2018.

Wavelet Method

In the finance literature, several studies (Aloui et al., 2016; Aloui et al., 2020; Dash & Maitra, 2018) demonstrates the time-varying frequency relationship between investor sentiment and stock returns. Many argued that different investment horizons are thought to have statistical and economic significance for investor sentiment and stock market returns. Investor trading is subject to various expectations, such as fundamentals, expected returns, market information, risk premium, and psychological characteristics like sentiment (Statman, 1999). Accordingly, investor trading frequency varies from one group of investors to the next group of investors, making the market more heterogeneous. The heterogeneity stems from market participants reacting differently to information shocks in the market (Tiwari, et al., 2013). Hence, this refers to the time-varying implication of short-run investment horizon (high-frequency) and long-run investment horizon (low-frequency) that are anticipated to be different between investor sentiment and stock returns. The wavelet method enabled the study to decompose the time series of the sentiment index and returns into high low and high frequency in examining the relationship between investor sentiment and Islamic and non-Islamic stock returns. Having said that, the wavelet approach was employed in this study to decompose the time series as a wavelet function (t) based on time-frequency. This is where the daughter wavelet is the component of the mother wavelet (t), which is uttered as the function of scale (s) and time position (t). The study followed the wavelet transform approach, which addresses the Fourier transform shortcomings, which appeals more to stationary time series data.

However, limiting the real-world economic and financial time series data, the analysis of a stationary time-series is not attractive since the traditional spectral tool may not adjust and overlook if the time series frequency is non-stationary (like, appear, disappear, and then reappear). Wavelet filter offers a platform that can deal with real-world financial and economic data, time-varying characteristics, and exempt the stationary assumption. In 108 wavelet transform, its frame is constantly changed from high to low and low to high frequency, owing to the presence of a long frame on low-frequency and a short frame on a high-frequency. It also develops time dilation or wrapping instead of frequency deviations in the adjusted signal gained from extrication of the tie axis into a series of consecutively short sectors.

Discrete Wavelet Transformations (DWT)

In the literature, heterogeneity among noise traders is one of the salient features of sentiment theories (Baker & Wurgler, 2006; Birru, 2018; Da et al., 2015). This creates different investment horizons in the market-based on time and frequency scales. The study also investigated the time-varying causality between investor sentiment and Islamic and non-Islamic stock return.

The study followed the orthogonal DWT method on weekly data of new investor sentiment and Islamic and non-Islamic stock returns to create different series based on frequency scales or bands from the original data series. These frequency bands display variations in the frequencies, where the smallest bands depict higher progressive variations while high bands represent low progressive variations (Tiwari et al., 2013). Here, the original series of investor sentiment and Islamic and non-Islamic stock returns were divided into six different orthogonal components (d1-d6) and one smoothed component (S6). The orthogonal series exhibited d1 (2-4 weeks), d2 (4-8 weeks), d3 (8-16 weeks), d4 (16-32 weeks), d5 (32-64 weeks), d6 (64- 128 weeks), s6 (128-256 weeks), also categorized into time domains (i.e., d1 + d2 (short-term), d3 + d4 (medium-term), d5+d6 (long-term) and s6 (very long-term).

To explain orthogonal DWT, the study presented a series, r(t), as a linear combination of the wavelet function (Alzahrani, Masih, & Al-Titi, 2014). The representation of the r(t) is shown below:

$$(t) \approx \sum SJ,k\ \phi J,k\ (t)\ k + \sum dJ,k\psi J,k\ (t)\ k + \sum dJ-1,k\psi J-1,k\ (t)\ k + \cdots \sum d1,k\ k\ \psi 1,k\ (t)$$

Where J signifies the level of decomposition which assigns different numbers to the scale crystal, k indicates translation parameters that attach the number of coefficients to the respective component, $\phi J, (t)$ and $\psi J,k\ (t)$ represent the father and mother wavelet family, computed as:

$\phi J, (t) = 2 - j\ 2\phi\ (t{-}2\ jk\ 2\ j)$ for j = 1 to J $\psi J,k\ (t) = 2 - j\ 2\psi\ (t{-}2\ jk\ 2\ j)$ for j = 1 to J

The father wavelet exhibits the high bands (low frequencies) that show small fluctuations in the decomposed series named as smoothed component (s). In contrast, mother wavelets denote low bands (high-frequency) that depict more significant changes in the decomposed series. sj, and dj,k are the scaling and detail coefficients represented in the following equations

$sj,k \approx \int \emptyset J,k\ (t) f(t) dt\ dj,k \approx \int \psi J,k\ (t) f(t) dt\ (j = 1, \dots .J)$

The sj, coefficients signify the smooth behavior of the decomposed series, while the dj,k coefficients depict the band deviation from the smooth process. The coefficients (named as crystals) are measures of the contributions of the respective wavelet function to the total series, where coefficients from level $j = 1 \dots .J$ are linked with the scale $\lfloor 2\ j{-}1 , 2\ j \rfloor$.

Wavelet Coherence

Wavelet Coherence (WC) The study used the bivariate structure, named WC, to examine the nexus between the two-time series of investor sentiment index and stock returns (Islamic and non-Islamic). First, to explain WC, the study needed to describe cross-wavelet transform and the cross-wavelet power where the cross-wavelet transform is defined by two-time series (t) and $y(t)$.

$Wx(m, n) = Wx\ (m, n)\ Wy * (m, n)$ Where, $Wx\ (m, n)$ and $Wy\ (m, n)$ are two CWT of $x(t)$ and $y(t)$.

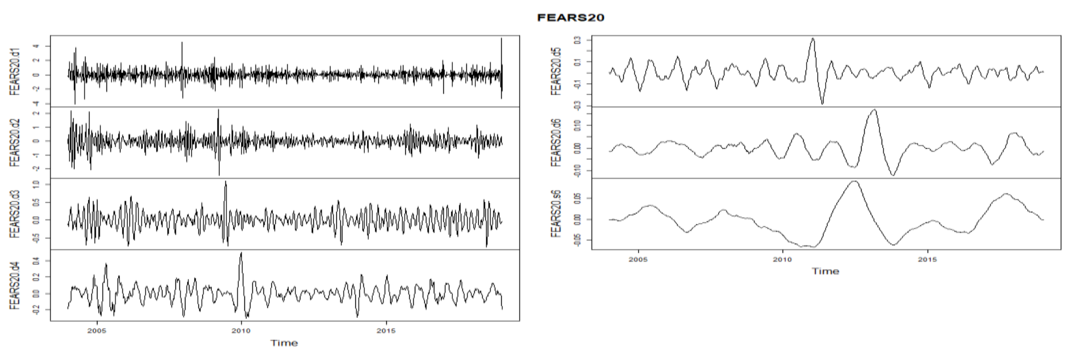
n illustrates the measure, while m signifies the location index, and an asterisk $(*)$ denotes a composite conjugate. The cross-wavelet power was measured by cross-wavelet transform as $|Wx\ (m, n)|$. Additionally, the cross-wavelet power spectra reveal regions in the time series frequency space; time-series posits an enormous joint power, which signifies the restricted covariance between the time series at each point. The WC can classify time frequency area where the observed time series simultaneously varies but does not evidence an enormous joint power. Torrence and Webster (1999) reported an adjusted coherence coefficient, as shown below:

$R\ 2\ (m, n) = |(N\ {-}1 Wxy(m, n))|\ 2\ N(N{-}1|Wx\ (m, n)|\ 2N\ (N{-}1|Wy\ (m, n)|\ 2)$, Where S signifies a smoothing mechanism. The series of squared coherence coefficient is $0 \leq R\ 2\ (m, n) \leq 1$. If it shows a value close to one (1), it has a strong correlation whereas, near to zero is considered a weak correlation. However, it does not reflect the hypothetical allocation of WC. Hence, the current study examined this with the help of the Monte Carlo method. This study followed Torrence and Compo (1998) and Grinsted, Moore, and Jevrejeva (2004) analysis method.

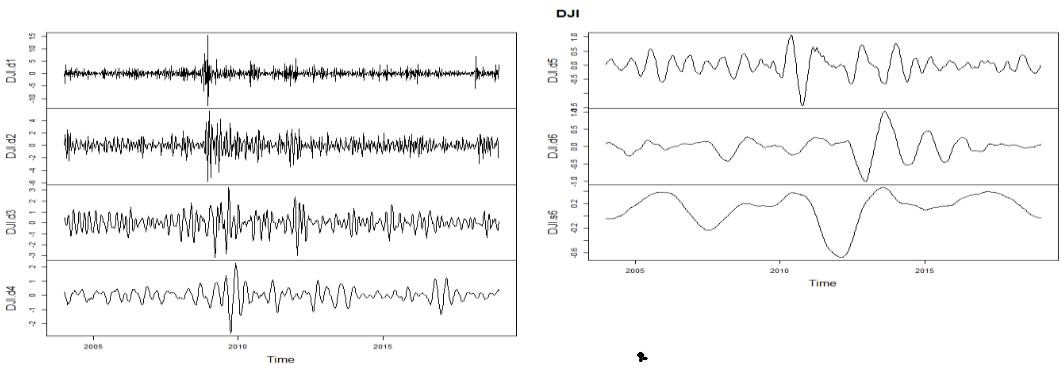
Results Analysis and Discussion

The study's second objective covered the time-varying relationship of the search-based investor sentiment index with US Islamic and non-Islamic stock returns. The study applied DWT to generate a hinder series from the original series of the search-based investor sentiment index and stock returns (Islamic and non-Islamic stocks) to examine the relationship across multiple time and frequencies. Further, CWT is employed to examine single series coherence with its lag values. Next, the WC method was used to analyze search-based investor sentiment coherency with the US Islamic and non-Islamic stock returns.

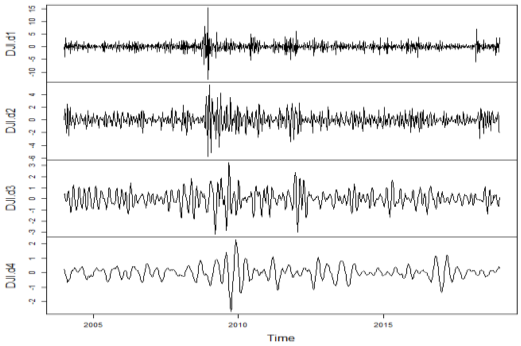
A2: Investor sentiment index

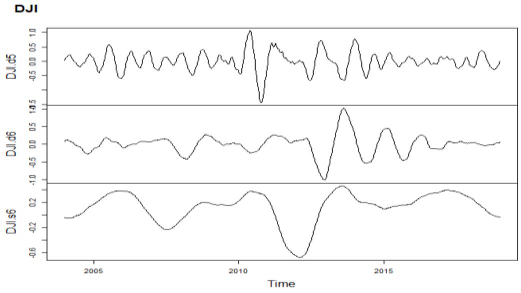


B2: Dow Jones stock index

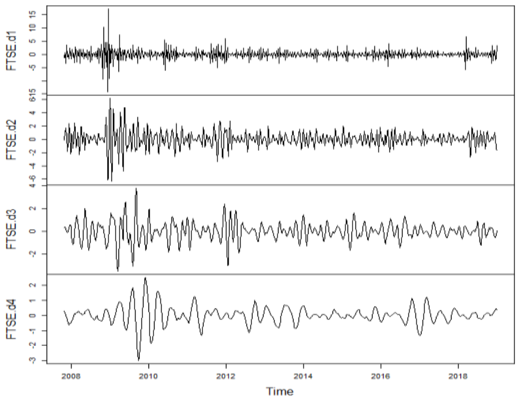


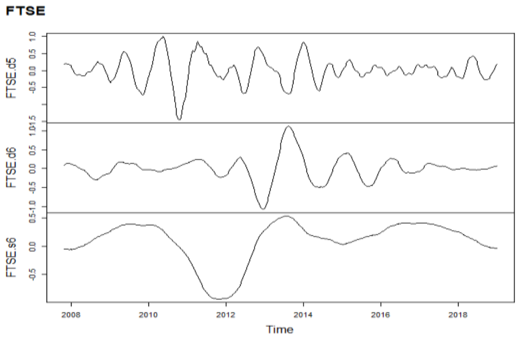
C2: Dow Jones Islamic stock index



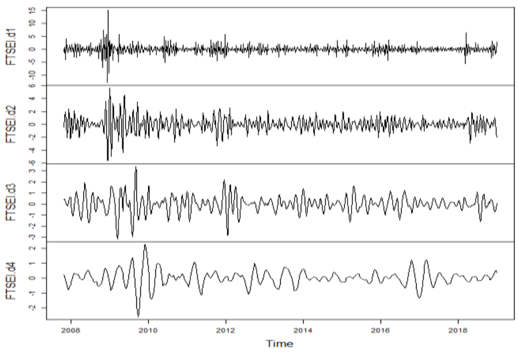


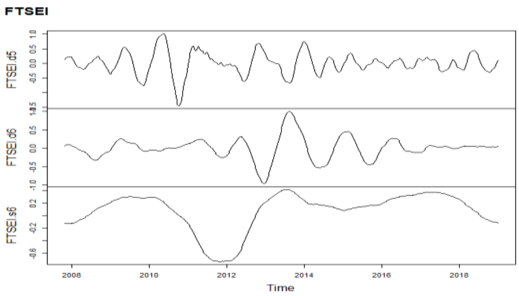
D2: FTSE stock index



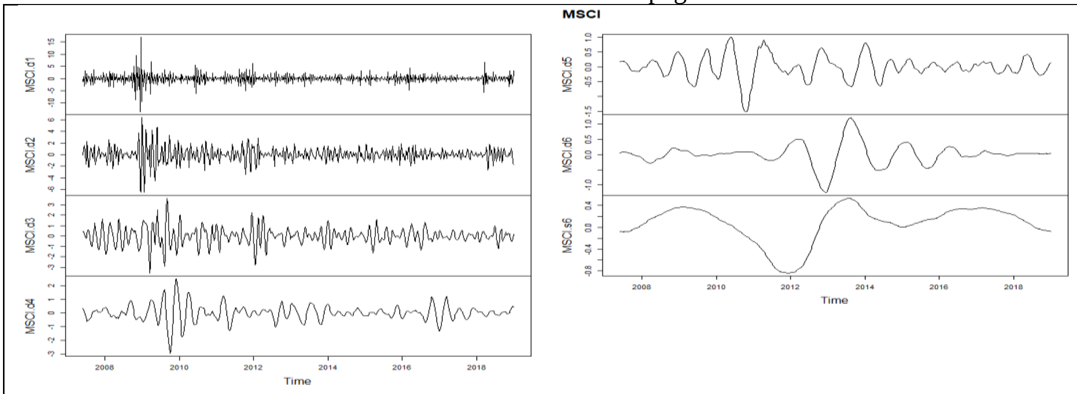


E2: FTSE Islamic stock index

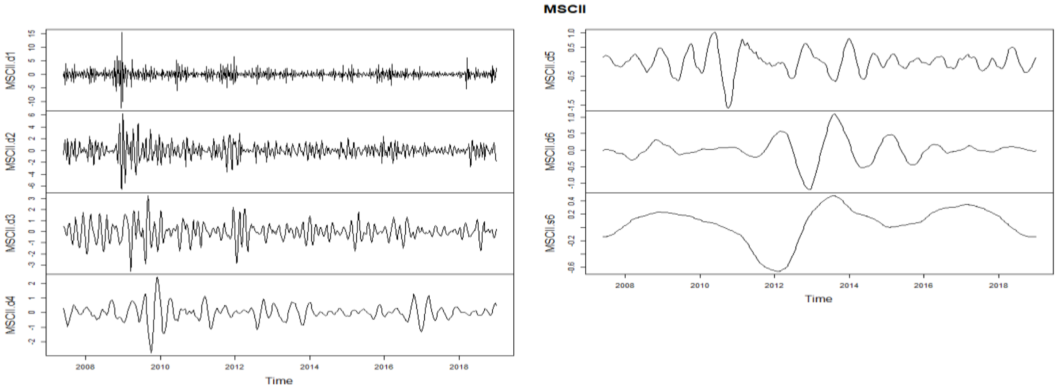




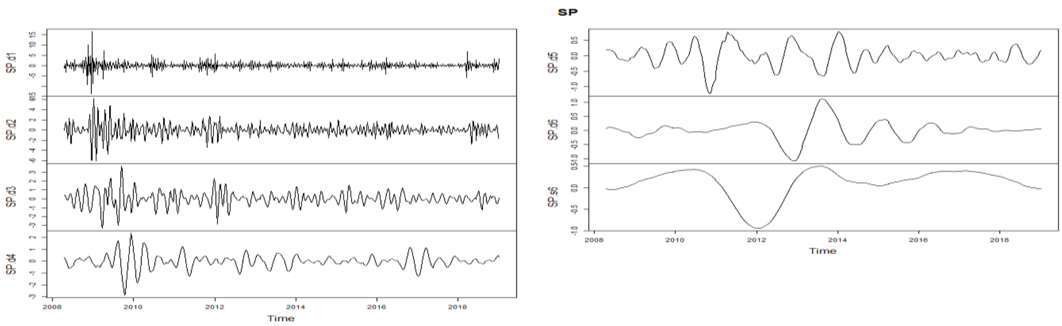
F2: MSCI stock index



G2: MSCI Islamic stock index



H2: SP 500 stock index



I2: SP 500 Islamic stock index

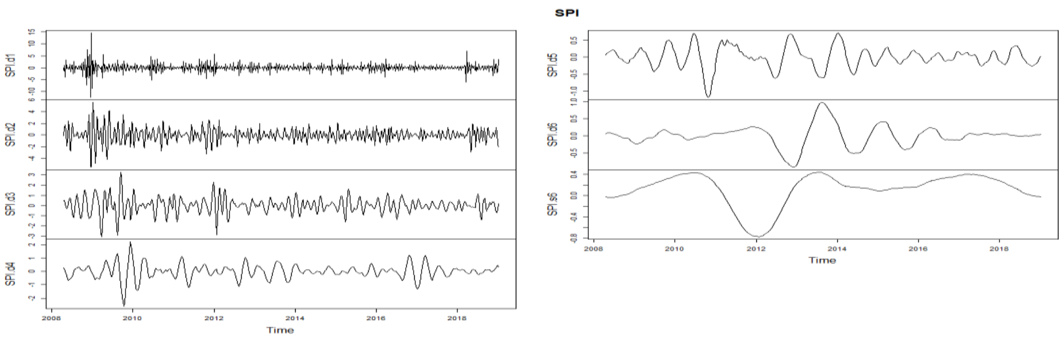


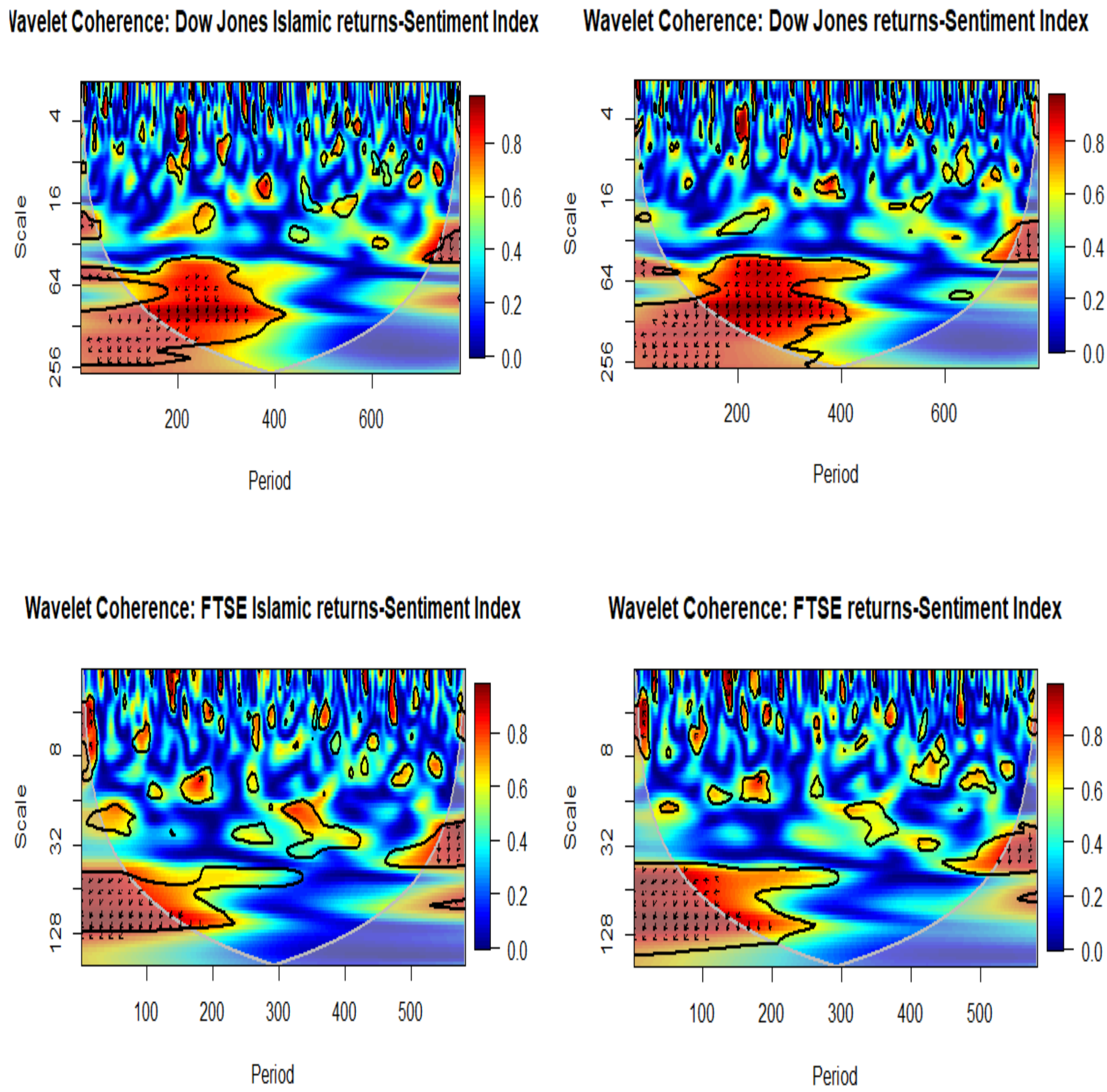
Figure 1: Investor sentiment and stock returns decomposed series

Using the DWT, the study extracted the impediments from the original series of investor sentiment and stock returns by dividing them into multiple frequencies over a period. Figure 1 displays the Morlet wavelet transform plots of the search-based investor sentiment index and US Islamic and non-Islamic stock indices returns for their respective sample periods. Accordingly, it was shown to transform the original series into high and low-frequency series to d6 scales and one smooth component. The d1 shows the highest, with s6 having the lowest frequency variations over the sample period. Specifically, d1 and d2 represent short-term, d3 and d4 indicate medium-term, d5 and d6 refer to long-term, while s6 illustrates very long-term variations in the variable. The benefit of the plots was to observe sharp dips and spikes in the series. Also, the Morlet wavelet transform helped to explore the hidden trends related to cyclical or periodic trends.

With reference to the Figure 1, plot A2 demonstrates the search-based investor sentiment index variation at multiple band scales (frequency) over the period between January 2004 and December 2018, while the d1 of the search-based investor sentiment index depicts higher variations during 2004, 2008-09, and 2018. Similarly, the d2 reveals the halving of the variation frequency of d1, which is decreasing until d6, showing more useful trends. The smooth component s6 of the search-based investor sentiment index demonstrated the dip in 2011 while a spike in mid-2012. The plots in B2 exhibit variations in the Dow Jones stock index returns transformed series where d1 observed extreme variations in the crisis period (2008-09), whereas the smooth component s6 had the highest dip during 2011. The search-based investor sentiment index and Dow Jones stock returns demonstrate a negative correlation in the very long-term by revealing a high spike in search-based investor sentiment index and a dip in stock returns. Moreover, in plot C2, Dow Jones Islamic stock index returns also revealed similar trends to its counterpart in plot B2 suggesting a high returns correlation between both.

The FTSE stock index returns in plot D2 and FTSE Islamic stock index returns in plot E2 demonstrated a similar trend for returns, where d1 reported the crisis period as being more sensitive, with s6 revealing a dip at the end of 2011. MSCI Islamic and non-Islamic stock indices return in F2, and G2 plots depict a high-frequency variation during the crisis period (2008-09) at d1. The smoothing component s6 of MSCI stock index returns observed a dip at the end of 2011, while MSCI Islamic stock index returns observed a dip at the beginning of 2012. Similarly, Plots H2 and I2 illustrated the transformed series of SP500 Islamic, and non-

Islamic stock indices return reporting a higher variation during 2008-09 in the high-frequency scale (d1). In contrast, in s6, a dip was observed at the beginning of 2012. Figure 1 illustrates the interest insights by showing consistency in the returns not only regarding their counterparts but within the stock indices as well. Moreover, it reports the high variation in search-based investor sentiment and stock returns (Islamic and non-Islamic stocks) during 2009 in the short-term (d1) whereas, in the very long-term (s6) in 2011. On the other hand, the search-based investor sentiment index depicts a spike, while stock return (Islamic and non-Islamic stocks) dip, suggesting a negative correlation.



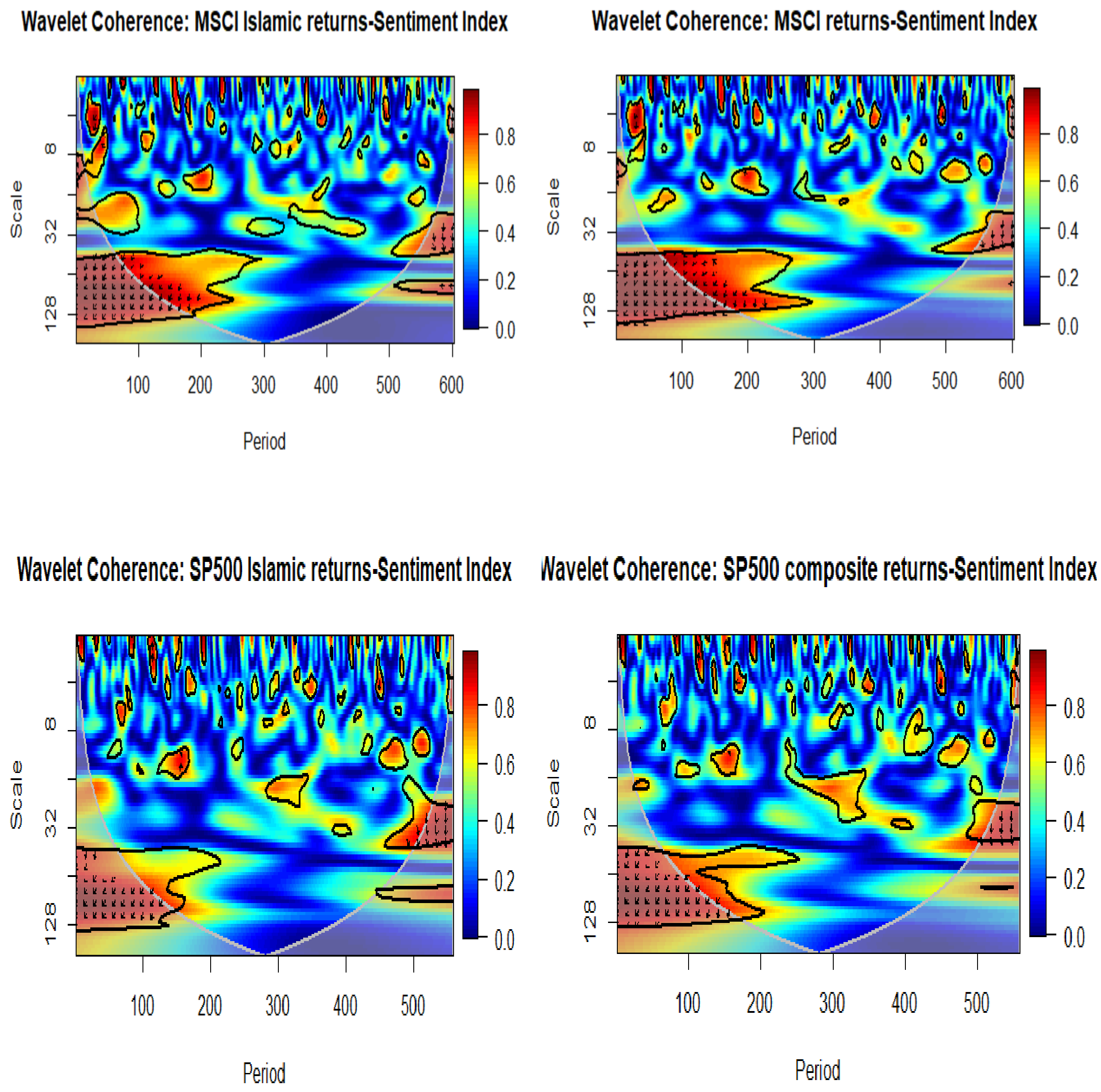


Figure 2: Continuous wavelet coherence between sentiment index and Islamic and non-Islamic stock returns

Figure 2 displays the continuous WC plots which demonstrate the coherence between search-based investor sentiment index and stock returns (US Islamic and non-Islamic stock indices) for the different sample periods. The figure depicts the period in years, as shown by the plot. The arrow denotes the direction and lead-lag relationship between the two series (sentiment and returns). The cone of influence posits the region's pretentiousness by the edge effects, which is drawn by a lighter black line not to distort the time series's plot. The thick black line signifies the significance level at 5% against red noise. The multiple colors displayed in the plot indicate the power of variance that ranges from red (high power) to blue (low power). The X-axis of the plot is the time frame (number of observations) of the study, while the y-axis is the period that illustrates the duration of the relationship range from short-term (4) to very long-term (256). The sample timeframe for each index is distinctly different given their availability, such as the Dow Jones, FTSE, MSCI, and SP500 Islamic and non-Islamic 2004M01-2018M12, 2007M11- 2018M12, 2007M06-2018M12, and 2008M04-2018M12, respectively.

Figure 2 shows the plot between Dow Jones Islamic stock returns and the search-based investor sentiment index displays an arrow toward quadrant III (see Appendix B2), indicating out of phase relations between 2007 and 2009 during the 64-128 weeks scale. It also shows negative coherence between investor sentiment and Dow Jones Islamic stock returns in the long-term, where the search-based investor sentiment index is a leading factor. When there is an increase in search-based investor sentiment index, it will decrease the contemporaneous Islamic stock returns. Moreover, the coherence between search-based investor sentiment index and stock returns is more pronounced during the crisis period. This result is consistent with Trichilli et al. (2020) findings showing that the Google-based investor sentiment index is the leading factor having a significant relationship with Islamic stock returns, particularly during crisis periods.

Similarly, the search-based investor sentiment index and Dow Jones non-Islamic returns plot demonstrated strong coherence of investor sentiment with non-Islamic returns in the crisis period. However, the size of the area of significance is larger than Dow Jones Islamic returns. These search-based investor sentiment index results for the Dow Jones Islamic and non-Islamic stock returns are consistent with Trichilli et al. (2018), in examining the co-movement between Google-based investor sentiment and stock returns (Islamic and non-Islamic) in the MENA countries. They documented the Google-based investor sentiment index with a significant predictability difference between Islamic and non-Islamic stock returns, thereby suggesting that investors consider differently Islamic or non-Islamic stock market returns, generating their sentiment. Hence, sharia faith does affect US market investor sentiment to adjust their investment decisions in the Islamic stock market.

The WC plot between the FTSE Islamic stock index returns and search-based investor sentiment index depicts a significant relationship in various episodes of investment horizons in the short, medium, and long-term. The red and yellow color areas in the cone of influence show strong coherence in the short-term, whereas moderate in the medium and long-term. However, the plot does not clearly illustrate in-phase or out-of-phase coherence between Islamic stock returns and search-based investor sentiment index. For instance, for 8-16 weeks frequency, an arrow points toward (quadrant I) showing in-phase (positive) coherency between investor sentiment and stock returns. Whereas, in the long-term (64-128 weeks scale), few arrows are pointing toward (quadrant III), shown at the edge of the cone of influence, suggesting out-phase (negative) coherency. However, in both positive and negative, the investor sentiment index's coherence is the leading factor. It is almost similar in directional co-movement except for the long-term frequency co-movement between FTSE non-Islamic stock returns and the search-based investor sentiment index. The larger size of the area of significance and the number of arrows is more for non-Islamic stock returns implying higher sensitivity toward investor sentiment throughout the crisis period between 2008 and 2009.

Furthermore, the plot of MSCI Islamic stock returns and the search-based investor sentiment index shows various significant small episodes between 4 and 8 weeks across the investment horizons. Then, between 60 and 130 weeks, investor sentiment revealed a large area of significant higher coherency between 2009 and 2011, while moderate coherence was depicted between mid-2011 and 2012 of around 64 weeks. The phase pattern arrow's direction is downwards to the left (quadrant III), indicating outer phase (negative) with a strongly significant coherence between 64 and128 weeks (long-term) in the period between 2009 and 2011. The coherence showed search-based investor sentiment index as a leading factor to the MSCI Islamic stock returns. The search-based investor sentiment index and MSCI non-Islamic stock return plots depict a nearly similar result as a counterpart with an expected longer time scale during 2009 and 2013. Also, search-based investor sentiment index showed higher coherence toward MSCI non-Islamic stock returns compared to Islamic stock returns, which is consistent with the limit to arbitrage concept showing higher coherence with non-Islamic stock returns than Islamic stock returns. Islamic stocks are shown to be safer given their ethical screening and lower bankruptcy.

The WC plot of SP500 Islamic stock returns and the FEARS20 sentiment index displayed stronger but smaller coherence episodes at multiple investment horizons. The phase pattern depicted outer phase co-movement for the 8 to 16 weeks scale for 2010. This suggests negative coherence between search-based investor sentiment index and SP500 Islamic stock return, where the SP500 Islamic stock return is the leading variable. Whereas in the long-term, the phase pattern demonstrates some arrowing at the edge of the cone of influence pointing toward the outer phase, but quadrant III at the beginning of 2010, suggesting negative coherence between the variables, where search-based investor sentiment index is the leading variable. Moreover, strong positive co-movement (in-phase) display in the 16-64 week scale for 2015-2016. In the co-movement SP500 Islamic stock returns is the leading variable. The plot depicting SP500 non-Islamic stock returns and search-based investor sentiment index is strongly negative, with the sentiment index as the leading variable co-movement during the 64-128 week scale at the edge of the cone of influence for the period between 2010 and 2011. The outcomes for sentiment index and SP500 Islamic and non-Islamic stock returns are different in the significant area of coherence.

The findings reflected in Figure 2 showing that search-based investor sentiment index has a relationship with Islamic and non-Islamic stock returns depending on the multiple frequencies and investment horizons. Investor sentiment revealed stronger coherence in the short-term but only for small episodes across time series. Whereas, in the long-term, it suggests higher coherence in the crisis period and following the crisis period. Moreover, almost all cases provide a search-based investor sentiment index as a leading factor. The negative coherence between the variables suggests will reduce Islamic and non-Islamic stock returns when sentiment is high in the market. These findings are consistent with the noise trader's theory showing that investor sentiment causes stock price movement.

Moreover, it suggests that the 'price pressure effect' is more dominant in US Islamic and non-Islamic stock markets, indicating greater disagreement among individual investors, which cancels their effect on price and provides more opportunities to arbitragers. The findings show that the magnitude of search-based investor sentiment index coherence with non-Islamic stock returns is bigger than Islamic stock returns, particularly in the long-term. The results confirm that non-Islamic stock markets are more vulnerable to investor sentiment risks. As such, investors might partially hedge their investment portfolios against investor sentiment risk by investing in the Islamic stock market during the high sentiment period. The current study results are consistent with Da et al. (2015), documenting a negative correlation between the FEARS sentiment index and conventional stock returns.

However, the time-varying approach moved ahead by identifying the effect at different investment horizons, consistent with Dash and Maitra's (2018) study results. The crisis period (2007-09) is the most sensitive timeframe that posits strong negative co-movement among search-based investor sentiment index and the Islamic and non-Islamic stock returns, which endorsed the findings by Maitra and Dash (2017) in their study. They reported that stock returns are more sensitive to investor sentiment during the crisis period. The figure also highlights the most attractive insight into heterogeneity response among stock indices of the same stock market (Islamic/non-Islamic) toward investor sentiment. Such heterogeneity in the market is useful for the investor by providing portfolio diversification within the market and in the same asset class.

Conclusion

The study investigated the search-based investor sentiment index lead-lag coherence with the US Islamic and non-Islamic stock returns at multiple times and frequency. The literature affirmed that investor sentiments are not static but rather varies with the investors' reactions toward information shocks and the level of uncertainty in the market. The second objective used a weekly Google search interval and indices price data for the period between January 2004 and December 2018. The study modified the search-based investor sentiment index methodology (explained in the first objective) by first removing any biasness related to keyword selection, in which the study used 149 sentiment-induced keywords listed in the Harvard IV dictionary. Next, via using Google trend, the first related ten keywords queries were added, resulting in a total of 1490 keywords. Following Da et al.'s (2015) keywords screening procedure (removed irrelevant, repetitive, and missing keywords), it resulted in 199 relevant and actively searched keywords in the study period.

Furthermore, the study calculated changes in the keywords series and adjusted for any apparent bias related to keyword frequencies in the GSV, such as outlier, seasonality, and standardization. The prices of US stock indices Islamic and non-Islamic index (Dow Jones Islamic index, Dow Jones non-Islamic index, FTSE Islamic index, FTSE non-Islamic index, MSCI Islamic Index, MSCI non-Islamic index, SP500 Islamic index, and SP500 composite index) were retrieved from DataStream for the period between January 2004 and December 2018. The study used continuous wavelet transform, continuous WC, DWT, and the linear Granger causality test. The continuous WC exhibited a strong covariance in the short and medium-term, while a moderate covariance in the long-term in Islamic and non-Islamic stock returns during the GFC period (2007-2009).

Accordingly, it demonstrated the negative coherency of search-based investor sentiment index on Islamic and non-Islamic stock returns, where the investor sentiment index was the leading factor. Interestingly, the GFC period (2007-09) was the most sensitive timeframe that revealed strong coherency of investor sentiment on Islamic and non-Islamic stock returns, which endorsed the findings of Chau et al. (2016) and Maitra and Dash (2017).

Also, search-based investor sentiment index revealed multiple small episodes during the short-term across investment horizons. Moreover, finding demonstrated search-based investor sentiment index slightly stronger coherence for non-Islamic stock returns. The study then decomposed the original series of search-based investor sentiment index and Islamic and non-Islamic stock returns into six short, moderate, long-term, and smoothing factors.

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