Investors' sentiment and US Islamic and conventional indexes nexus: a time-frequency analysis

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Abstract:

This paper is the first attempt to 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, we show that the time-varying nature of co-movement exists for both the Islamic and conventional indexes. Application of asymmetric causality test unveils that middle cap firms are susceptible from negative innovations in investors' sentiment. We conclude that the Sharia rules have no influence on the connectedness between sentiment and Islamic equity returns.

JEL classification: G11, G14, E32
Keywords: Investors' sentiments, Islamic and conventional stock indexes, wavelets, asymmetric causality

1. Introduction

Throughout the last two decades, the question of whether investor sentiment affects financial asset prices has received a considerable attention in the literature. Baker and Wurgler (2007) argue that sentiment measures do have predictive power with respect to equity returns. The Islamic finance industry witnessed a rapid growth over the past decade, and such growth has been reinforced in the wake of the global financial crisis and by the introduction of Islamic equity indexes. The Islamic market indexes are significantly differing from their conventional

index counterparts since the former are sharia-compliant and perceived as ethics-filtered assets[1].

The sentiment-equity return relationship for conventional markets has been intensively investigated in the literature, especially in the U.S. (see, among others, Brown and Cliff, 2004, Verma and Soydemir, 2009 and Lux, 2011). Brzeszczyński, Gajdka and Kutan (2015) review the literature on sentiment with respect to public information arrival in emerging markets. Authors claim that the role of investor sentiment needs more careful attention and the future research should analyze the multilevel relationship between institutional and individual investor sentiment variables and stock returns[2]. Thus this paper adds knowledge to the exiting literatures by further analyzing the relationship between sentiments and Islamic and conventional indexes. We investigate whether Islamic indexes behave differently in terms of their reactions to investor sentiments. Our findings provide novel evidence for the role of sentiment in Islamic markets by using conventional indexes and considering three different sub-indexes for large Cap, mid Cap, and small Cap listed firms.

Despite the growing importance and interest on the Islamic markets, scarce evidence exists in the literature on the relationship between sentiment and Islamic equity returns, and comparison to conventional indexes is even rare[3]. Unlike previous studies, this paper uses continuous wavelet and asymmetric causality methodology to address the following questions: How strong are the co-movements between sentiment and Islamic equity returns in

[1] For investors to be sharia compliant, they must adhere to several criteria. They should exclude firms from holding interest-bearing debt, receiving interest, impure income or trading debts for more than their face values. They should avoid firms whose debt-income ratio is equal to or exceeds 33%. They should shun firms "impure plus non-operating interest income" revenue equal to or greater than 5%. Finally, they should eschew firms whose accounts receivable-to-total assets is equal to or exceed 45% or more.

[2] Chau, Deesomsak, & Lau (2011) found evidence that when investors are optimistic they are more likely to follow trend-chasing investment strategies in the conventional exchange-traded fund markets.

3 A notable exception of recent work on this area is Rashid et al.(2014) and Ghorbel et al. (2014)

the time-frequency space? Do Islamic equities differ from their conventional counterparts in terms of co-movements?

There is ample empirical evidence that devoted to the investors' sentiment and equity returns nexus without reaching a uniform consensus[4]. The major advantage of the wavelet methodology is that it can distinguish between short-term and long-term co-movement dynamics between sentiment and equity returns. The wavelets allow one to consider for time and frequency jointly in a single framework when examining the co-movement between the two time series in a unified time-frequency band space. Moreover, the wavelet method is useful for investors that are concerned with different investment horizons (short or long) (Chakrabarty et al., 2015). On another side, wavelet method can model a non-linear relationship between sentiment and equity returns while linear models may lead to spurious conclusion on the relationship between two variables[5]. Furthermore, we use Hatemi-J (2012) causality test to explore how the positive and negative changes in US investor sentiments index affect Islamic equity returns. To our best knowledge, this study is the first attempt to analyze the co-movements between sentiment and Islamic equity returns in the time-frequency space using both wavelet coherence (WSC) and asymmetric causality methodologies.

The paper is proceeds as follows. Section 2 presents the methodology, Section 3 provides the empirical findings and Section 4 concludes.

2. Methodology

2.1. Data

4 For instance, Rashid et al. (2014) found low predictive power of sentiment for the Malaysian Islamic equity markets. In contrast, Ghorbel et al. (2014) discover a strong predictive content of sentiment on Islamic returns during the 2008-2009 crisis using a GARCH framework.

5 Dergiades (2012) unveil a non-linear connectedness between sentiment and aggregate US equity returns, Ni et al. (2015) finds a non-linear and time-varying effect of sentiment on the Chinese equity returns.

This study employs the US monthly Islamic (i.e. The Dow Jones Islamic index) and conventional equity indexes over the period 1990:4 to 2010:12. Besides, we consider three different sub-indexes for large Cap, mid Cap, and small Cap listed firms. Monthly returns are taken from DataStream and computed by taking the natural logarithm of the ratio of two successive prices. The US investors' sentiment indexes and their monthly changes were sourced from Baker and Wurgler (2007)[6]. The beginning of the sample period is restricted by the starting year of the availability of the sentiment indexes for the US market. Descriptive statistics is available upon request.

2.2. The wavelet methodology

The wavelet method decomposes a time series as a wavelet function $\psi(t)$ that depends on the time parameter (t). In the decomposition, the daughter wavelets are derived from the mother wavelet $\psi(t)$ which is expressed as a function of the time position (τ) and the scale (s). Following Grinsted et al. (2004), we employ the Morlet wavelet function: $\psi(\eta) = \pi^{-1/4} e^{i\omega\eta} e^{-1/2\eta^2}$, where ω *is* the dimensionless frequency and η is the dimensionless time. We set $\omega_0 = 6$ for its good balance between time and frequency localization. Torrence and Compo (1998) consider the wavelet method as a combination of a feature extraction and multi-resolution analysis. The wavelet process of a discrete time series $x(t) = 1, \dots, nx(t), t = 1, \dots, n$ is defined as the convolution.

$$W_x(s,\tau) = \sqrt{\frac{1}{s}} \sum_{t=1}^{N} x(t)\psi * \left(\frac{t-\tau}{s}\right) \tag{1}$$

where s is the scale, $\frac{1}{\sqrt{s}}$ is a normalization factor, τ is the time position and * refers to a complex conjugate. The wavelet transforms W_x and W_y of two time series, $x(t)$ and $y(t), t = 1, \dots, N$, we construct a cross wavelet transform $W_{xy} = W_x W_y^*$, from which the cross wavelet power $|W_{xy}|^2$ is computed. The cross wavelet power indicates the areas in the time-frequency

[6] Available at: http://people.stern.nyu.edu/jwurgler

space where the two time-series share a high common power. To identify the areas in the time-frequency space where the two time series co-move, we calculate the WSC by dividing the smoothed cross-wavelet power by the individual smooth wavelet power spectra:

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

where S refers to the smoothing parameter. This definition closely resembles that of traditional correlation coefficient and wavelet coherence could be seen as a localized correlation coefficient in the time-frequency space. The smoothing operator is written as $S(W) = S_{scale}(S_{time}(W_n(s)))$, where S_{scale} denotes the smoothing along the wavelet scale axis and S_{time} is the smoothing operator in time. The smoothing operator is given as in Torrence and Webster (1998):

$$S_{time}(W)\Big|s = (W_n(S) * c_1^{\frac{-t^2}{2s^2}})\,|s, S_{time}(W)|s = (W_n(S) * c_2\Pi(0.6s))|n \tag{3}$$

where c_1 and c_2 are the normalization constants and Π is the rectangle function (Grinsted et al., 2004, p. 565). Additionally, the WSC coefficient is in range of $0 \leq R^2(u,s) \leq 1$, where values close to zero indicate a week correlation, while those close to one confirm the existence of high correlation.

2.3 Asymmetric causality test.

We use asymmetric causality test with bootstrap simulation approach for calculating of critical values developed by Hatemi-J (2012). The cumulative sums of positive and negative shocks of each underlying variables can be defined as follow:

$$y_{1t}^{+} = \sum_{i=1}^{t} \Delta\theta_{1i}^{+},\ y_{1t}^{-} = \sum_{i=1}^{t} \Delta\theta_{1i}^{-},\quad y_{2t}^{+} = \sum_{i=1}^{t} \Delta\theta_{2i}^{+},\quad y_{2t}^{-} = \sum_{i=1}^{t} \Delta\theta_{2i}^{-} \tag{4}$$

where positive and negative shocks are defined as: $\theta_{1t}^{+} = \max(\Delta\theta_{1i},0)$; $\theta_{2t}^{+} = \max(\Delta\theta_{2i},0)$; $\theta_{1t}^{-} = \min(\Delta\theta_{1i},0)$, and $\theta_{2t}^{-} = \min(\Delta\theta_{2i},0)$.

3. Empirical results

As the first step of this research we follow Rua and Nunes, (2009) and Madaleno and Pinho, (2012) and use the Monte Carlo simulations to assess the statistical significance[7]. In the WSC plots (Figures 1 and 2), the horizontal axis is time intervals, whereas the vertical axis designates the scale. The red colored area at the bottom (top) of the WSC plots shows a strong co-movement at low (high) frequencies, while the presence of red area at the left-hand (right-hand) side represents the existence of significant co-movement at the beginning (the end) of the sample period. WSC can detect whether the co-movement has increased or decreased through time and frequencies, seizing possible varying patterns in the co-movement between the sentiment and US returns in both time and frequencies. The black thick line isolates the regions where the sentiment-equity return co-evolutions are statistically significant at 5% level[8].

[Figure 1 to be placed here]

In Figure. 1, (Panel a to d), high level of co-variation between the sentiment changes and Islamic equity returns is detected. The WSC of the couples exhibit similar patterns at low (high) and high (low) scales (frequencies), and similar pattern is found for Large Cap and Mid. Cap firm' returns. Besides, we find a high degree of synchronization at low frequency band during the whole sample period. Interestingly, a big island of orange color is localized at high frequency band (correlation between 0.7 and 0.8 level) at the beginning of the period (between 1999-the end of 2001) following the terrorist attacks of September 11. In the late 2010, we identify a big island of red color localized at low frequency (long-run investment horizon) signifying a strong relationship between sentiment and Islamic returns, which

[7] The 5% significance level was calculated from a Monte Carlo simulation of 10,000 white noise time series pairs with the same length.
[8] All the computations are performed using MATLAB.

responds to the Eurozone debt crisis. Altogether, the WSC analysis unveil a strong co-movement between the investors sentiment and Islamic equity returns confirming the predictive content of the sentiment with respect to Islamic equity returns.

Figure. 2 (Panel a to d) demonstrates the WSC plots between the investor sentiment changes and conventional returns. It reveals that all couples share similar patterns. US conventional returns for large Cap, mid Cap, and small Cap are positively correlated with sentiment changes at both high and low scales indicative of a co-movement in the long run and short-run horizons. For all couples, higher strength in the co-movements of equity returns at higher scale, where a high co-movement occurred between 2008 and 2010. Overall, US investor sentiment and all equity returns share the same pattern in the time-frequency space, implying that the Sharia rules have no influence on the connectedness between sentiment and Islamic equity returns.

[Figure 2 to be placed here]

As a second step of this research we employ the asymmetric causality tests to test the impact of positive and negative changes in US investors sentiment index on returns on the Islamic equity indices and conventional equity indices. The results reported in Table 1 support the findings discussed showing similar patterns for couples in both panel A and Panel B. There are no evidences of causalities between positive innovations are identified, however, the causal linkages between negative innovations in investor's sentiment and Mid. Cap firms returns are identified at 5 % significance level for both Islamic and conventional indexes.

[Table 1 to be placed here]

4. Conclusion

This paper distinguishes itself from prior works on two foremost aspects. First, we perform the wavelet methodology to analyze the co-movement between sentiment and US equity returns, considering time-scale and frequencies when analyzing the behavior of the sentiment-equity return co-evolution. Second, the sentiment-equity return connectedness is investigated for both Islamic equity markets and their conventional counterparts using asymmetric causality test. Our empirical findings reveal that the co-movement is shifting over time and frequencies. The Islamic equity returns do not behave differently from their conventional counterparts. Thus, the US investors should consider simultaneously short- and long-run co-movement in the sentiment-equity return when picking up Islamic equities in their portfolios.

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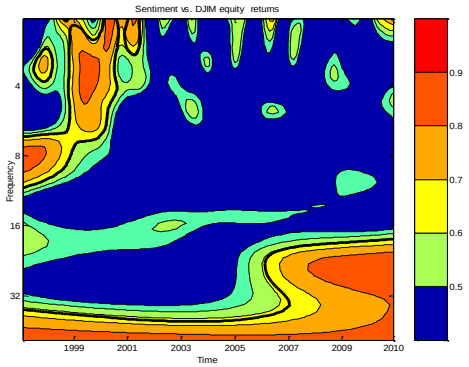
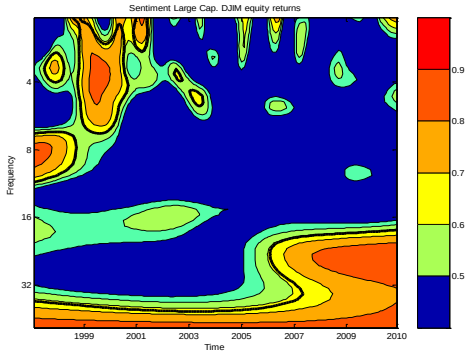
Figure 1. The WSC plots: sentiment vs. Islamic equity returns

(a) Sentiment vs. DJIM equity returns

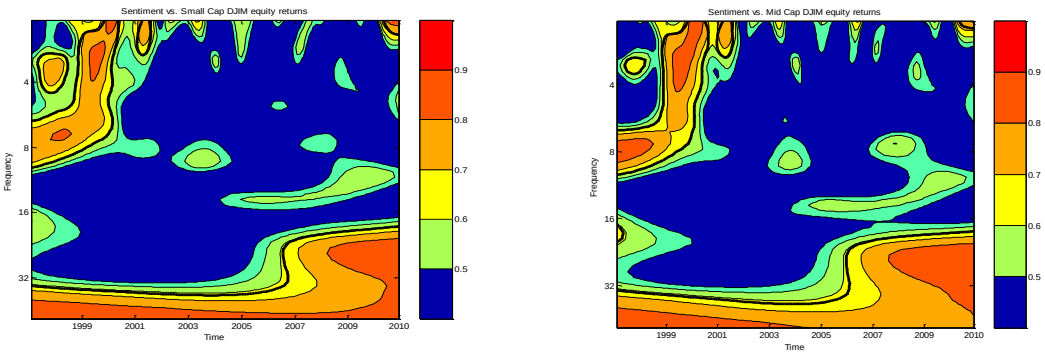


(b) Sentiment Large Cap. DJIM equity returns



(c) Sentiment vs. Small Cap. DJIM equity returns

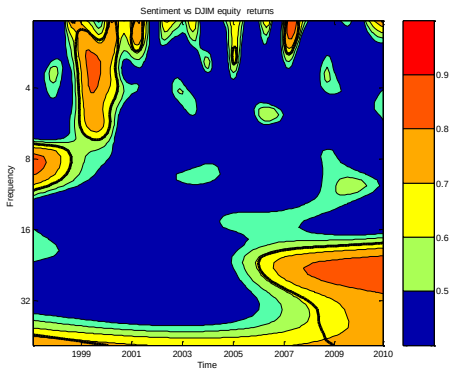
(d) Sentiment vs. Mid Cap DJIM equity returns



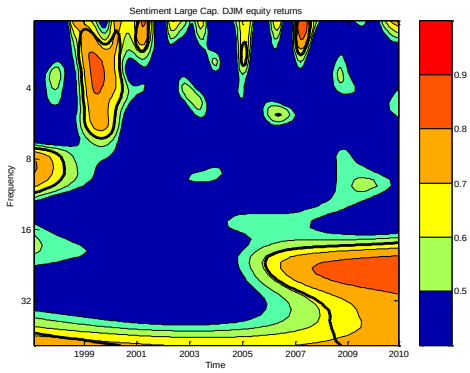
Notes: The red color corresponds to a growing value of the WSC. Time and frequency are reported on the horizontal and the vertical axis, respectively. Frequency is converted into years. The thick black continuous line in the figures isolates the regions where the WSC is statistically significant at the 5% level. The colors in the color bar measure the degree of the co-movement between the two variables.

Figure 2. The WSC plots: sentiment vs. conventional equity returns

(a) Sentiment vs DJ equity returns

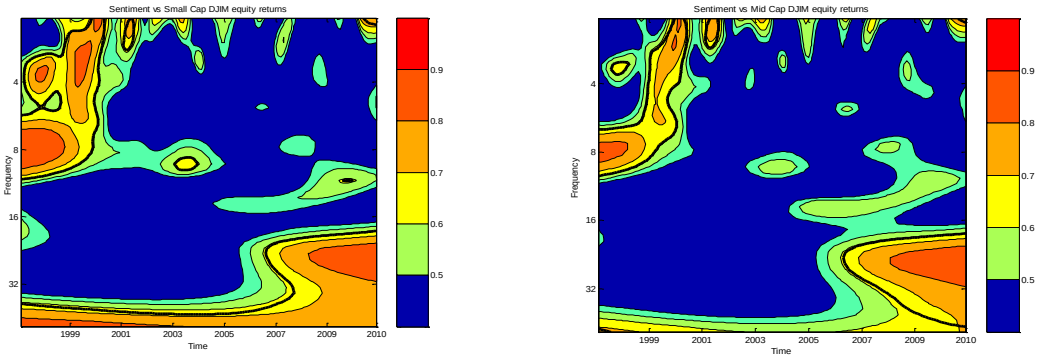


(b) Sentiment vs Large Cap. DJ equity returns



(c) Sentiment vs Small Cap DJ equity returns

(d) Sentiment vs Mid Cap DJ equity returns



Notes: The red color corresponds to a growing value of the WSC. Time and frequency are reported on the horizontal and the vertical axis, respectively. Frequency is converted into years. The thick black continuous line in the figures isolates the regions where the WSC is statistically significant at the 5% level. The colors in the color bar measure the degree of the co-movement between the two variables.

Table 1. The asymmetric Causality Test Results

Null Hypothesis	Test value	Bootstrap CV at 1%	Bootstrap CV at 5%	Conclusion
Panel A: Sentiment vs. Islamic equity returns				
Sentiment+ ≠> DJIM +	0.031	6.975	3.953	Sentiment+ ≠> DJIM +
Sentiment- ≠> DJIM -	5.346	9.239	6.653	Sentiment-≠>DJIM -
Sentiment+ ≠>LarCap+	0.024	7.194	4.130	Sentiment+ ≠>LarCap+
Sentiment- ≠> LarCap-	2.299	6.924	3.729	Sentiment- ≠> LarCap-
Sentiment+ ≠>MidCap +	0.371	7.015	3.840	Sentiment+ ≠>MidCap +
Sentiment- ≠> MidCap -	**6.796***	11.154	6.310	**Sentiment- => MidCap -**
Sentiment+ ≠> SmallCap+	1.118	8.009	3.753	Sentiment+ ≠> SmCap+
Sentiment- ≠> SmallCap -	1.730	10.143	6.254	Sentiment- ≠> SmCap -
Panel B: Sentiment vs. Conventional equity returns				
Sentiment+ ≠> DJ+	0.270	8.139	3.762	Sentiment+ ≠> DJ+
Sentiment- ≠> DJ-	2.393	6.823	3.712	Sentiment- ≠> DJ-
Sentiment+ ≠>LarCap DJ+	0.180	8.585	3.958	Sentiment+ ≠>LarCap DJ+
Sentiment- ≠> LarCap DJ-	1.998	6.629	3.710	Sentiment- ≠> LarCap DJ-
Sentiment+ ≠>MidCap DJ+	2.345	12.424	6.355	Sentiment+ ≠>MidCap DJ+
Sentiment- ≠> MidCap DJ-	**6.376***	9.986	6.387	**Sentiment- => MidCap DJ-**
Sentiment+ ≠> SmallCap DJ+	0.943	7.075	3.835	Sentiment+ ≠> SmCap DJ+
Sentiment- ≠> SmallCap DJ -	2.502	10.387	6.125	Sentiment- ≠> SmCap DJ -

Notes: The critical values for the asymmetric causality test are calculated using a bootstrap algorithm with leverage correction. *The rejection of the Null Hypothesis of no causality at the 5% significance level.