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Awartani, B., Abdoh, H. and Maghyereh, A.I.

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Basel Awartani, Hussein Abdoh, Aktham I. Maghyereh

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Corresponding Author :

Professor Aktham I. Maghyereh

Institution: United Arab Emirates University

Department: Deparment of Economics & Finance

Address: United Arab Emirates University
Deparment of Economics & Finance

Email: a.almaghaireh@uaeu.ac.ae

Country : United Arab Emirates

Group of authors : Basel Awartani (University of Westminster), Hussein Abdoh (United Arab Emirates University)

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Abstract

In this paper, we use wavelet coherence analysis to find that sentiment has a significant effect on crude oil returns that lasts over various investment horizons. While oil returns are positively associated with the sentiments of optimism and trust, it is negatively linked to fear and anger. These relations are more pronounced over the medium and the long term. Additionally, we find that short-term oil returns are relatively more sentiment-sensitive during turbulent periods than in normal conditions. These results highlight the importance of sentiment and investor psychology in the crude oil market.

Keywords: Co-movement, Crude oil, Emotions sentiments, Wavelet analysis

JEL Code: C58, G41

1. Introduction

Over the past two decades, theoretical studies have shown that marketable assets returns are mostly driven by the behavioral factors rather than by the fundamentals. The psychological biases of investors' is found to trigger asset pricing anomalies (Daniel et al., 1998; Barberis et al., 1998; Baker and Nofsinger, 2002), to undermine traditional risk-return tradeoff (Yu and Yuan, 2011), and to influence asset prices at equilibrium through price pressures (Wang et al., 2006).

Moreover, many recent studies have found that the investors' emotions and mood have significant influence on financial markets' returns.[1] For example, Hirshleifer and Shumway (2003), Edmans et al., (2007), Novy-Marx (2014), Hobson et al., (2012), Goetzmann et al., (2014), and Lepori (2016), among others, document that investors' emotional states and feelings are creating trends and anomalies in the markets of financial assets.

The focus of most of these works is placed on how aggregate behavioral biases may explain irrational bubbles and crashes of equities and there are little studies that talked about how the crude oil market is influenced by investors' sentiments. This is important as the crude oil market is relatively large as oil is the underlying of many derivative contracts with huge open interests. Therefore, in this paper, we fill this gap and we investigate how investors' emotions affect the returns of the crude oil over multiple horizons.

In the literature on oil and sentiment, we find two pieces that explain how oil behaves around sentiments. The event study by Borovkova (2011) which shows that sentiment matters particularly negative sentiment and its influence lasts for long. The paper also shows that after a bad sentiment the forward curve becomes steeper in contango markets and flatter in backwardation markets and this creates an opportunity for profitable spread strategies. The

[1] These emotions are driven by news and social media content.

study by Zhang et al., (2019) finds that negative sentiments Granger cause extreme tail risk in the crude oil market.

Our paper is related to these studies, but we use a different approach to look into how sentiments influence the crude oil market. In particular, we apply a wavelet coherence analysis in order to assess how sentiments are linked to oil. Furthermore, we check whether current sentiment predicts future oil returns or if it leads to oil price changes.

For that purpose, our choice falls on five of Thompson Reuters' emotion indices that we believe are effective in driving crude oil returns. These are: the sentiment, the optimism, the trust, the fear and the anger index. All indices range from -1 to 1 and in that sense, they may assume both sides of the emotional dimension. The market sentiment is popular in financial markets and it is related to the spirit of the trading activity. The optimism and trust feeds into traders' overconfidence which subsequently may spur rallies in the crude oil market. On the other hand, the fear and anger may trigger fire sales and market crashes. All indices are collected from structural and unstructured social media.[2]

The contribution of this paper is threefold. First, this paper is among the first studies to look into the relation between the media's emotions and the crude oil returns. Second, while prior research used market-wide measures as proxies for investor sentiment, we use multiple dimensions of the emotions that are created by the crude oil-specific news in the social media.[3] Third, the wavelet coherence analysis to obtain dependencies over various horizons is a new approach for this type of analysis that is novel and has not been used before.

The assessment using the wavelet coherence analysis is able to capture the linkages over various time scales which is important to get because of the heterogeneity of investors'

[2] The other market psychology indices are not directly related to the popular investors' biases in the literature. These indices include for instance, volatility, love, hate, violence, conflict and joy.
[3] See for instance, Smales (2014); Deeney et al., (2015); Dowling et al., (2016); Shen et al., (2017); Sun et al., (2018); Qadan and Nama, (2018); Qianga et al., (2019); Zhang and Li., (2019); among others.

holding periods (Reboredo and Rivera-Castro, 2013). That is, investors exhibit different horizons due to the varying levels of their risk tolerance levels, different assimilation and absorption of information, and different institutional constraints (Chakrabarty et al., 2015). These heterogeneities may imply various relationships at different investment horizons.

Therefore, the segregation of the time series data into different frequencies using the wavelet analysis is useful to obtain the association over various investment horizons (e.g., short or long). Moreover, it allows us to test how co-movements between investor emotions and crude oil returns change over time in high and low volatility regimes and at different frequencies. All in the context of the same framework. Moreover, the wavelet analysis controls for nonlinearities, structural breaks, non-stationary series, as well as for any seasonal or cyclical patterns in the relationship between variables (Crowley, 2005).

Our results show that the investors' specific sentiment leads oil returns. Moreover, we find that there is a high degree of synchronization between oil and sentiment for horizons longer than 128 days. Fear and anger have statistically significant effect on crude oil returns over short and medium tenors particularly during turbulent periods.

The rest of the paper is organized as follows. Section 2 describes the datasets and empirical methodology. Section 3 reports the empirical results. Finally, Section 4 concludes the paper.

2. Data and methodology

2.1 Data

The daily closing prices for Brent crude oil are obtained from Thomson Reuters Datastream database.[4] The daily emotions indices related to the crude oil market, the TRMI, are thankfully provided to us free of charge from Thompson Reuters. These indices are: the general sentiment index, the optimism index, the trust index, the anger index and the fear index. The second and the third are pleasant indices, while the fourth and fifth are unpleasant.[5]

The TRMI's sentiment indices are word-count indices that are developed by Thomson Reuters in collaboration with MarketPsych LLC. It is derived from textual data taken from news wires, financial news, and social media. The data contributing to it includes more than 2 million daily news articles and posts that reflects the investors' psychology regarding a particular commodity. The information used to build the indices are coming from investor groups, analysts, journalists, and economists. Thus, it reflects related information to market psychological bias. The granularity of the data is at the minute level but the daily index reflects an average of information that is collected over the past 24 hours.

More specifically, the TRMI measures provide a 24-hour rolling average scores of all news and social media references. As compared to market based indices[6], TRMI is available in real time and thus users avoid delays (Ammann et al., 2014). The other advantage of TRMI

[4] The West Texas Intermediate (WTI) spot price is not used as the recent evidence suggests that Brent is the main global benchmark price reference in the crude oil markets. Approximately 70% of all international trade is priced directly or indirectly using the Brent price (Fattouh, 2011; Chen et al., 2015; Dowling et al., 2016).

[5] These four emotional indices are chosen because its data is available for longer periods of time. More details can be found in https://www.marketpsych.com/guide/

[6] The market-based indices include the sentiment endurance index, the bull-bear spread index, the close-end fund discount index, the Baker and Wurgler's (2006) investor sentiment index, the University of Michigan Consumer Sentiment Index, the VIX index, the trading volume index, the closed-end fund discounts index, the number of IPOs index , and IPO returns index.

is that it provides marginal information that can't be confused with common macroeconomic and financial predictors as it is independent.[7]

Table 1 summarizes the TRMI daily indices for the crude oil market. The sentiment and the emotion indices are available at minutely basis. In this study, we use a daily average sentiment measure that is computed by aggregating sentiments of news wires, financial news and social media scores of all articles on each day and then averaging and normalizing these scores.[8] Borovkova (2011) argues that using daily frequency sentiment data has several advantages such as reducing the noise of intra-daily raw news datasets and the complications caused by the market microstructure. Finally, the daily data are more relevant than the data measured over higher frequencies as it is more related to the fundamental factors of supply and demand rather than to market microstructure and noise trading. [9]

[INSERT TABLE 1 HERE]

Our data set covers the period that extends from January 1, 1998 to July 30, 2018 and it contains 5,363 observations. The crude oil returns are computed as the log-difference of daily closing prices. Figure 1 presents the time-series plot of crude oil returns and emotion indices. Table 2 provides descriptive statistics for all variables. The cross correlations between crude oil and emotion indices are provided in Table 3. As shown in the table, the correlation coefficients between oil returns and the general sentiment is 0.325. It is 0.29 and 0.121 with optimism and trust respectively. The correlation with fear and anger are negative -0.224 and -

[7] The word- search sentiment measure is more transparent than statistical-based measures. Da et al., (2015) note that "*Although market-based measures have the advantage of being readily available at a relatively high frequency, they have the disadvantage of being the equilibrium outcome of many economic forces other than investor sentiment*" (pp.2). In addition, Li et al., (2019) indicate that these sentiment measures are "more primitive" than other alternatives because they do not directly rely on equilibrium market prices and quantities.

[8] We would like to acknowledge the support of MarketPsych LLC. for providing the daily frequency sentiment data.

[9] The vast majority of empirical studies use aggregate daily frequency sentiment measure (see for example, Borovkova (2011); Da et al., (2014); Shen et al., (2017); Han et al., (2017); Wang et al., (2018); Ballinari and Behrendt (2019); among many others).

0.176 respectively. Moreover, as expected the correlations between pleasant and unpleasant emotions are negative.

[INSERT FIGURE 1 HERE]
[INSERT TABLES 2&3 HERE]

While Pearson correlation is the most commonly used method to study synchronous cross-correlation, it there exists intervening variables that drive the relationship and thus the cross correlations may be spurious.[10] A possible approach to overcome this issue is to use partial correlation (Baba et al., 2004; Dror et al., 2015). The partial correlation analysis measures the linear relationship between the two variables while controlling (i.e., subtract) for the potential effects of all of the other variables. The partial correlations are presented in Table 4.

As shown in the table, the partial correlation of oil return is relatively higher with general sentiment, 0.233, and optimism, 0.251. The correlation with trust is low, 0.083; the same is the partial correlation with fear, -0.151, and anger, -0.074.

Two conclusions can be inferred from these computations. First, the positive (negative) sentiments lead to positive (negative) oil return. Second, the effect of sentiments on oil return is asymmetric as positive sentiments have larger impact than negative sentiments. The partial correlations also show that the emotion sentiment variables are consistent as the general sentiment is positively correlated with the pleasant emotions such as trust, 0.304, and negatively correlated with the unpleasant emotions such as anger, -0.154.

Note that the correlations between the sentiment variables are not large which provides support to our approach in using more than one emotional variable when studying the sentiment effect on oil returns.

[10] This point has been raised to us thankfully by one of the referees.

2.2 *Methodology*

To explore the effect of investors' emotional sentiments on crude oil returns, we use wavelet coherence analysis (Whitcher and Craigmile, 2004), which is localized in both time and frequency domains and allows the strength of association between two-time series over time as well as across frequencies. The wavelet coherence of two-time series $x(t)$ and $y(t)$ with continuous wavelet transforms (CWT) is given as (Reboredo et al., 2017):

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

where $W_{xy}(u,s) = W_x(u,s)W_y^*(u,s)$ is the cross-wavelet transform, u is the position index, and s is the scale. The cross-wavelet spectrum is correspondingly defined as $\left|W_{xy}(u,s)\right|^2 = |W_x(u,s)|^2\left|W_y(u,s)\right|^2$, the "*" indicating the complex conjugate of the basis wavelet. $W_x(u,s)$ and $W_y(u,s)$ are the wavelet transforms of $x(t)$ and $y(t)$, respectively, and S refers to the smoothing operator for both time and frequency. Smoothing is achieved by convolution over time and scale, represented by $S(W) = S_{scale}\left(S_{time}\left(W_n(s)\right)\right)$, where S_{scale} and S_{time} are smoothing on the wavelet scale axis and time, respectively (Gallegati and Ramsey, 2014).

The squared wavelet coherence coefficient $R^2(u,s)$ would satisfy $0 \leq R^2(u,s) \leq 1$ in the time–frequency space. A value of $R^2(u,s)$ nearer to zero shows that the time series investigations are weakly correlated and is shown in blue. A value close to one indicates strong correlation and is shown in red. The blue regions show that the important areas characterize uncorrelated time and frequencies between the time series. Since the theoretic distribution of the wavelet coherence coefficient is unknown, the statistical significance level of the coherence, $R_{xy}^2(u,s)$, can be estimated by Monte Carlo simulations using surrogate red-noise time series (Aguiar-Conraria and Soares, 2014, Torrence and Compo, 1998). This method can be briefly described in two steps. First, it generates a large ensemble of surrogate data pairs (1000 simulations) using classical bootstrap technique on input datasets that have the same lengths and first-order autoregressive (AR1) coefficients. Second, it calculates the wavelet coherence for all of the simulated data pairs. Finally, the significance level of coherence can be determined by comparing the statistical distribution with those obtained from the surrogate data pairs at each time and wavelet scale (Grinsted et al. 2004).

To distinguish between negative and positive correlations in the time–frequency space, as well as the lead–lag relationships between examined time series, we use the wavelet phase-difference analysis suggested by Torrence and Compo (1998). The wavelet coherence phase difference ($\text{i.e.}, \emptyset_{xy}(u,s)$) between two time series $x(t)$ and $y(t)$ (i.e., $x(t)$ and $y(t)$ are the first and second time series, in this order) is:

$$\emptyset_{xy}(u,s) = tan^{-1}\left(\frac{\Im\left(S\left(s^{-1}W_{xy}(u,s)\right)\right)}{\Re\left(S\left(s^{-1}W_{xy}(u,s)\right)\right)}\right) \tag{2}$$

Phase dissimilarities are graphically shown in the figure similar to the wavelet coherence as arrows inside the regions that are categorized by high coherence. Arrows pointing to the right mean that $x(t)$ and $y(t)$ are in phase or moving in a similar way. If arrows point to the left (antiphase), then two series are negatively correlated. Furthermore, arrows pointing to the right and up suggest that variable $x(t)$ is leading and the two variables are positively correlated; if arrows are pointing to the right and down, $y(t)$ is leading. On the other hand, arrows pointing to the left and up signify that the first variable, $x(t)$, is lagging and the correlation is negative, while arrows facing the left and down indicate that the first variable, $x(t)$, is leading but with a negative correlation (see Li et al., 2015).

3. Empirical results

3.1 Main results

Our analysis starts with examining causality between the emotion indices and oil returns. To check a potential non linearity in the causal relationship, we use the BDS test of Brock et al., (1996). The test results are reported in Table 5. It strongly rejects the null hypothesis that the series are independently and identically distributed at 1% significance level implying embedded nonlinearity and the appropriateness of the nonlinear causality test.[11]

Panel A and B of table 6 displays the linear and nonlinear causality test respectively. The tests in Panel A and B of the table examine the effect of sentiment variables on oil returns and vice versa.[12] The hypothesis that the overall sentiment does not Granger cause the oil return is supported at one, two and three lags. However, some specific sentiment emotions, such as trust still significantly Granger cause oil returns.

On the other direction, it is clear that oil returns do not Granger cause any of the emotion variables with the exception of anger. However, these results do not hold the same in the nonlinear tests as there is a limited a support for the hypothesis that oil returns do not Granger cause general sentiment, optimism and fear.

Now we turn to our main empirical results. Figure 2 presents the estimated wavelet coherence between oil-specific investors' sentiment and oil returns. The horizontal axis represents time while the vertical axis represents the frequency, which is converted to time units (day) and it ranges between the highest frequency of 2 days (at the top of the plot) to the lowest frequency of 1024 days-four years (at the bottom of the plot). The time scales of fewer than 32 trading days are categorized as short-run time horizon (i.e., high-frequency bands),

[11] The nonlinear causality approach is the most commonly used test in the literature. Compared to Granger causality, the Dikes and Panchenko (2006) test detects nonlinearity, persistence and structural breaks. This test is based on the nonparametric use of the correlation integral between the time series and it is based on the work of Baek and Brock (1992). The technical details of this test can be found in Bekiros and Diks (2008).

[12] Before examining the linear causality, the ADF unit root with intercept and trend is carried out (results are not reported but available upon request). We find that all series are stationary.

those between 32–128 trading days as medium-term (i.e., medium-frequency bands), and those more than 128 trading days as long-term (i.e., low-frequency bands). Note that, the color code of wavelet coherency ranges from blue (low coherency – close to zero) to red (high coherency – close to one). Significant areas lie within the thick black curve, which is significant at 5% level, and obtained from the Monte Carlo simulations using the phase randomized surrogate series.

For the oil-specific sentiment, we observe a statistically significant coherence with oil returns both over time and frequencies. The arrows point right and up, suggesting correlations are positive and investors' specific sentiment is leading oil returns. Further, we observe a relatively high degree of synchronization in the long-run investment horizon (at lower frequencies) with periods longer than 128 days.[13] This is consistent with Yang et al. (2019) who find that investor sentiment has significant effects on the predictability of crude oil future fluctuations over long-term horizons.[14] Nonetheless, these results are in contrast to Shen et al. (2017) who find that commodity specific emotional variables have predictive power on commodity returns but only over short-term period that do not extend beyond five days.

The oil returns also appear to be the most sentiment-sensitive during turbulent periods but over short-run investment horizons. Specifically, the figures show a large area of red color over short-run investment horizons during periods that are less than 32 days. The correlations range between 50% and 70% during the following crisis periods: the Russian financial crisis in 1998, Argentine debt crisis in 1999, the IT bubble in 2000, the 9/11 terror attack in 2001,

[13] These results are consistent with the findings of Borovkova (2011) who demonstrated that the shape of the forward curve of crude oil futures is influenced by strong or weak news sentiment as measured by the Thomson Reuters News Analytics. Similarly, Shen et al., (2017) find that commodity-specific emotions, including crude oil, exert significant influence on individual commodity returns.

[14] These results however contradict some studies on the effect of investors' sentiment on stock returns, volatilities, and liquidity. For instance, Audrino et al., (2019) find that sentiment and attention measures have a short-lasting effect (one-day horizon) on volatility of US stocks.

the sub-prime crisis in 2008 and 2009, the Eurozone turmoil in 2009, 2010 and 2011, and the oil price crash in 2014, 2015 and 2016.

These results imply that excessive investor sentiment during the crisis periods may lead to short-term fluctuations in the crude oil prices. This finding is highly consistent with Zhang and Li. (2019) who find that within a short period of time, the investor sentiment is an important driver of extreme risk changes in the crude oil market particularly during the financial crisis periods.[15] Han et al., (2017) and Wang et al. (2018) produce similar results, and they find that investor attention is related to oil events and it can help to predict oil price fluctuations at short-horizons.[16]

[INSERT FIGURE 2 HERE]

Regarding the coherences between optimism, trust and oil returns, we could not find considerable variation in the coherence patterns across both emotions. The crude oil specific optimism shows a strong coherence with oil returns at the medium to low frequencies (within a period that lies between 128 days to about 512 days) throughout the sample period. The arrows point right and down, showing positive correlations between optimism sentiment and lags of oil returns. Similarly, in the case of trust the arrows point right and down, showing positive correlations and that oil returns are leading investors' trust. Overall, these findings may indicate that the market traders are more sensitive to changes in the market situation, and that their positions and strategies are highly affected by the oil price changes.

For crude oil-specific unpleasant sentiments of fear and anger, we find a statistically significant effect on the crude oil returns at the medium and at the low frequencies (within a period longer between 128 days to about 512 days), mostly during turbulent periods. For

[15] Zhang and Li. (2019) constructed a sentiment endurance index by using the strength of bullish and bearish market conditions and the possibility that highest and lowest prices eventually approach the closing prices. They examined the relationship between this investor sentiment index and extreme tail risk in the crude oil market at different time-frequency domains using the wavelet method.

[16] These results also consistent with Chau et al., (2016) and Maitra and Dash (2017) who find that the effect of sentiment on the stock market volatility is more pronounced during periods of crises within short as well as medium run investment horizons.

instance, the scales of sentiments and oil returns exhibit relatively strong coherence during the burst of technology bubble in 2003 over a period that exceeds 128 days in general. Similarly, the scales exhibit more coherence for periods longer than 64 days but less than 128 days and during the global financial crisis in 2008. The strong coherence between the fear sentiment and the oil returns may also be seen during the European sovereign debt crisis that occurred from April 2010 to June 2012 and during the oil price crash from 2014 to 2016; all with a period exceeding 128 days.

Overall, the results suggest that coherence between oil returns and unpleasant sentiments are not continuous over time or different frequencies, but rather it is discontinuous and changes according to market conditions.

For fear, the phases, represented by the arrows pointing to the left and up most of the time and for almost all frequencies, indicate that local correlations are positive and that investors' long-term sentiments are leading crude oil returns. These results show that, when the market fears supply shortages in the medium and long term, the required return on crude oil will be elevated to compensate for the uncertainty which ultimately increases crude oil prices (Shen et al. 2017).

The results here confirm the predictive content of the long-term sentiments with respect to the crude oil market. In the case of anger, where crude oil acts as a leading indicator, we observe low coherence at the low frequency. However, we still obtain a reasonable coherence at medium and longer frequencies particularly during turbulent periods such as: the IT bubble in 2000, the 9/11 terror attack in 2001, the sub-prime crisis in 2008 and 2009, the US debt-ceiling crisis in 2013, the political turmoil in Libya in 2011, the political turmoil in Syria in 2012, the war in Iraq in 2013, and the oil price crash in 2014, 2015 and 2016. The result probably implies that the investors and market traders become anxious during crisis periods and that this accumulated feeling is long-lived. This finding indicates that the co-movements between oil market and anger sentiment becomes more noticeable in crisis periods. These results complement the findings of Chau et al. (2016) and Maitr and Dash (2017) who documented the more pronounced influence of sentiment in crisis periods.

3.2 Trading Strategies

In this subsection, we investigate the usefulness of the MarketPsych indices for daily traders. For that purpose, we designed three simple trading rules:

i. Take a long (short) position today if the sentiment is positive (negative) today.

ii. Take a long (short) position tomorrow if the sentiment is positive (negative) today.

iii. Take a short (long) position tomorrow if the sentiment is positive (negative) today.

Note that the first strategy assumes that the trader takes positions according to the sentiment on the day. The second strategy is a momentum strategy. The trader longs (shorts) oil on the following day only if the sentiment is positive (negative) today. The third strategy is a contrarian strategy as the trader goes against the sentiment the following day. The performance of these three strategies is compared to a passive buy and hold strategy of $1 invested in oil and left invested for the whole sample period.

Figure 3 depicts how wealth is accumulated over the sample period for each of the five Psychology indices. The black line represents the performance of the buy and hold passive. The red line, the contrarian strategy; The green line, the momentum; and finally, the blue line represents the accumulation of trading according to the sentiment of the day.

Figure 3 does not show a clear verdict that trading according to the market psychology information improves on the performance of a buy and hold strategy. On the contrary, in many instances, the accumulation of buy and hold as shown by the black lines is higher. However, the figure shows clearly that trading tomorrow against today's sentiment is damaging to wealth and in all indices as the red line accumulation is among the lowest in the figures.

Figure 3 also shows that trading according to the sentiment of the day is useful for wealth accumulation. The blue lines finish the sample with a higher accumulation than the other lines. Trading on the same day is possible given that these indices are available in real time. Hence, oil traders should not plan their intended positions the day before but should wait to sense the market and decide after the start of each day.

[INSERT FIGURE 3 HERE]

To formally test the returns of the strategies against a buy and hold, we test the difference in the daily returns by using a simple t-test. Columns 2 and 3 of Table 7, presents the average of the difference and the t statistics respectively. The table shows that the difference is insignificant for most strategies. The buy and hold daily returns are significantly higher than the returns of trading according anger (Anger) and / or trading the following day against the sentiment (sentiment-contrarian). Same day trading using the trust Psych index has significantly higher returns than buy and hold. The t test for the differences of wealth accumulation at every point over the sample period is computed and presented in Columns 4 and 5. The columns show that there is significant difference in the accumulation pending on what strategy is chosen compared to a buy and hold. For instance, the columns show that trading against the index in the following day is inferior to buy and hold as averages are negative and significant on all of the contrarian strategies. Trading according to the Psychology indices on the day is a good strategy compared to a buy and hold. The difference in accumulation is positive and significant. The paper turns now to discuss the predictability of these indices for future returns.

[INSERT TABLE 7 HERE]

3.3 Forecasting oil prices

To investigate the predictive information of the emotions sentiments in forecasting oil returns, we decompose the time series data of oil and of emotion sentiments into various timescales using the maximal overlap discrete wavelet transformation (MODWT hereafter) in a Multi-Resolution Analysis (MRA) framework.[17] Then, we test whether the emotion sentiments have any predicting power of oil returns over these time-scales.

Following the related empirical literature (i.e., Masset, 2015), we use the least asymmetric wavelet method of with a filter length of L=8 $(d_1, \dots, d_8, s_8)$ to obtain multiscale decomposition of the series.[18] The wavelet scales are: $d_1([2-4\,]\,days)$, $d_2([4-8\,]\,days)$, $d_3([8-16\,]\,days)$, $d_4([16-32\,]\,days)$, $d_5([32-64\,]\,days)$, $d_6([64-128\,]\,days)$, $d_7([128-256\,]\,days)$, $d_8([256-512\,]\,days), and\ s_8[(>512\,days)]$. Fig. 3 plots the wavelet scales together with the smoothed component over the sample period. The frequency domain is classified into three investment horizons as follows (See Khalfaoui and Boutahar, 2012; Huang et al., 2016; Maghyereh et al., 2019a,b): The short-term horizon (2–32 days) is defined as $\{D_1 = (d_1 + d_2 + d_3 + d_4)\}$. The medium term horizon (32-128 days) is defined as $\{D_2 = (d_5 + d_6)\}$, and long-term horizon (256 days and more) is defined as $\{D_2 = (d_7 + d_8 + s_8)\}$. The wavelet decomposition of the oil returns and oil-specific sentiments are presented in Figure 4.

[INSERT FIGURE 4 HERE]

Given the three investment horizons, we adopted the following typical predictive regression model which is based on a single forecasting variable (e.g., Campbell and Thompson, 2008; Li and Yu, 2012):

$$r_t = \alpha + \beta \Delta ES_{t-1} + \varepsilon_t \quad (3)$$

[17] For detailed information on the properties of MODWT see Crowley (2007). Note that we could have transformed using the discrete wavelet transform method, however this method is sensitive to the choice of the starting point (Percival and Walden, 2000).
[18] The filter length of L=8 has been shown as an ideal band-pass filter in the wavelets (In and Kim, 2013).

where r_t denotes the oil returns, ΔES_{t-1} refers to the change emotion sentiment index, and ε_t is the zero-mean normally distributed residual. In the above specification Eq. (3), the null hypothesis of no predictability in sample is $H_0\colon \beta = 0$. We apply a HAC estimator to get a robust estimate.

To investigate whether the forecasting power remains significant after controlling for the lag of the oil returns (r_{t-1}), we consider a regression specification of the form:

$$r_t = \alpha + \beta_1 \Delta ES_{t-1} + \beta_{21} r_{t-1} + \varepsilon_t \tag{4}$$

The null hypothesis of Eq. (4) is that the indicators have no in-sample predictability $H_0\colon \beta_1 = 0$.

Tables 8 & 9 report the in-sample forecast of oil returns based on the general sentiment measure and the four emotion sentiment measures. The estimation results show that the null hypotheses ($\beta = 0$) regarding the coefficient corresponding to the overall sentiments and fear is rejected and that it is statistically different than zero. The change in the sentiment index exerts a positive effect on the oil price returns while the change in fear exerts a negative effect. This remains true over both specified models in (3) and (4).

It can be also noted that emotion variables exhibit higher predictability over longer time scales. For example, all emotion variables, except anger, significantly leads oil returns. A positive change in sentiment, optimism, and trust forecast higher oil returns while a positive change in fear forecast a negative returns.

[INSERT TABLES 8&9 HERE]

To assess the out of sample predictability of emotions sentiments, we split the sample into two samples, an estimation sample and a prediction sample. In particular we estimate from January 1, 1998 to December 31, 2008 and use the estimated parameters to generate returns forecasts for the rest of the sample from January 1, 2009 to July 30, 2018. These out of sample forecast are evaluated by their ability to reduce the mean squared forecast error

(MSFE) compared to forecasting with unconditional average oil return. The statistic used is written as

$$R_{os}^2=1-\frac{\sum_{t=1}^{T}(r_t-\hat{r}_t)^2}{\sum_{t=1}^{T}(r_t-\bar{r}_t)^2} \tag{5}$$

where $\hat{r}_t$ is the forecast given the information filter until $t-1$, and $\bar{r}_t$ is the unconditional historical average return estimated up to $t-1$.[19] As can be seen in 5, if the prediction ability of the model is similar to the unconditional average then $R_{os}^2=0$. However, if $R_{os}^2>0$ then the generated forecasts $\hat{r}_{t+1}$ improves on the accuracy of the historical average forecast in the mean squared error loss.

To this end, we test whether these improvements in the accuracy of forecasts is statistically significant. In particular we test the null $(H_0: R_{os}^2=0\ against\ H_A: R_{os}^2>0)$. A suitable statistic is the *MSFE-adjusted statistic* provided by Clark and West (2007).

Table 10 presents the out-of-sample forecasting results. These findings conform to the in-sample analysis as the R_{os}^2 statistics is positive and significant at the 5% level for all emotion variables, except for anger. This is true over medium- and long-term time scales. Hence, we may conclude by saying that there is significant predictive content of sentiments in forecasting oil returns over medium and long horizons.

[INSERT TABLE 10 HERE]

Further we investigate based on rolling estimation and forecasting procedure to check robustness against the forecasting scheme.[20] This method captures the evolution of emotions on oil over time. This is crucial as our sample extends over periods of financial turbulences such as the global financial crisis and the subsequent European sovereign debt crisis. A daily rolling window of 200 trading days is used to implement this exercise.

[19] Small values of R_{os}^2 (e.g.,$R_{os}^2 \cong 0.5\%$) indicate forecasting performance. For more information see, Campbell and Thompson (2008), s

[20] Shi et al. (2019) show that rolling scheme is more accurate than recursive in integrated systems.

The time-varying coefficients (β_t) in equation (3) along with its 95% confidence intervals are displayed in Figure 5. It is evident that the coefficients which show the influence of emotion sentiments on of the returns of oil changes over time but remain significant. More importantly, the figure shows that the coefficients reached their maximum during the sub-prime crisis in 2008, 2009, and during the oil price crash in 2014, 2015 and 2016. In general, these results are largely consistent with the conclusions based on wavelet coherence analysis.

[INSERT FIGURE 5 HERE]

4. Conclusion

Understanding oil price changes is important for many applications in finance such as energy risk management and portfolio diversification. In the recent years, there has been a lot of interest on how behavioral biases impact financial markets returns and volatilities. This study analyzes the relationship between crude oil returns and oil-specific sentiments. These sentiments are: the general sentiment, the optimism, the trust, the fear, and the anger sentiment.

In order to assess linkages of oil and sentiment over various investment horizons, we implement the wavelet coherence analysis from January 1, 1998 to July 30, 2018.

Our findings indicate that investors' specific sentiment leads oil returns. Further, there is a relatively high degree of synchronization particularly over the long-term but also across time. The unpleasant emotional sentiments such as fear and anger significantly affect crude oil returns at the medium to the low frequencies but mostly during turbulent periods.

In order to check the validity of our findings, we run non-linear and linear causality tests to find that sentiments cause oil price changes and not the other way around. The predictive content of sentiments in the oil market is further confirmed by the significance of the parameter corresponding to the lagged sentiment changes when regressing future oil returns.

Overall, the results have important implications for asset pricing and investment risk management decisions. Specifically, investors should be aware of the level of the emotions of optimism, trust, fear, and anger as these leads and helps in forecasting the direction of the crude oil market.

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Table 1: The TRMI daily indexes for Brent crude oil

Index	Description: 24-hour rolling average score of references in news and social media to	Range
Sentiment	overall positive references, net of negative references	-1 to 1
Optimism	optimism, net of references to pessimism	-1 to 1
Trust	trustworthiness, net of references connoting corruption	-1 to 1
Fear	fear and anxiety	0 to 1
Anger	anger and disgust	0 to 1

Sources: Thomson Reuters MarketPsych Indices, User Guide. (2017).

Table 2: Summary statistics of return series

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Oil Return	0.0001	0.0780	-0.0813	0.0102	-0.0135	7.6355	4747.12
Sentiment	-0.1067	0.3778	-0.3617	0.0788	1.4890	9.4743	11221.13
Optimism	-0.0202	0.0772	-0.3240	0.0237	-3.8533	38.5724	292667.3
Trust	0.0021	0.0288	-0.0269	0.0028	0.8891	12.2142	19443.77
Fear	0.0114	0.0640	0.0000	0.0081	1.3908	6.9397	5128.67
Anger	0.0032	0.0260	0.0000	0.0022	1.9010	10.0025	13867.26

Table 3: Pearson correlation coefficients

	Oil Return	Sentiment	Optimism	Trust	Fear	Anger
Oil Return	1.0000					
Sentiment	0.3253*	1.0000				
Optimism	0.2901*	0.4875*	1.0000			
Trust	0.1216*	0.3947*	0.2183*	1.0000		
Fear	-0.2243*	-0.1809	-0.2151*	0.0128	1.0000	
Anger	-0.1764*	-0.2795*	-0.2710*	-0.1832*	0.2500*	1.0000

Note: ***, **,* significant at 1%, 5% and 10% respectively.

Table 4: Statistically significant partial correlations

Pair	Partial Correlation	P-value	Pair	Partial Correlation	P-value
Oil Return/ Sentiment	0.2327***	(0.0000)	Sentiment/ Anger	-0.1538***	(0.0001)
Oil Return/ Optimism	0.2509***	(0.0002)	Optimism / Trust	0.1275***	(0.0000)
Oil Return/ Trust	0.0828**	(0.0175)	Optimism / Fear	-0.0906***	(0.0000)
Oil Return/ Fear	-0.1511***	(0.0002)	Optimism / Anger	-0.0484***	(0.0005)
Oil Return/ Anger	-0.0745	(0.2952)	Trust/ Fear	0.0861	(0.1750)
Sentiment/ Optimism	0.1001	(0.9914)	Trust/ Anger	-0.1053***	(0.0000)
Sentiment/ Trust	0.3038***	(0.0000)	Fear/Anger	0.1928***	(0.0000)

Sentiment/ Fear	-0.1104***	(0.0000)

Note: ***, ** significant at 1% and 5% respectively.

Table 5:The BDS test results (fraction of pairs)

H0 = independent and identically distributed (iid)

	Embedding dimension					V-Statistic
	2	3	4	5	6	
Oil Return	0.0116***	0.0257***	0.0358***	0.0432***	0.0470***	0.7028
	(9.6534)	(13.4752)	(15.7994)	(18.3207)	(20.6994)	
Sentiment	0.0580***	0.0910***	0.1075***	0.1132***	0.1117***	0.7042
	(53.9968)	(53.3645)	(53.0393)	(53.6538)	(54.9933)	
Optimism	0.0365***	0.0589***	0.0712***	0.0746***	0.0738***	0.7047
	(34.0436)	(0.0017)	(0.0021)	(0.0021)	(0.0021)	
Trust	0.0232***	0.0414***	0.0520***	0.0568***	0.0569***	0.7041
	(17.5239)	(19.6513)	(20.6940)	(21.6907)	(22.5215)	
Fear	0.0781***	0.1324***	0.1660***	0.1844***	0.1942***	0.7037
	(60.2567)	(64.2796)	(67.6958)	(72.1930)	(78.8161)	
Anger	0.0296***	0.0510***	0.0633***	0.0684***	0.0694***	0.7034
	(24.2491)	(26.2989)	(27.4693)	(28.5249)	(30.0225)	

Note: The table reports the BDS statistic for embedding dimension 2 to 6 and for epsilon value of 0.7 times the standard deviation of the series. Parentheses reports corresponding z-statistic of BDS. *** indicates the statistical significance at the 1% level.

Table 6: Causality test results

Panel A: Linear Granger causality tests

	Lag length = 1		Lag length = 2		Lag length = 3	
	F-stat	P-value	F-stat	P-value	F-stat	P-value
Sentiment does not Granger Cause Oil Return	10.078***	(0.001)	5.853***	(0.003)	4.917***	(0.002)
Oil Return does not Granger Cause Sentiment	11.489***	(0.000)	13.313***	(0.000)	8.680***	(0.004)
Optimism does not Granger Cause Oil Return	1.978	(0.159)	1.005	(0.366)	0.880	(0.450)
Oil Return does not Granger Cause Optimism	20.893***	(0.000)	11.708***	(0.000)	8.635***	(0.000)
Trust does not Granger Cause Oil Return	0.924	(0.336)	2.751*	(0.063)	1.992	(0.112)
Oil Return does not Granger Cause Trust	8.390***	(0.001)	9.468***	(0.000)	11.850***	(0.000)
Fear does not Granger Cause Oil Return	4.269**	(0.013)	5.682***	(0.008)	4.017**	(0.019)
Oil Return does not Granger Cause Fear	19.517***	(0.000)	13.618***	(0.000)	11.258***	(0.000)
Anger does not Granger Cause Oil Return	2.240*	(0.098)	3.135**	(0.043)	2.260*	(0.079)
Oil Return does not Granger Cause Anger	1.334	(0.248)	0.661	(0.516)	0.778	(0.505)

Panel B: Diks and Panchenko (2006) nonlinear causality tests

	Embedding dimension=1		Embedding dimension=2		Embedding dimension=3	
	T-stat	P-value	T-stat	P-value	T-stat	P-value
Sentiment does not Granger Cause Oil Return	4.714***	(0.000)	3.649***	(0.000)	1.848**	(0.032)
Oil Return does not Granger Cause Sentiment	1.497	(0.309)	0.449	(0.326)	0.833	(0.202)
Optimism does not Granger Cause Oil Return	1.147	(0.125)	1.240	(0.107)	2.596***	(0.004)
Oil Return does not Granger Cause Optimism	0.204	(0.419)	2.179***	(0.014)	2.344***	(0.009)
Trust does not Granger Cause Oil Return	1.358	(0.912)	0.002	(1.524)	0.253	(0.400)
Oil Return does not Granger Cause Trust	3.534***	(0.000)	0.499*	(0.063)	0.301	(0.381)
Fear does not Granger Cause Oil Return	2.334***	(0.003)	2.002***	(0.009)	1.901**	(0.038)
Oil Return does not Granger Cause Fear	-0.334	(0.630)	1.524*	(0.063)	0.253	(0.400)
Anger does not Granger Cause Oil Return	1.751***	(0.026)	2.011***	(0.008)	2.634***	(0.006)

Oil Return does not Granger Cause Anger	1.573*	(0.083)	1.251*	(0.100)	0.927	(0.228)

Note: Considering the fact that we have a large sample size of 5,363 observations and following the suggestion of Diks and Panchenko (2006), the bandwidth in nonlinear causality tests was set to 0.7. ***, **, and * Significant at the 1%, 5%, and 10% levels, respectively.

Table 7: Testing the differential mean returns against buy and hold

	Difference	t-statistics	Sum difference	t-statistics
Sentiment	1.2273e-04	0.4474	0.3858	37.9134
Sentiment-Momentum	-1.3059e-04	-0.4735	-0.6339	-98.3905
Sentiment - Contrarian	-1.2754e-04	-2.6074	-0.5018	-144.8675
Optimism	1.1929e-04	0.4463	0.0252	2.5252
Optimism-Momentum	-2.1270e-04	-0.7954	-0.6878	-94.1648
Optimism - Contrarian	-5.4911e-05	-0.6652	-0.4477	-186.1055
Trust	3.5037e-04	3.1727	4.9107	123.1656
Trust-Momentum	4.7662e-05	0.2446	0.1339	38.6914
Trust- Contrarian	-3.0575e-04	-1.5202	-0.9474	-157.3374
Fear	1.9228e-05	1.0220	0.1249	235.3666
Fear-Momentum	5.4184e-06	0.0273	0.0628	213.3526
Fear- Contrarian	-2.6350e-04	-1.3330	-0.9079	-132.3421
Anger	-7.6390e-05	-2.1976	-0.4095	-173.0596
Anger-Momentum	1.1734e-05	0.0593	0.0124	11.3708
Anger- Contrarian	-2.6982e-04	-1.3613	-0.8930	-132.0819

Table 8: Bivariate in-sample predictability of daily crude oil returns

	Sentiment	Optimism	Trust	Fear	Anger
Panel A: Short-term horizon (2–32 days)					
ΔES_{t-1}	0.0056**	0.0012	-0.0789	-0.0697**	-0.0559
	(0.0280)	(0.843)	(0.253)	(0.0436)	(0.3119)
Panel B: Medium term horizon (32-128 days)					
ΔES_{t-1}	0.2790***	0.7634**	-0.0040	-0.0580***	-0.0078
	(0.000)	(0.000)	(0.851)	(0.0000)	(0.599)
Panel C: Long-term horizon (256 days and more)					
ΔES_{t-1}	0.2887***	0.7830**	0.7126***	- 0.0803***	-0.0114
	(0.000)	(0.000)	(0.001)	(0.000)	(0.578)

Note: This table reports in-sample results using model (3) incorporate various emotion sentiment indicators (ES_{t-1}) where the independent variable is oil returns r_t. The p-values are in brackets. ***, **, and * Significant at the 1%, 5%, and 10% levels, respectively.

Table 9: Multivariate in-sample predictability of daily crude oil returns

	Sentiment	Optimism	Trust	Fear	Anger
Panel A: Short-term horizon (2–32 days)					
ΔES_{t-1}	0.0089**	0.0023	-0.0602	-0.0710**	-0.0562

	(0.0010)	(0.7181)	(0.2539)	(0.0040)	(0.4010)
r_{t-1}	0.0666***	0.0498***	0.04729***	0.0503***	0.0495***
	(0.0000)	(0.0027)	(0.0049)	(0.0023)	(0.0000)
Panel B: Medium term horizon (32-128 days)					
ΔES_{t-1}	0.0522***	0.0496**	-0.0003	-0.0192	-0.0015
	(0.000)	(0.000)	(0.8513)	(0.0000)	(0.4630)
r_{t-1}	0.5606***	0.5827***	0.5876***	0.5879***	0.5876***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Panel C: Long-term horizon (256 days and more)					
ΔES_{t-1}	0.0288***	0.0402**	0.7628***	- 0.1052***	-0.0022
	(0.000)	(0.0000)	(0.001)	(0.000)	(0.778)
r_{t-1}	0.5996***	0.5987***	0.5996***	0.5964***	0.5996***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Note: This table reports in-sample results using model (4) incorporate various emotion sentiment indicators (ES_{t-1}) and lage of oil returns where the independent variable is oil returns r_t. The p-values are in brackets. ***, **, and * Significant at the 1%, 5%, and 10% levels, respectively.

Table 10: Out-sample predictability of daily crude oil returns

	Sentiment	Optimism	Trust	Fear	Anger
Panel A: Short-term horizon (2–32 days)					
R^2_{os}	0.0545	0.0015	0.0072	0.0415	-0.0032
$MSFE\!-\!adjusted$	12.6607***	-3.6159	-6.7883	9.5564***	-19.7748
	(0.0000)	(0.6948)	(0.8647)	(0.0014)	(1.0000)
Panel B: Medium term horizon (32-128 days)					
R^2_{os}	0.0613	0.0550	-0.0178	-0.1310	-0.0854
MSFE−adjusted	15.8075***	7.5846**	-4.1095	-13.4727	16.4653
	(0.0000)	(0.0335)	(0.9703)	(0.9910)	(1.0000)
Panel C: Long-term horizon (256 days and more)					
R^2_{os}	0.04109	0.05691	0.0898	0.2219	-2.0244
$MSFE\!-\!adjusted$	9.1337***	13.0904***	14.8291***	21.5293***	46.5628
	(0.0047)	(0.0000)	(0.0000)	(0.0000)	(1.0000)

Note: This table reports out-of-sample performances of various emotion sentiment indicators in predicting daily oil returns. The table presents the Campbell and Thompson (2008)'s out-of-sample R^2 statistic (R^2_{os}) and Clark and West (2007)'s MSFE-adjusted statistics. The out-of-sample evaluation period is over January 1, 2009 to July 30, 2018. The p-values are in brackets. ***, **, and * Significant at the 1%, 5%, and 10% levels, respectively.

Figure 1: Time series plots for oil returns and investors' emotion sentiments

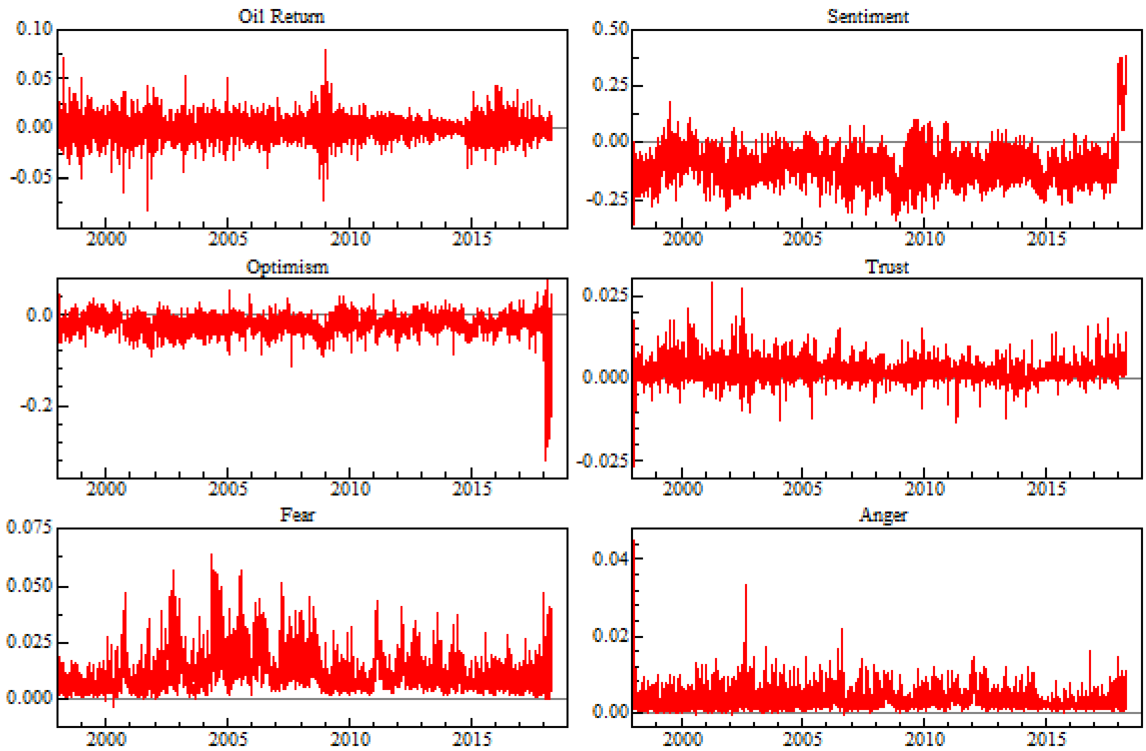
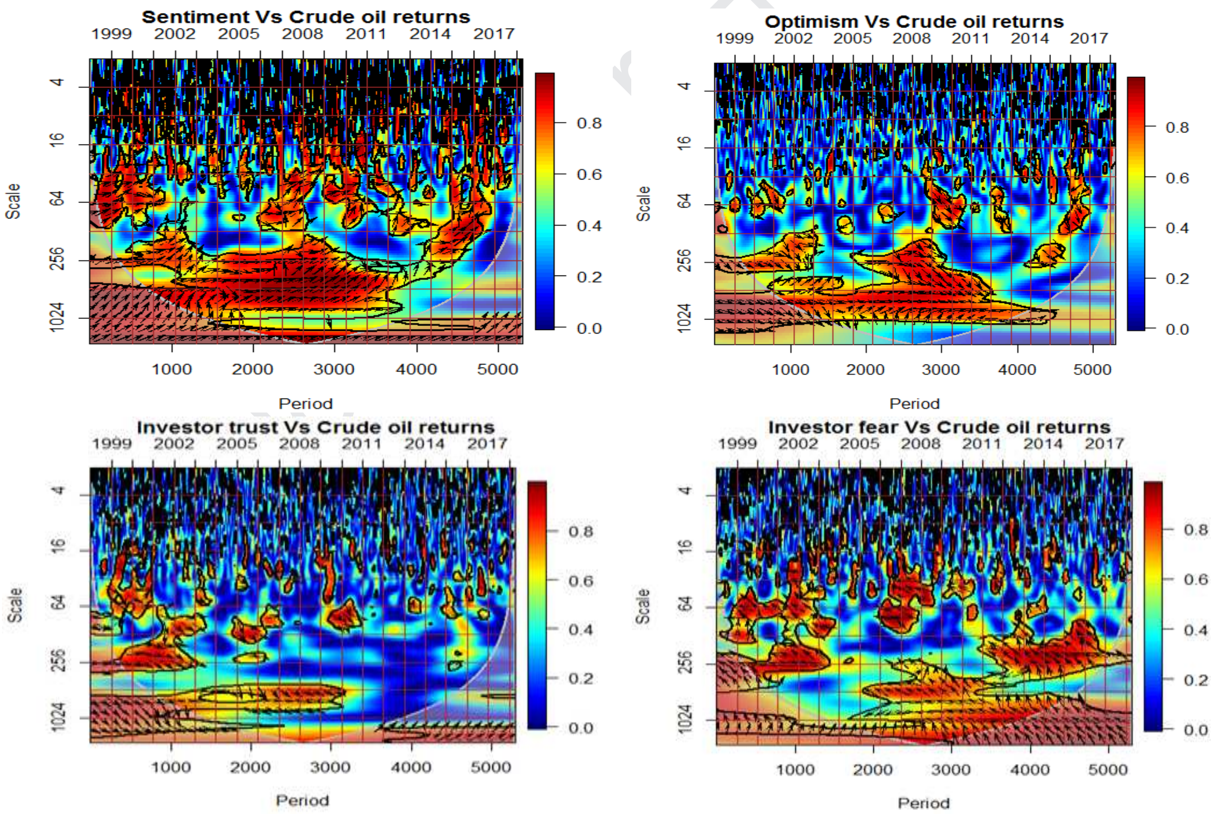
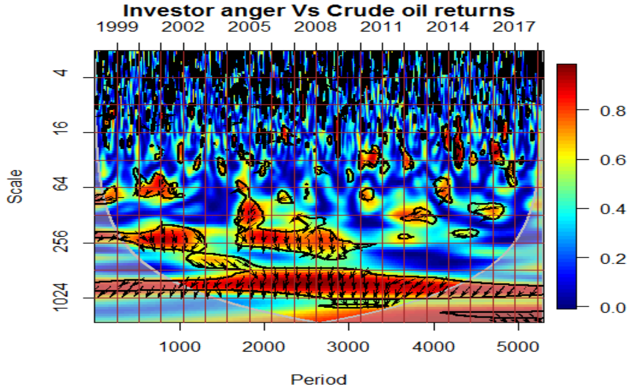


Figure 2: Wavelet coherence between emotional sentiments and crude oil returns





Notes: This figure plots the Wavelet coherence for pairs of oil-specific sentiments and oil returns from January 1, 1998 to July 30, 2018 using daily sampling. Time is represented on the horizontal axis, while the vertical axis shows frequencies (the lower the frequency, the higher the scale). The level of correlation is indicated by the color on the right-hand side of the chart; the warmer the colors (red) the higher the absolute correlation between the pairs, while colder colors (blue) indicate lower dependence between pairs. Cold regions beyond the significant areas represent time and frequencies with no dependence in the series. The warmer the color of a region, the greater the coherence between the pairs is. The black solid lines isolate the statistically significant area at the 5% significance level, where significance values were generated through Monte Carlo simulations. An arrow represents the lead/lag phase relations between the two series. A zero phase difference means that the two time series move together on a particular scale. Arrows point to the right (left) when the time series are in phase (anti-phase). Arrows pointing to the right-down or left-up indicate that the first variable is leading, while arrows pointing to the right-up or left-down show that the second variable is leading.

Figure 3: The performance of psychology indices against buy and hold

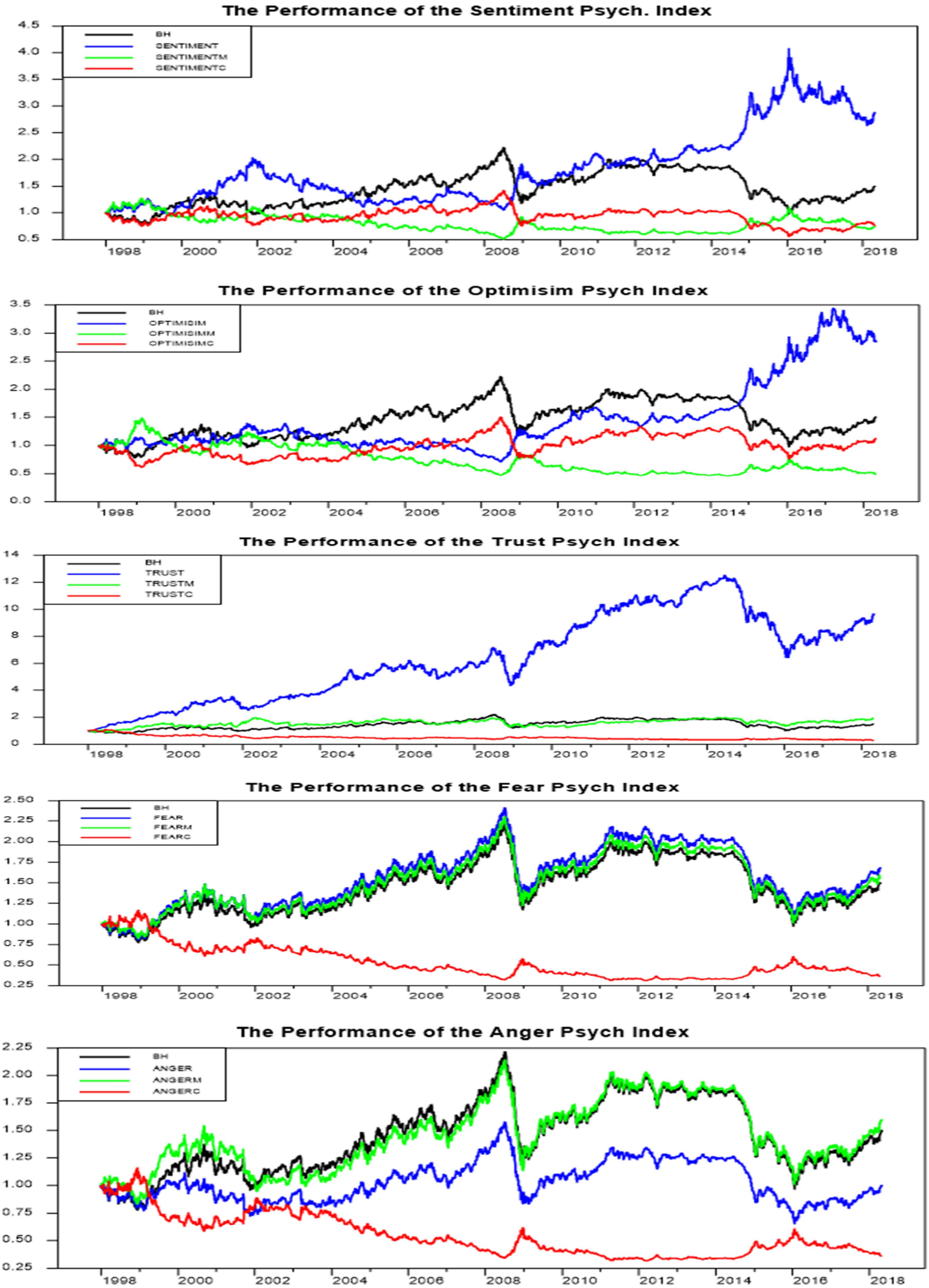
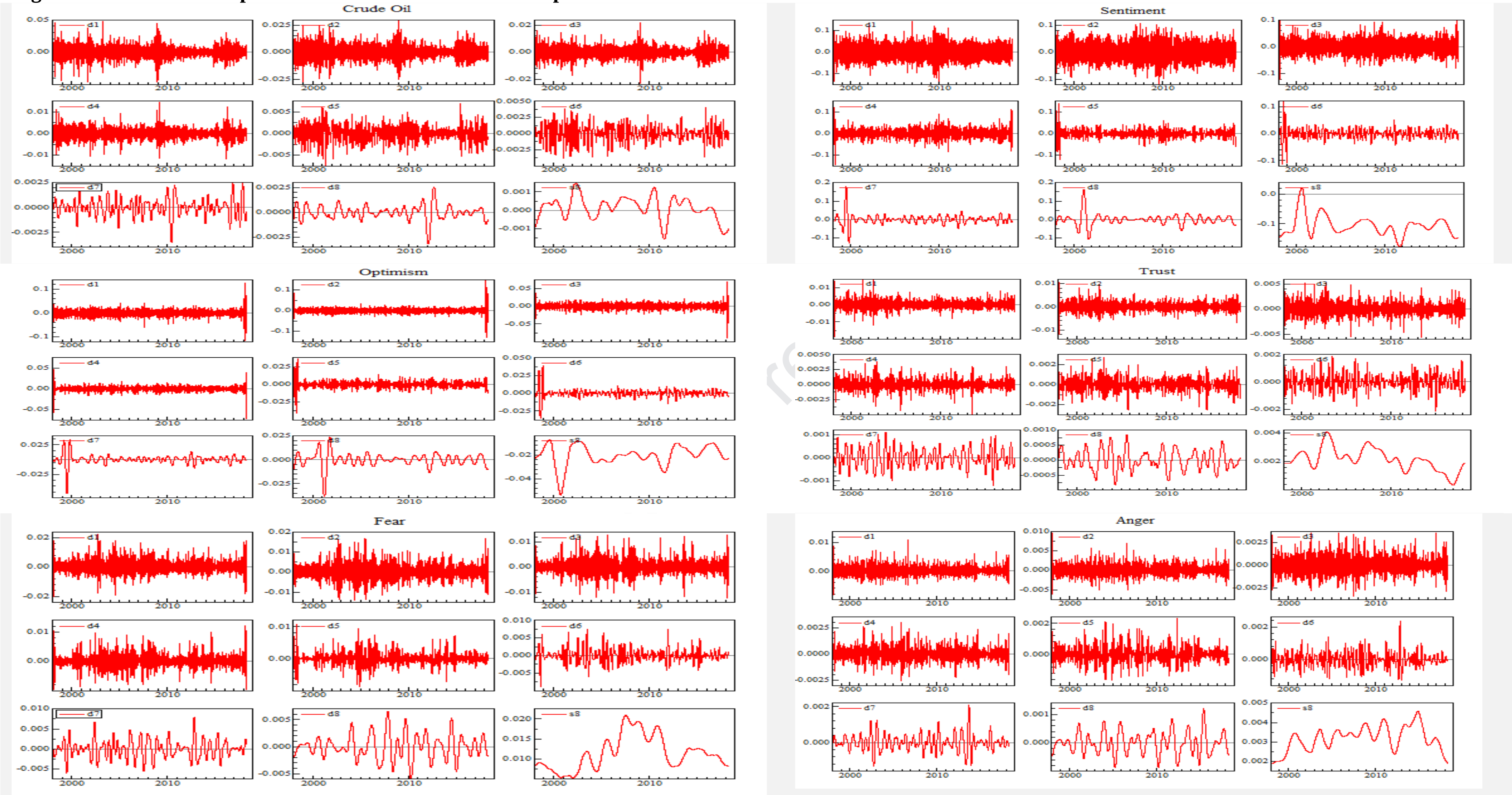
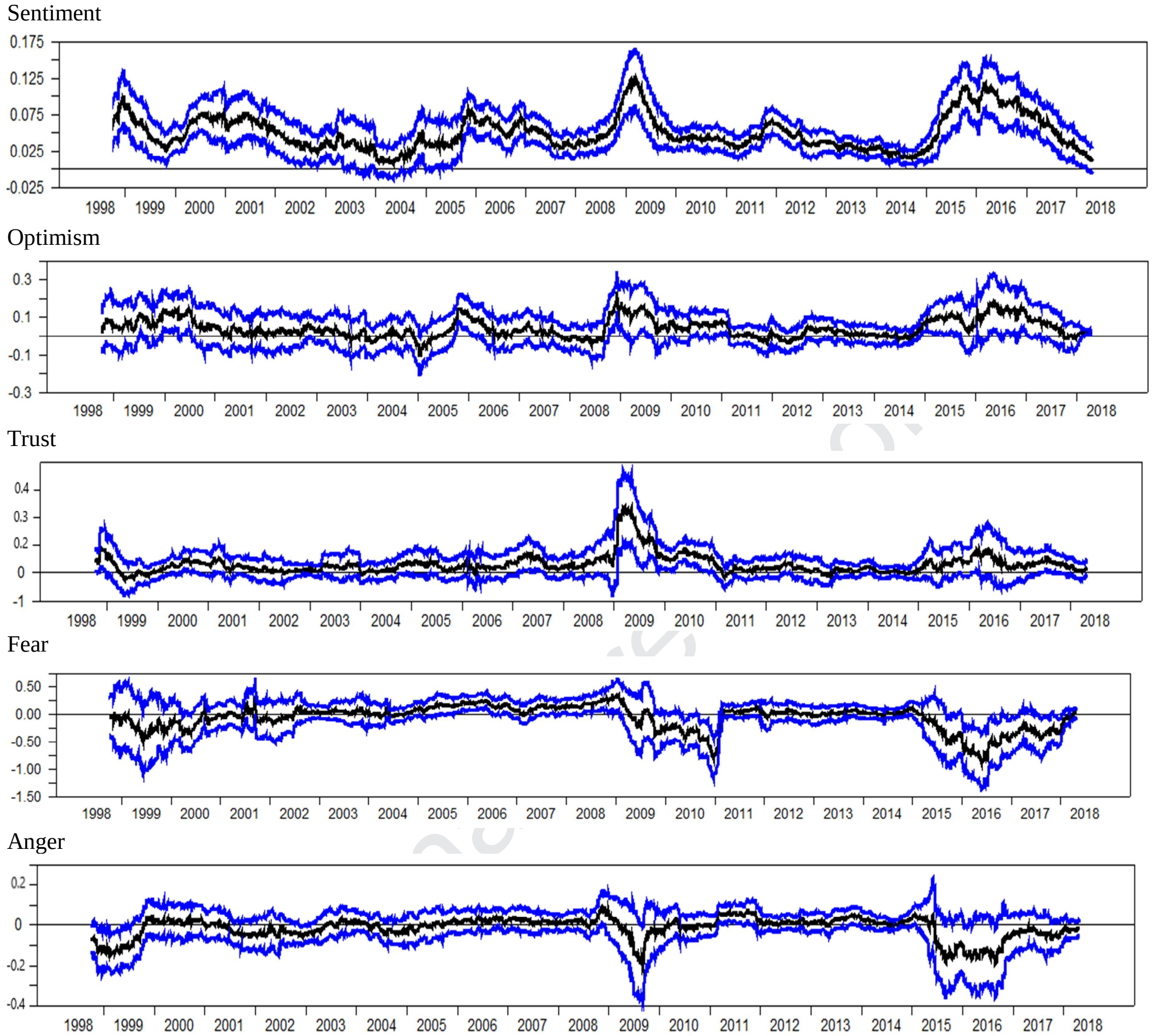


Figure 4: Wavelet decomposition of the oil returns and oil-specific sentiments



Note: Each detail represents the contribution of fluctuations of a specific time scale to the oil returns and oil-specific sentiments, while the smooth s8 represents its trend. The Wavelet decomposition scales are: $\boldsymbol{d_1}([2-4\,]\,\boldsymbol{days})$, $\boldsymbol{d_2}([4-8\,]\,\boldsymbol{days})$, $\boldsymbol{d_3}([8-16\,]\,\boldsymbol{days})$, $\boldsymbol{d_4}([16-32\,]\,\boldsymbol{days})$, $\boldsymbol{d_5}([32-64\,]\,\boldsymbol{days})$, $\boldsymbol{d_6}([64-128\,]\,\boldsymbol{days})$, $\boldsymbol{d_7}([128-256\,]\,\boldsymbol{days})$, $\boldsymbol{d_8}([256-512\,]\,\boldsymbol{days}), \boldsymbol{and}\ \boldsymbol{s_8}[(>512\ \boldsymbol{days})]$.

Figure 5: Rolling-window testing the dependence from oil-specific sentiments to oil returns



Note: Estimated oil-specific sentiments and oil returns coefficients (black color) and their 95% confidence intervals (blue color). These coefficients are extracted based on a rolling-window estimation of Eq. (3), where the window is set to 200 days.

Conflicts of Interest Statement

Manuscript title: The effects of investor emotions sentiments on crude oil returns: A time and frequency dynamics analysis

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and approved by all named authors and that

there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

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Authors:

Aktham I. Maghyereh,

Basel Awartani,

Hussein Abdoh