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# INVESTORS' SENTIMENTS AND INDUSTRY RETURNS: WAVELET ANALYSIS THROUGH SQUARED COHERENCY APPROACH

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***Abstract****: This study for the first time explores the time frequency relationship between investors' sentiments and industry specific returns. A sentiment index proxy is constructed using level and lag values of six indicators of investors' mood swing through Principle Component Analysis. The data on investors' sentiments and nine major industry's returns is used from 2001 to 2011. Wavelet Coherency analysis reveal that investors' sentiments and industry returns are significantly related and are in phase (cyclical). An optimistic view of the investors regarding an industry's performance results in higher returns and pessimistic view results otherwise. The relationship is significant on 0 ~ 8 and 32 ~ 64 months scale. Financial and energy crises play major role in the sentiment led industry's return. These findings are unique and were not possible through the traditional econometric estimates.*

***Keywords:*** *Investors' sentiments, stock returns, wavelet analysis*

## Introduction

Traditional financial theories postulate that the stock markets are efficient, the investors are rational in their behavior and they utilize complete (possible) information for decision making, so the capital asset prices are adequate and reflect their intrinsic values without being effected by investor sentiment. However, financial crises and resulting research on price anomalies, made market efficiency and its implications for asset pricing a debatable topic. Many researchers (Fama, 1991 among others) critiqued the unrealistic assumption underlying market efficiency, hence the idea of behavioral finance developed. Behavioral finance concludes that many of traditional finance assumption does not hold in reality e.g. traditional finance assumes that investors are risk averse whereas behavioral finance highlights that investors are loss averse. The investors' decision making is therefore impacted by their behavior at a certain point in time. Similarly, the idea of perfect rationality was replaced with bounded rationality (ability of investor to collect and evaluate all available market information) and hence the asset prices do not fully reflect the private and public information.

During last two decades, behavioral finance theorists contributed by clarifying the role of various emotional aspects of investors in their decision making process. According to Li et al (2008), many investors now believe on the investors sentimental approaches. Wang et al., (2009) concludes that sentiments as compared to economic variables are better indicator of final security prices. There are two distinctions proxies i.e. explicit and implicit to measure the investor's reactions directly and indirectly, respectively. Implicit or indirect proxies (Finter and Ruenzi, 2010, Lahmiri, 2011, Glaser et al., 2009 and Lux, 2008) utilize trading patterns and/or market statistics to measure investors' sentiments.

There are three different types of financial markets investors. First, the rational traders, those utilize fundamental knowledge while making financial decisions. Second are the emotional investors, mainly driven by emotions and self-perceptions. Finally the "noise traders" who make random guess on the price movement (Kuzmina 2010). These noise traders without any specialized knowledge mainly rely on emotion while making investment decisions. They are present in all types (developed and emerging) of markets but their impact is more influential on developing markets. The investment decisions of noise traders disrupt the regularity of rational investors and distort the market equilibrium, and hence have impact on the stock market returns and vice versa (Glaser et al., 2009). These irregular investors get inferior returns and, in long run, thus are eventually driven out of the market (Schmitz et al., 2005).

Investor's sentiments result in different stock market anomalies e.g. the Ramadan effect (Bialkowski et al., 2012), calendar anomalies (Depenchuk et al., 2010), Saturday effect or so called Monday effect (Al Khazali et al., 2010). Media contents and its reputation is also known to have implications on the stock market returns (Tetlock, 2005). Different proxies e.g. investors' mood, closed end fund discount and trading volume have the impact on the investors' decision making process (Lahmiri, 2011). Baker and Wurgler (2006) identified proxies which affect the investors' sentiments. These indirect mood proxies include trading volumes, dividend premium, closed end mutual fund discount, initial public offerings (IPO) 1$^{st}$ day returns, IPO's volume, and total new equity issues. These investors' sentiments are used as a proxy measure of noise trader's behaviors. These sentiments may have both short- and long-term effects and result in higher returns volatility (Liu et al 2011). Yang and Wu (2010) examined the stock price and investors' sentiment relationship in Taiwanese stock market and concluded the presence of a sequential relationship. Bad performing stocks or having low current market prices are perceived to continue their low performance in the future (Liang and Ouyang 2010). And hence sentiments may also have the stock returns' forecasting power. Huiwen (2012) measured the impact of investors' sentiments on stock returns under different market regimes and concluded that irrational investment decisions result in deviations from fundamental values. The buy and sell imbalances i.e. investors buy (sell) securities in groups and two investors groups buy (sell) the same stocks were also examined by Kumar and Lee, (2006). Researchers (Lux, 2008; Finter et al., 2010; Michelfelder and Pandya, 2005) have concluded significant impact of sentiment on the developed market's return.

These proxies may not portray a complete picture when considered in isolation. Different stocks may have different sensitivity towards investor's sentiments (Finter et al, 2010). Glushkov (2005) concluded that stock's sensitivity may have been due to their sentimental beta. Investors' sentiments are able to explain the excessive returns of retail investors because it becomes the part of systematic risk (Lux, 2008). Mutual fund flows portray a negative market sentiment due to higher individual investments (Qiu and Welch, 2005). Chi et al., (2012) found a significant impact of higher mutual fund flows on the Chinese markets. The impact of sentiments on stock's returns is also determined by the number of large institutional investors, analysis skills and information systems (Michelfelder and Pandya, 2005). If the retail investors are in great number then there will be a greater sentiment's impact on the returns (Finter et al., 2010). Intuitional investors and skilled analyst are less in number in emerging markets as compared to developed ones. And even in the developed market, less time is spent on investment analysis in comparison to the trading activities

(Kumar and Lee, 2006). However, impact of investors' sentiments is more profound in the emerging markets (Huerta and Liston, 2011). The higher volatility shocks also impact the investor's sentiments (Huiwen, 2012). Meijin and Jianjun (2004) concluded that sentiments may also correct the return fluctuations.

Historical literature indicates that investors' sentiments significantly impact the stock returns and this impact may last longer in developing stock markets. However, the emphases has been placed on measuring the influence of sentiments on overall stock returns and volatility and only a few have studied the industry differential impact (see e.g. Huang, 2012 and Huang et al. 2014). This study is the first effort, to the best of our knowledge, to investigate the investor's sentiments relationship with industry returns in Pakistan. Further, wavelet based time-frequency analysis approach has never been applied in the field of behavioral finance.

## Data, Methodology and Discussion

*Investor's Sentiment Index*

There are two different methods to measures investors' sentiments i.e. direct and indirect approach. The measurement of investor's sentiments through direct approach e.g. survey and questionnaire, is subjective, time consuming and obtains limited feedback from the investors. The indirect approach measures the sentiment through proxies and form an index following Baker and Wurgler (2006) methodology. We have used following six indicators – number of Initial Public Offerings (IPO), average 1st day return on IPOs (RIPO) – (Finter et al; 2010), Karachi Stock Exchange (KSE-100) Index average daily turnover (TURN) – (Rehman, 2013), Equity/Debt ratio, closed end mutual fund discount (CEFD) – (Chi et al; 2012), and dividend premiums (DP) - (Baker et al, 2009)[1]. The data on these variables has been obtained from the listed companies at Karachi Stock Exchange of Pakistan and spans from 2001 to 2011.

Table 1 indicates the descriptive statistics and correlation matrix of all six investors' sentiment indicators used in this study. All the indicators are high to moderate correlated with each other thus provide a strong basis to formulate Principle Component Analysis (PCA) for index construction.

[1] Details on the indicators can be found in the co-authors previous work i.e. Rehman (2013).

Table 1: Descriptive statistics and pair-wise correlation of investor's sentiment indicators.

| | IPO | RIOP | TURN | EDR | CEFD | DP |
|---|---|---|---|---|---|---|
| Mean | 7.727 | 35.70 | 6.981 | 28.48 | 8.482 | 4.834 |
| Std. Dev. | 5.029 | 18.61 | 9.584 | 2.673 | 7.189 | 0.671 |
| Skewness | 1.106 | -0.591 | 1.196 | -0.908 | 1.202 | -0.530 |
| Kurtosis | 2.935 | 2.213 | 3.330 | 2.310 | 3.598 | 1.897 |
| JB Statistics | 26.95*** | 11.08*** | 32.08*** | 20.78*** | 33.80*** | 12.87*** |
| IPO | 1 | | | | | |
| RIOP | 0.370** | 1 | | | | |
| TURN | -0.030 | 0.374** | 1 | | | |
| EDR | 0.520*** | 0.200* | -0.321** | 1 | | |
| CEFD | 0.306** | 0.114 | -0.408** | 0.444** | 1 | |
| DP | 0.192 | 0.551*** | 0.554*** | -0.254* | -0.619*** | 1 |

Note: ***, ** & * indicate significance at 1&, 5% & 10% level, respectively. JB stands for Jarque Bera test.

First, we estimated the principle components by using all six variables with their lag terms. Thus, it provides a raw sentiment index of level and lagged variables. The cumulative influence of first four components to the raw sentiment index is 89.72%. The estimated raw sentiment index and estimated co-efficients for level and lagged sentiment indicators is as follow:

$$Sentiments_t^{Raw} = -0.019 * IPO_t - 0.017 IPO_{t-1} + 0.008 * RIPO_t + 0.008 * RIPO_{t-1} + 0.036 * TURN_t + 0.036 * TURN_{t-1} - 0.100 * EDR_t - 0.097 * EDR_{t-1} - 0.049 * CEFD_t - 0.049 * CEFD_{t-1} + 0.587 * DP_t + 0.587 * DP_{t-1} \quad (1)$$

Further, we calculated the correlation of raw sentiment index constructed as the first principle component through PCA with level and lagged values of all six indicators. Investor's sentiments are known to have a time differential impact on the stock returns and thus selection of appropriate order is essential. Table 2 provides the correlation values of level and lagged indicators. It indicates that $\mathrm{IPO_t}$, $\mathrm{RIPO_{t-1}}$, $\mathrm{TURN_t}$, $\mathrm{EDR_t}$, $\mathrm{CEFD_t}$, and $\mathrm{DP_{t-1}}$ have the higher correlation with raw sentiment index. Therefore, these indictors have been used to construct the synthetic sentiment index.

Table 2: Correlation matrix of raw investor's sentiments index and indicators.

| | $IPO_t$ | $RIPO_t$ | $TURN_t$ | $EDR_t$ | $CEFD_t$ | $DP_t$ |
|---|---|---|---|---|---|---|
| $Sentiments_t^{Raw}$ | **-0.206** | 0.326 | **0.764** | **-0.591** | **-0.787** | 0.844 |
| | $IPO_{t-1}$ | $RIPO_{t-1}$ | $TURN_{t-1}$ | $EDR_{t-1}$ | $CEFD_{t-1}$ | $DP_{t-1}$ |
| $Sentiments_t^{Raw}$ | -0.181 | **0.345** | 0.759 | -0.582 | -0.781 | **0.853** |

PCA is again applied on the selected five indictors (The cumulative contribution of first four components is 91.46%) with higher correlation values (see Table 2) and first principle component is used as the sentiment index in this study hereinafter. The estimated specification of the final sentiment index is as follow:

$$Sentiments_t = -0.026 * IPO_t + 0.012 * RIPO_{t-1} + 0.052 * TURN_t - 0.139 * EDR_t - 0.069 * CEFD_t + 0.819 * DP_{t-1} \qquad (2)$$

Figure 1 plots the investors' sentiment index from 2001 to 2011. The pessimistic sentiments are evident from the starting period of the study, a possible indication of post 2001 crises impact on the investor's behavior. Investor's behavior became optimistic after 2005 and remained so till 2011. These positive expectations may have resulted due to banking reforms, foreign portfolio flows and continuous upward trending market. A deep dip during 2007-08 indicates the impact of subprime mortgage crises in United States and hence this crises was perceived to have slump stock market performance. These behavioral reactions helps to conclude that the sentiment index is a reason approximation of the investor's sentiment.

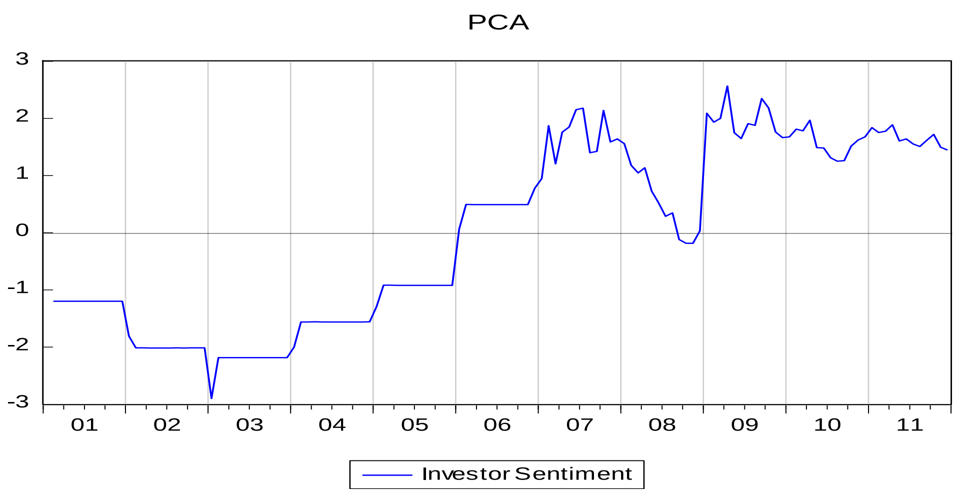


Figure 1: Investors' sentiment index over time

*Industry-wise Returns*

The monthly returns for nine major industries of KSE have been calculated by $r_{i,t} = \ln(p_{i,t}/p_{i,t-1})$, where $r_{i,t}$ and $p_{i,t}$ is return and closing price of industry $i$ at time $t$. Descriptive statistics of all industries are shown in Table 3. Automobiles assembler and oil & gas exploration industries have the first (1.9%) and second (1.6%) highest monthly returns. The higher profitability of automobile industry may have been due to higher sales (lower prices) resulting from decrease in import duty. Oil & gas exploration witnessed high profitability due energy crises and resultant higher demand (prices) of energy products. Textile industry has the lowest (0.3%) average monthly return possibly due to higher raw material prices (floods and resulting lower crop yield). Standard deviation is highest (14.1%) for transport industry. Higher and unstable petroleum prices may have increased the volatility in this sector. Food & personal care industry, being the essential products with consistent demand, has the lowest risk (6.3%).

Table 3: Descriptive statistics of industries returns.

| | Mean | Std. Dev. | Skewness | Kurtosis | JB Statistics |
|---|---|---|---|---|---|
| Automobile Assembler | 0.019 | 0.089 | 0.133 | 3.619 | 2.494 |
| Cement | 0.015 | 0.115 | 0.638 | 5.996 | 58.35*** |
| Engineering | 0.009 | 0.093 | -0.238 | 3.593 | 3.182 |
| Food & Personal Care Products | 0.020 | 0.063 | 0.041 | 3.986 | 5.390* |
| Oil & Gas Exploration | 0.016 | 0.134 | -1.918 | 12.20 | 547.2*** |
| Power Generation & Distribution | 0.004 | 0.104 | 0.649 | 7.584 | 124.8*** |
| Textile Composite | 0.003 | 0.094 | 0.148 | 3.779 | 3.819 |
| Tobacco | 0.020 | 0.106 | 0.289 | 4.451 | 13.42*** |
| Transport | 0.015 | 0.141 | 0.780 | 5.457 | 46.59*** |

Note: ***, ** & * indicate significance at 1&, 5% & 10% level, respectively. JB stands for Jarque Bera test.

*Cross or Squared Wavelet Coherence (WTC) Approach*

We have utilized wavelet methodology developed by Hudgins et al. (1993) and Torrence and Compo (1998) to study the relationship between investors' sentiments and industry returns. The Cross-Wavelet Coherency (WTC) and the Phase Difference (PD) is used to analyse the time-frequency dependencies between the time series. The WTC may be understood as the correlation coefficient in a time-frequency space. On the other hand, phase difference provides information regarding the delay or synchronization between the movements of two different time series" (Aguiar-Conraria et al. (2011), p. 2867). Further, Aguiar-Conraria et al. (2011, p. 2872) defined WTC as "the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local (both in time and frequency) correlation between two time-series".
So, similar to correlation, the wavelet coherency indicates higher similarity if it is equal to 1 otherwise there is no association between the variables in time-frequency scale. The series variance

is shown by wavelet power spectrum. The large variation in wavelet power spectrum indicates higher power. And thus cross wavelet power spectrum indicates the higher covariance between the two variables over different time and/or frequencies. Following is the Torrence and Webster (1999) specification of the Wavelet Coherence for two variables:

$$R_n^2(S) = \frac{\left|S\left(s^{-1}W_n^{xy}(s)\right)\right|^2}{S(s^{-1}|W_n^x(s)|^2).S\left(s^{-1}\left|W_n^y(s)\right|^2\right)} \qquad (3)$$

Where, S indicates the smoothing operator. The above definition can be viewed as a traditional correlation coefficient which helps to explain the WTC as a localized correlation coefficient in a time-frequency space. The equation-1 can be re-written, if the smoothing function S=1 and it time-scale complication can be specified as follow:

$$S(W) = S_{Scale}\left(S_{Time}\left(W_n(s)\right)\right) \qquad (4)$$

In Eq. 4 $S_{Scale}$ and complication indicate smoothing along wavelet scale axis and time, respectively. Gaussian function and regular window is used for time and scale convolution, respectively (Torrence and Compo, 1998). The smoothing power according to Morlet wavelet can be articulated as under:

$$S_{time}(W)\Big|_s = \left(W_n(s) * c_1^{-t^2/2s^2}\right)\Big|_s \qquad (5)$$
$$S_{sclae}(W)\big|_n = \left(W_n(s) * c_2\Pi(0.6s)\right)\big|_n \qquad (6)$$

Where, $c_1$ and $c_2$ are the normalized constants and Π indicates the rectangular function. The co-evolutions and normalized coefficients are determined directly and indirectly, respectively. We have used Monte Carlo simulation to analyze the distribution of WTC. PD among the components is estimated through mean and confidence interval of time series. The mean phase with different angles ($a_i$, $i$ = 1, ……, $n$) is as follow:

$$a_m = \arg(X, Y)\ with\ X = \sum_{i=1}^{n} \cos(a_i)\ and\ X = \sum_{i=1}^{n} \sin(a_i) \qquad (7)$$

The independence of phase angles helps to calculate reliable confidence interval for mean angle. The scale resolution can be used to set the number of angles. Higher resolution means higher angles. The circular standard deviation may be specified as:

$$s = \sqrt{-2\ln(R/n)}, \qquad (8)$$

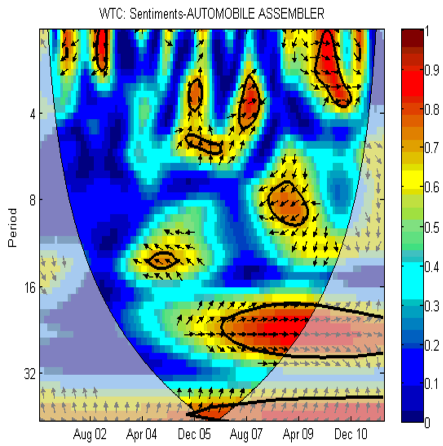
Where, $R = \sqrt{(X^2 + Y^2)}$. The circular standard deviation has the similar definition and meaning like a tradition standard deviation measure. We have used Monte Carlo simulation to identify the statistical level of significance. The lag length in phase can be written as:

$$\phi_{x,y} = tan^{-1}\frac{I\{W_n^{xy}\}}{R\{W_n^{xy}\}}, \phi_{x,y} \in [-\pi, \pi] \quad (9)$$

Where, *I* and *R* indicate the real and imaginary parts, respectively. This phase relation between the variables can be characterized using path difference. A zero value of phase difference indicates that both variables moves together with stated frequency. First series "x' lags second series "y" (sentiments and industry returns in this case), if $\phi_{x,y} \in [0, \pi/2]$. On the other hand "x" leads when $\phi_{x,y} \in [-\pi/2, 0]$. When there is a negative association between the two series (an anti-phase relationship) i.e. phase difference of $\pi\ (or - \pi)$; meaning $\phi_{x,y} \in [-\pi/2, \pi]$ U $[-\pi, \pi/2]$. If $\phi_{x,y} \in [\pi/2, \pi]$ then "x" leads, and "y" leads if $\phi_{x,y} \in [-\pi/2, -\pi]$.

Resulting figures of cross wavelet coherence between investor's sentiments and nine major industries are shown below. First evidence from the WTC analysis is that for all of the industries, investors' sentiments and returns are in phase. They have a cyclical nature i.e. both have a positive correlation. An optimistic view of the investors regarding an industry's performance results in higher returns and pessimistic view results otherwise. Similarly, up (down) industry performance also results in good (bad) investors' expectations. However, this specific direction, the lead (down arrow) and lag (up arrow) relationship can only be determined by examining the figure of each industry separately. For automobiles industry, on 0 ~ 8 months scale, investor's sentiments lead returns at 5% level of significance. An optimistic (pessimistic) view of investors leads to higher (lower) returns of automobile industry. There is also evidence of high association between investor's sentiments and automobile industry's returns during the financial crises 2007-08, however, the arrow are straight right indicating that during crises bad expectations and performance does not have a distinct lead-lag relation rather occur simultaneously. Similar results with low magnitude are evident for cement industry but there is no significant relationship during crises. We safely can conclude that investors' sentiments and cement industry returns have an insignificant relationship and thus sentiment or returns do not cause each other.

The sentiments had a cyclical lagging relationship with engineering industry's returns on 0 ~ 8 month scale and cyclical leading relationship over 32 ~ 64 months scale during the crises period. Food and personal care industry returns and investors' sentiments are also in phase and sentiments lead returns on 0 ~ 8 month scale. There is no significant relationship over longer time scale which also confirms our previous findings (lower risk) as the food products are necessities and do not change with the change in economic conditions. There is no significant relationship between Oil & Gas exploration industry returns and investors' sentiments on 0 ~ 8 month scale. But on 8 ~ 32 month scale, investors' sentiments lead returns, at 5% significance level, especially during the crises period (2007-8) and afterwards. Power generation industry and sentiments also have a similar relation over varying scales. These findings suggest that financial crises coupled with energy crises are the conditions that increase the impact of investors' sentiments on returns and vice versa. Thus, the investors' sentiment and industry return relationship is not persistent in nature and depends on the overall economic conditions. For textile industry, sentiments lag returns on 2 ~ 6 and there is no impact of financial crises. Tobacco and transport industries returns indicates mixed result with sentiments even few counter-cyclical relation where sentiments lag returns. However, tobacco industry shows a significant impact of sentiments on returns on 32 ~ 64 month scale.


WTC: Sentiments-AUTOMOBILE ASSEMBLER
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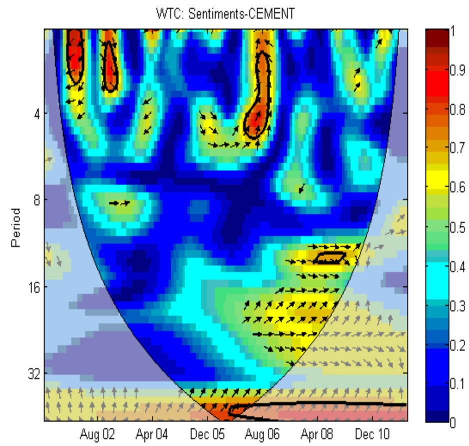
WTC: Sentiments-CEMENT
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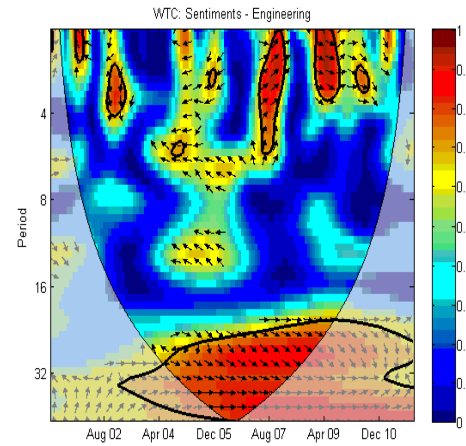
WTC: Sentiments - Engineering
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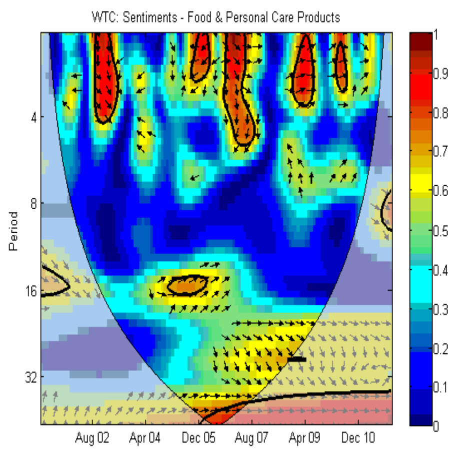
WTC: Sentiments - Food & Personal Care Products
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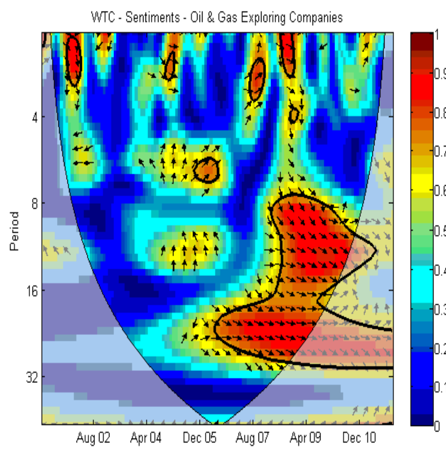
WTC - Sentiments - Oil & Gas Exploring Companies
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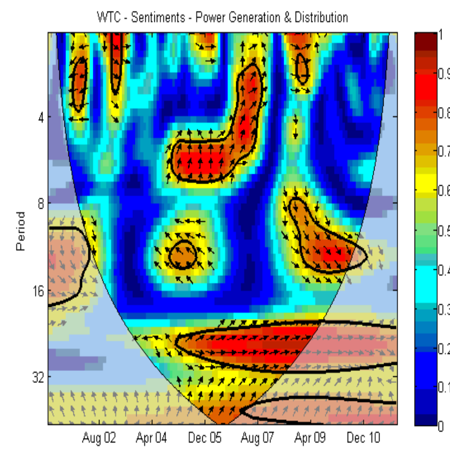
WTC - Sentiments - Power Generation & Distribution
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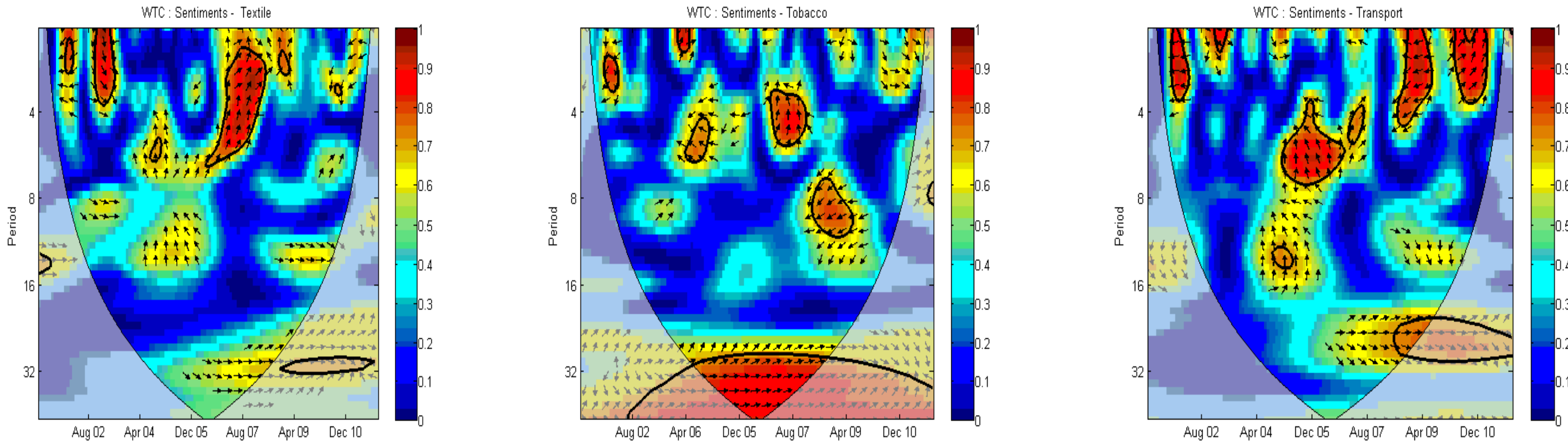
**Cross-wavelet (squared wavelet) coherency between investors' sentiments and industry returns.**




Note: The dense black outline indicates the 5% significance level against the red noise. The lighter shade cone shows the edge effect also named as cone of influence (COI). Color code is indicated to the right of each picture where blue indicates the low power and red shows high power. Y-axis measures the frequencies or scale and X-axis represent the time in weeks. Arrows indicate the phase difference between the two series. Interpretation of the direction is a follow:

(→) = variables are in phase (cyclical effect on each other); (↗) = Investors' sentiments are lagging; (↘) = Investors' sentiments are leading; (←) = variables are out of phase (anti-cyclical effect); (↖) = Investors' sentiments are leading; (↙)Investors' sentiments are lagging.

**Cross-wavelet (squared wavelet) coherency between investors' sentiments and industry returns**

## Conclusion

Emergence of behavioral finance identified irrationality in the investors' behavior and its implications for the market efficiency. Investors' sentiments or mood swings have been studied and found to have relationship with stock market returns and volatility. However, little focus has been given to the impact of sentiments on industry returns. This study for the first time explores the time frequency relationship between investors' sentiments and industry specific returns. A sentiment index proxy is constructed using level and lag values of six indicators of investors' mood swing through Principle Component Analysis. The data on investors' sentiments and nine major industry's returns is used from 2001 to 2011.

Wavelet Coherency analysis reveal that investors' sentiments and industry returns are significantly related and are in phase (cyclical) for all nine industries. An optimistic view of the investors regarding an industry's performance results in higher returns and pessimistic view results otherwise. Similarly, up (down) industry performance also results in good (bad) investors' expectations. The relationship is significant at 5% level of significance and on 0 ~ 8 and 32 ~ 64 months scale. Financial and energy crises play major role in the sentiment led industry's return. Import oriented industries i.e. Automobile assemblers, engineering and tobacco industry's returns evident increased impact of sentiments during financial crises of 2007-08. Energy oriented segment i.e. Oil & gas exploration and power generation industry returns are also seems to have enhanced sentiment impact due to energy prevailing crises. These findings are unique and were not possible through the traditional econometric estimates. Our findings of high cyclical association between investors' sentiments and industry returns during crises open up possibility of two new dimensions. First, overall economic, political and social conditions may have simultaneously impacted both investors' sentiments and returns or second, macro-economic conditions first change investors' behavior and resulting investors' sentiments impact stock market returns. We leave this interesting debate for future research.

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