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Two Essays on Investor Emotions and Their Effects in Financial Markets

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TWO ESSAYS ON INVESTOR EMOTIONS AND THEIR EFFECTS IN FINANCIAL MARKETS

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ABSTRACTS

TWO ESSAYS ON INVESTOR EMOTIONS AND THEIR EFFECTS IN FINANCIAL MARKETS

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This dissertation provides empirical evidences on media-based investor emotions in predicting stock return, conditional volatility, and stock and bond return comovements.

We first studied the interaction between US media content and the US stock market returns and volatility. We utilize propriety investor sentiment measures developed by Thompson Reuters MarketPsych. We select four measures of investor sentiment that reflect both pessimism and optimism of small investors. Our objective is two-fold. First, we examine the ability of these sentiment measures to predict market returns. For this purpose, we use dynamic Vector Auto-Regressive models. Second, we are interested in exploring the effects of these sentiment measures on the market returns and volatility. For this purpose, we utilize a Threshold-GARCH model.

Next, we investigated the effect of investor emotions (fear, gloom, joy and optimism) in financial futures markets by using Thompson Reuters MarketPsych Indices. The purpose of this study is three fold. First, we investigate the extent of usefulness of informational content of our sentiment measures in predicting stock futures and treasures futures returns using daily data for different measures of emotional sentiments. Second, we investigate whether emotion sentiments affect financial futures returns and volatilities. Third, we explore the role of emotion sentiment factors in volatility transmission in financial futures markets. To the best of our knowledge, this is the first study that extensively explores the role of investors' sentiment in the most liquid contracts (S&P 500 futures and 10-year Treasury notes) in futures markets.

Members of Dissertation Committee: Dr. Licheng Sun
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INTRODUCTION

Emotion, as a major part of reflection on our affective processes, can produce a transient but significant impact on economic decision makings and activities in both the individual and market level. (Lowenstein, 2000; Camerer, Loewenstein and Prelec, 2005) Investors' psychological biases in their information processing and financial decision making have been found highly related to investor emotions (Kuhnen and Knutson, 2011; Mayew and Venkatachalam, 2012).

In essay one, we empirically tested the four commonly documented investor emotions (fear, gloom, joy, and stress) and their effects on the stock market. We utilize propriety investor emotion measures developed by Thompson Reuters MarketPsych. In our Vector Auto Regressive (VAR) models, we use five trading days (a calendar week) and find that investor emotions have strong predictability power on short run stock return reversals. Out of the four measures of investor emotions (Fear, Joy, Gloom, and Stress), fear is significant at lags up to four to five days. This indicates that fear Granger causes returns and should be exploitable to predict future market returns up to five days. This effect is bi-directional and runs from fear to stock returns, up to five days, and from the stock returns to fear, up to two days. In the Threshold - GARCH (1,1) model, we regress stock returns on the emotion indicators. The results also support that the effect of investor emotions is both statistically and economically significant on the market return and conditionally volatility. We find that the fear among investor emotions has major and lasting effects on the market returns and conditionally volatility. The findings regarding market return and conditional volatility confirm our findings in VAR(5) model -- fear in the market place causes high volatility that lasts up to four days. Overall, the empirical findings suggest that the media-based investor emotions are useful for predicting stock return and volatility.

In essay two, we empirically examined a group of four investor emotions (fear, gloom, joy, and optimism) and their predictability power on the stock index and Treasury futures returns, and the return comovements. In our VAR (5) models, we find that fear can predict SP500 index futures return up to four days, while joy and optimism can forecast Treasury notes futures return up to two or four days. In the Threshold-GARCH (1,1) model, we regress stock index and Treasury futures returns on investor emotions separately. The results show that stock index futures returns are significantly correlated with all four investor emotions, and Treasury futures returns are highly correlated with fear and optimism. So the findings support that fear and optimism among investors has major and lasting effect on the market return and conditionally volatility in the futures market. We also find that there is significant volatility interdependence in financial futures markets. In the multivariate GARCH(1,1) specification, the results further suggest that there is significant volatility interdependence between stock index and Treasury futures markets. We find that both fear and joy affect the stock market futures returns and volatility. The coefficient for fear is negative, indicating that change is fear is associated with market decline; while the coefficient for optimism is positive, indicating that increase in optimism is associated with increase in the stock index futures returns. The Treasury Notes futures return is influenced by fear and optimism and is not affected by the lag of the index futures returns. The positive sign for change in fear indicates that increase in fear would lead to higher prices for treasury notes (flight to safety). The negative sign for optimism indicates that increases in optimism leads lower treasury futures returns.

EMOTIONS IN THE STOCK MARKET

INTRODUCTION

The development of neuroscience over the last two decades has shown that human behavior, including economic behaviors is strongly influenced by the finely tuned affective processes operated in our brain system. (Elster, 1998; Lowenstein, 2000; Camerer, Loewenstein and Prelec, 2005) Emotion, as a major part of reflection in our affective processes, can produce a transient but significant impact on economic decision making and activities in both individual and market level (Lowenstein, 2000; Camerer, Loewenstein and Prelec, 2005). Neuro-economists in their experiments have also found that human's emotion and cognitive thinking are intertwined together all the time (Lo, Repin and Steenba, 2005; Fenton-O'Creevy, Soane, Nicholson and Willman, 2010). The scientific proof of the correlation between human emotions and economic outcomes provides guidelines for the finance researcher to study investors' emotions and their effects on the financial market.

The two most famous financial anomalies, stock price momentum and stock price reversal, can be explained by investors' over-reaction or under-reaction to public information triggered by their psychological biases. Investors' overconfidence about private signals and their biased self-attribution contribute to under- and overreactions in the securities market, where market fundamentals correct the investors' psychological biases in the long run (Daniel, Hirshleifer, and Subrahmanyam, 1998). Additionally, representativeness, heuristics, and conservatism are other psychological biases that can trigger asset pricing anomalies. Investors underreact to inadequate pieces of good news, while they overreact to an abundance of good news. The overreaction leads to subsequent low returns in the correction (Barberis, Shleifer, and Vishny 1998). Different styles of traders generate different types of biases toward the securities' pricing. Newswatchers tend to underreact to private information, and momentum traders tend to form investment portfolios conditional upon a subset of past prices. Under and overreactions arise from the interaction of momentum traders and news watchers, which can be corrected by market fundamentals in the long run (Hong and Stein, 1998). All the above papers addressing investors' psychological biases suggest the basic reasons that lead financial market anomalies which do not perfectly conform to the traditional risk-return tradeoff beliefs in the short run; however, these anomalies submit to the efficient market equilibrium in the long run.

Those investors' psychological biases in their information processing and financial decision making have been found highly related to investors' emotion or mood. Hirshleifer and Shumway (2003) confirm the "sunlight effect" that the happy mood, induced by morning sunshine in the city of a country's leading stock exchange, is significantly correlated with daily market index returns across 26 countries. Goetzmann, Kim, Kumar, and Wang (2014) introduced weather-based indicators of mood, and showed that investor optimism, associated with lower values of deseaonalized cloud cover, is significantly correlated with investors' propensities to buy, stock overpricing, and stock return comovement. Additionally, Edmans, Garcia, and Norli (2007) documented that a negative mood, affected by a soccer game loss, could lead to a significant market decline.

Very little empirical research has been conducted to show how investors' moods and emotions affect securities valuations; however, there is already adequate research to support the idea that investors' sentiment has a large impact on expected return and stock price volatilities. Lee, Jiang and Indro (2002) employed GARCH models to test the investors' sentiment effect on weekly return volatility and excess return using the DJIA, S&P 500, and the Nasdaq indices during the period 1973 – 1995. Their results supported the observation that there is a positive correlation between excess return and investors' sentiment shift, and a negative correlation between the return volatility and investors' sentiment change. Brown and Cliff (2004, 2005) documented the observation that sentiment affects asset valuations. They found that sentiment is strongly correlated with contemporaneous market returns, but has little predictive power for near-term returns. They further found that two to three year horizon market returns are negatively related to investors' sentiment. Baker and Wurgler (2006) studied the investor sentiment effects on a cross-section of stock returns. Based on their study, the cross section of future stock returns is conditional on the beginning-of-period proxies for sentiment. Sentiment has the strongest effect on those stocks that are characterized as small, young, high volatile, unprofitable, non-dividend-paying, extreme growth, or distressed. The above investor sentiment research adopted economy-based or survey-based sentiment metrics. The traditional investors' sentiment measures basically take a range of methods including investor surveys (Brown and Cliff, 2004), closed-end fund discounts (Zweig, 1973; Neal and Wheatley, 1998), trading volumes (Baker and Stein, 2004), and composite sentiment indices based on the first principal component of common sentiment proxies (Baker and Wurgler, 2006; Gao and Suss, 2014).

In recent years, more accurate and efficient sentiment measures have been invented from increasingly sophisticated textual content analysis coupled with more extensive field-specific dictionaries. Tetlock (2007) implemented content analysis in financial research by running a word counting method based on the Harvard Psycho-social Dictionary. Loughran and McDonald (2011) argued that the words identified as negative by Harvard Dictionary are typically not negative words in financial contexts. They developed a financial context based dictionary incorporating six word classifications. Jegadeesh and Wu (2013), in a recent content analysis model, proposed that the appropriate choice of term weighting in content analysis is more important than a complete and accurate compilation of the word list. The availability of the advanced content analysis methodologies allows financial professionals to capture market sentiments and emotions from different news media and social media contents.

The media plays an essential role to diffuse information in financial markets (Peress, 2014). The effect of investor sentiment and emotion is also propagated rapidly through the media among different groups of journalists, financial analysts, and investors. The media has become the key player in setting the stage for market moves and provoking them (Shiller, 2000; Garcia, 2013). The news media and social media are the two most popular channels to communicate information in written forms. Research papers have documented the fact that stock prices are influenced by sentiments reflected in both market-level media sources and firm-specific news stories. Tetlock (2007) found that high media pessimism predicts downward pressure on market prices followed by a reversion to fundamentals. Tetlock, Saar-Tsechansky, and Macskassy (2008) extended this line of research into a cross-sectional study of the individual firms' news sentiment effects on their accounting earnings and stock returns. Their main findings indicate that the negative content in firm-specific news is related to low firm earnings; firms' stock prices underreact to the information embedded in negative words, which suggests a short-run momentum trading strategy. Negative words in news about fundamentals have a larger predictive power on both earnings and returns. A time series study of stock returns response to financial news sentiment during 1905 – 2005 was done by Garcia (2013). Research suggested that news content predicts stock returns on a daily basis. The predictive power is particularly strong during economic recessions, because investors' sensitivity to news is heightened when they encounter hard times. Along with the rapid growth of social media applications in online communication, a line of research on social media based information and sentiment's impact on stock market activities has recently arisen as a frontier study area. Chen, De, Hu and Hwang (2014) studied whether investor opinions that appear on social media have predictive power on future stock returns and earnings surprises. They found that in addition to information reported in news media, the views expressed in both articles and commentaries on social media are strongly correlated to future stock returns and earnings surprises. Karabulut (2013) treated Facebook's Gross National Happiness (GNH) Index as an equivalent measure of investor sentiment. In an empirical study, he found that changes in both daily returns and trading volume in the US stock market can be affected by Facebook's GNH, and those influences are shown to be as temporary effects. Sun, Najand, and Shen (2015) further explore the predictive relation between high-frequency investor sentiment and stock market returns. The empirical evidence suggested that intraday S&P 500 index returns are predictable using lagged half-hour investor sentiment. The sentiment index used in this study is from Thomson Reuters MarketPsych Index (TRMI), which is computed based on a comprehensive collection of both traditional and social media sources.

Many other media caused biases on asset prices have also received increasing attention in academic research. Several financial studies investigated how news coverage and investors' attention could affect stocks' performance in the financial market. Fang and Peress (2009) documented that stocks not covered by the news media earn higher future returns than those that are highly covered. Their interpretation is that the high media covered stocks have a lower informational risk, so those stocks require a lower return to compensate for the lower risk. Da, Engelberg and Gao (2011) applied search frequency in Google as a measure of investor attention. They found that an increase in search volume leads to the higher stock price in a two-week time horizon and the stock price eventually drops in the long run. Barber and Odean (2008) hypothesized that investors' attention can be a scarce resource for individuals, but not as scarce for institutional investors. However, Fang, Peress, and Zheng (2014) in a recent paper found that mutual funds tend to buy stocks with high media coverage, whereas their sells are less influenced by media coverage. This suggests that institutional investors are at least partially subject to limited attention. Previous research also indicated “media bias” towards local investors’ and local firms’ interests (Mullainathan and Shleifer, 2005; Gentzkow and Shapiro, 2005; Engelberg and Parsons, 2011; Gurun and Butler 2012). Engelberg and Parsons (2011) investigated the behavior of traders in 19 mutually exclusive trading regions, in which those traders are subjected to different media coverage of the same news event. They documented that the local media coverage of a news event is strongly related to local trading activities. Gurun and Butler (2012) provided evidence that local news provides favorable news reports to local companies. The local positive slant is related to the firms’ local media advertising expenditures.

Because there is a tremendously rich content of financial information in modern media sources, quantifying the information of investors’ psychology embedded on those media contents becomes beneficial for financial professionals. With the high development of content analysis and machine learning technologies, researchers are able to transform the qualitative information of investors’ psychology appearing on media sources into quantitative measurements, and then to apply those measurements of investors’ psychology to study the financial market anomalies. To follow up this pattern, numerous subscribable financial news databases were developed in the past several years, including RavenPack, Thomson Reuters News Analytics (TRNA), Thomson Reuters MarketPsych Index (TRMI), Bloomberg News Analytics, and LexisNexis. The availability of market wide investors’ psychology datasets offers opportunities for empirically studying the investors’ psychology related investment activities in financial market.

In this paper, we empirically tested four commonly documented investors' emotions, fear, gloom, joy, stress, and their effects on stock market. We applied a Threshold-GARCH model to study the correlation between SP500 index returns and six distinct investor emotions from 01/01/1998 to 12/31/2014. Furthermore, vector auto-regression results suggested that emotion-associated abnormal returns experience rapid reversals within five days, which is consistent with the short-term predictive model of media-based sentiment on stock returns up to five days (Tetlock, 2007; Garcia, 2013). Our four market level emotion indicators (fear, gloom, joy, stress) are from Thomson Reuters MarketPsych Indices (TRMI), which is constructed based on the comprehensive textual analysis of sources from news wires, internet news sources, and social media with a set of proprietary psychology dictionaries. Compared to the previous media-based sentiment studies, we expand the single dimension of investor sentiment index to multiple dimensions of emotion indices. More importantly, our emotion indicators were established based on a collection of media sources covered by over two million news articles and posts every day (Peterson, 2013); whereas most of the prior textual analysis of media contents relied exclusively on a single source. The collective source approach in studying media related investor psychology is more likely to reflect the true information of the market psychological bias. In the collective level of media sources, the consensual knowledge of the investor emotion covered from all single media sources further contribute to cancel out noisy opinion, and rumors from unreliable sources.

The rest of the paper is organized as follows. The second section summarizes previous studies of the effects of the four common investor emotions, fear, gloom, joy, and stress, on financial markets. The third section describes the datasets and the empirical methodology. Then the fourth section provides a description of research data, and empirical models. Further followed by fifth section to provide empirical results based on several predictive models of investor emotion and SP500 index returns. The robustness checks examine investors' emotion effect among alternative measures of TRMI emotion indicators. The paper concludes with a list of several main contributions, and a suggested avenue for future research.

EMOTIONS IN FINANCIAL MARKETS

Emotion psychologists believe that investors' emotions affect their assessments of risk and the monetary value of investment securities (Lerner and Keltner, 2000; Han, Lerner and Keltner, 2007). The "valence-based" approach and the "appraisal-based" approach are the two main approaches that dominate the human emotion studies. Valence in discussing emotion refers to the effects of positive versus negative feeling states (Barrett, 2006). Researchers argued that specific emotions in the same valence could have different effects on decision making, such as fear promotes pessimistic risk estimates and risk-averse choice, while anger encourages optimistic risk estimates and risk-seeking choices (Lerner, Goldberg, & Tetlock, 1998; Lerner and Keltner, 2000; Lerner and Keltner, 2001; Tiedens and Linton, 2001). On the other hand, appraisal theorists contend that emotions can be distinguished at a more fine-grained level as a person's appraisal or cognitive response to a specific situation (Lerner and Keltner, 2000; Tiedens and Linton, 2001). "Buy on fear, sell on greed" illustrated how distinct dimensions of emotions can be influential to investors' investment strategies.

With the emergence of experimental finance and neurological finance in the last two decades, researchers utilize modern neurological technologies (FMRI, Voice Analysis, Facial Recognition) to detect investors' or corporate managers' emotion, and further to study their financial decision making and investment performance. Kuhnen and Knutson (2011) verified that emotional states influence risk taking. They documented that positive emotional states motivate investors to take risky investment portfolios, while negative emotional states inhibit them from doing so. In two different studies, Mayew and Venkatachalam (2012) and Price, Seiler and Shen (2016) utilized Layered Voice Analysis software to isolate managers' vocal cues in their earnings conference calls. Mayew and Venkatachalam (2012) showed that investors react to managers' vocal cues in a pattern that picked up cumulative abnormal returns around the conference calls, and those returns extended out six months. Price, Seiler and Shen (2016) found that investors appear to overreact to managers' emotional vocal cues in the conference calls, whereas there is a rapid correction to this short run overreaction.

Recent finance literature documented empirical evidences on four different investor emotions, fear, gloom, joy, stress, and their effects on financial markets separately. The most commonly documented emotion in the existing finance research is fear. Financial crises often inject a lot of fear into the future market movement, and that effect usually slows down the financial recovery process, or even creates more turmoil in the market. The implied volatility indices are often used as proxies for market fear. High levels in implied volatility indicate that investors are fearful about market future prospects, so previous research adopted the implied volatility indices (VIX among others) to forecast forward looking stock returns and other financial security returns. (Rubbaniy, Asmerom, Rizvi and Naqvi, 2014; Esqueda, Luo and Jackson, 2015). Da, Engelberg and Gao (2015) established a daily fear index based on the internet search volume from millions of households. They further found that the internet search based fear index can predict asset prices, volatility and mutual fund flows.

The other commonly documented emotions in recent finance literatures are: gloom, joy, stress. Investors tend to lose their faith and hope in stock market after experiencing a long-lasting recession. The gloomy stage of market downturn may take years to recover, because investors are more sensitive to fragile markets (Lauricella, 2011). Azzi and Bird (2005) found that the market boom or gloom state affects analysts' recommendation tendencies, where analysts' recommendations favor more towards high momentum growth stocks during the boom years than during the gloom years. On the other hand, a recent paper proved that investments made on hotels during booms underperform for a few years (Povel, Sertsios, Kosova, Kumar, 2015). Researchers speculate that people's happiness is highly correlated with their personal income, although the causal relationship between the two may be bilateral. (Di Tella, MacCulloch and Oswald, 2003) Finance researchers often regard sunshine and temperature as indicators of investors' joy or happiness. Hirshleifer and Shumway (2003) confirmed that the stock market performs better during sunny days rather than cloudy days. This documented "sunlight effect" attributes to investors' joyful mood to sunshine rather than to long-term value growth. Karabulut (2013) adopted Facebook's Gross National Happiness (GNH) as a measure of investors' happiness manifested on social media. He further found that "an increase of one standard deviation in GNH is associated with an increase of 11:23 basis points in market returns over the next day." Engelberg and Parsons (2016) in a recent study revealed that daily stock return is inversely linked to stress-induced psychological illness. Preis, Kenett, Stanley, Helbing and Ben-Jacob (2012) proposed that average correlation among the stocks listed on Dow Jones Industrial Average (DJIA) increases with the increase of the market stress, so the benefits of portfolio diversification diminishes during the state of a stressful market. Research also suggested that investors' herding behavior picks up with stress in the stock market, and herding towards the market portfolio occurs often during the high market stress (Hwang and Salmon, 2004; Blasco, Corredor and Ferreruela, 2012).

With the recent research successes of the single dimension investor emotion, there is still a need for a complete empirical model for investor emotion based asset pricing. In this research, we aim to provide a range of tests on the robustness of different investor emotion model based on the multiple dimensions of investors' emotion indices, and to suggest a complete investor emotion associated asset pricing model.

DATA AND METHODOLOGY

We obtain data for our analysis from MarketPsych of Thomson Reuters. The Thomson Reuters MarketPsych Indices (TRMI) are updated every minute and derived from a collection of premium news, global internet news coverage, and a broad group of social media (Peterson, 2013). TRMI utilizes contents derived both from news and social media to reflect sentiments from both professional and individual investors. For the first category, MarketPsych sources of text include The New York Times, The Wall Street Journal, Financial Times, Seeking Alpha and dozens more sources available to professional investors. Less formal news sources are obtained from Yahoo! and Google News. For the second category, TRMI utilizes over 2 million social media sites including StockTwits, Yahoo! Finance, Blogger, chat rooms and other sources. MarketPsych employs lexical analysis to extract sentiment indices by scrapping all sources minutely, which includes over 2 million news articles and posts every day. Each sentiment index is a combined news and social medial content and each minute value is a simple average of the past 24 hours (1440 minutes) of information (Peterson, 2013). Thus, the TRMI represent an unmatched collection of premium news and a broad range of social media.

i) Emotion Sentiment Variables

For our analysis, we choose five TRMI emotion sentiment measures. These measures are fear, joy, gloom, stress, and volume. Each sentiment index (except for volume) is a 24-hour rolling average score of references in news and/or social media to that particular measure. All the measures range from 0 to 1, except for volume. TRMI sentiment ranges from -1 to 1 which reflect overall positive reference net of negative references. The data is daily data from January 1, 1998 through December 31, 2014. We use the log returns on the S&P 500 index as the measure of market returns, obtained from the Global Finance database.

Table 1 provides the descriptive statistics and the correlation matrix for the changes of investor emotions and market returns used in this study. The market return (spr) is positively correlated with changes in joy, and is negatively correlated with changes in fear, gloom, and stress.

[Insert Table 1 about here]

ii) VAR Analysis of Sentiment and Returns

The predictive power of sentiment has always been as source of great interest to researchers. Brown and Cliff (2004, 2005) examine the usefulness of sentiment in predicting stock returns. They find that stock returns Granger-cause sentiment, while sentiment is not helpful in predicting stock returns. Verma et al. (2008), on the other hand, find some predictive power of sentiment when they decompose the sentiment into rational and irrational components. Thus, the extent of usefulness of sentiment in predicting returns beyond the informational content of past returns has been controversial. In this study, we investigate the extent of usefulness of informational content of our sentiment measures in predicting stock returns using daily data for different measures of emotional sentiments.

We employ a VAR model in which market returns and different measures of sentiment act as a system with the goal of identifying causality between sentiments and market returns. We use a specification similar to that of Brown and Cliff (2004). The model we propose is

(1) $Y\mathrm{t} = \lambda + \sum_{i=1}^{5} \psi Yt - i + \mathcal{E}\ t$

where Y_t is a vector that contains market returns and different measure of sentiment (Fear, Joy, Gloom, Stress, and Volume).[1] We estimate VAR models of up to 5 days, based on selection criteria such as AIC and BIC, to investigate the causal structures and forecasting capabilities of sentiment measures. We estimate the models using both the levels and the changes in the sentiment measure. Brown and Cliff (2004) argue that this is appropriate "since it not easily determined which specification should reveal the primary effects of sentiment." They argue that from a theoretical standpoint both levels and changes in sentiment may affect stock returns.

iii). Sentiment Measures and Stock Returns Volatility

The effect of sentiment on stock returns and volatility is not very clear. Some researchers find that sentiment affects both the mean and variance of stock returns (Lee et. al, 2002; Verma & Verma, 2007). However, Wang et al. (2006) find that the forecasting power of sentiment for volaitlity disappears if lagged returns are included in the models. We utltize a TGARCH model to investigate the effect of sentiment measures on stock me and return and volatility. The TGARCH model incorporates a leverage effect since it has a certain term for negative return innovations (see Zakoian, 1994). We employ the following TGARCH (1,1) model to investigate the effects of sentiment measures on the market returns volatility:

[1] We include volume in the model since volume is one of the oldest measures of sentiment used by practitioners. There is an old adage on Wall Street "it takes volume to move prices."

(2) $R_{S\&P,\,t} = \alpha_0 + \alpha_1\, R_{S\&P,\,t-1} + \alpha_2\, Fear_t + \alpha_3\, Joy_t + \alpha_4\, Gloom_t + \alpha_5\, Stress_t + \varepsilon_t$

(3) $H_t = \omega + (\psi + \beta,\ 1_{\{\varepsilon t\ -1<0\}})\ \varepsilon^2_{t-1} + \gamma_1\, H_{t-1}$

In the above TGARCH model, the coefficient to the lagged square error in a GARCH model is allowed to attain different values, depending on the sign of lagged error term. In this TGARCH model, the indicator function is 1 if $\varepsilon_{t-1} < 1$, and 0 otherwise. In this model, for positive lagged errors, the coefficient is just the ψ parameter, while the coefficient for the negative error terms is $\psi + \beta$.

EMPIRICAL RESULTS

i). Sentiment Measures and Return Predictability

Table 2 presents the estimated daily parameters for the VAR (5) model with five sentiment level measures (Fear, Joy, Gloom, Stress, and Volume). Out of the five measures of sentiments, only Fear is significant and capable of predicting the market returns up to five days. The coefficient for Fear where the market return is the dependent variable is significant at lag two and has a t-statistics of 1.78, which is statistically significant at the10% level. The coefficient for Fear at lag four has a t-statistics of 1.72, which is also statistically significant at the10% level. The coefficient for fear at lag five has a t-statistics of -2.08 and is significant at 5% level. Turning our attention to Fear as the dependent variable, we find that lagged values of Fear and market returns influence this sentiment measure. The market return at lag one has a t-statistics of -10.22 and is statistically significant at the 1% level. The market return also influences Fear at the lag of two days and has a t-statistics of -1.73 and is statistically significant at the 10% level.

The sentiment measure Joy is influenced by the lag of market return up to two days and the other measures of sentiment. It is influenced by Stress up to one day, Gloom up to three days, and Fear up to four days. Joy is related to its past values up to five days. The sentiment measure Stress is influenced by the previous day market return, Gloom up to four days, Volume up to three days, and Gloom up to four days. Volume is influenced by the market return up to two days, Fear and Stress up to five days.

[Insert Table 2 and Table 3 about here]

Table 4 shows the results for estimating the system using the *change in sentiment* measures. The market return is affected by Fear (cMP_FEAR) at lags of 2 and 4 days and statistically significant for both lags at the 5% level. The market return is also influenced by the sentiment measure of stress (cMP_SRESS) at lag of one day at 10% level. The other measures of sentiment (Joy, Gloom, and Volume) have no effect on the market return. The sentiment measure of Fear is influenced by the market return at lag one and is statistically significant at the 1% level. The results for other measures of sentiment resemble those reported in Table 2, i.e., the sentiments do not affect the market return but are influenced by the market return.

There is strong evidence that the relationship between the change in fear and the market return is bi-directional. Fear affects the market returns up to four lags and in turn it is influenced by the market return at one-day lag. This finding is in contrast with Brown and Cliff (2004) finding where they report that the market returns influence investor sentiment but "the effects of investor sentiment on subsequent returns are quite small." It is quite clear to us that the choice of the sentiment affects this relationship. Fear appears to have a substantial influence on future market returns while other measures of investor sentiment (Joy, Gloom, and Stress) have little or no effect on the future returns. Our results are also consistent with Tetlock's (2007) findings on the sentiment theory where the theory predicts that the results will be reversed in short-horizon. Also consistent with Tetlock's findings, we find that high levels of Fear and Gloom predict downward pressure on market prices, and high values of these pessimism sentiments predict high trading volume and serve as a proxy for investor sentiment trading.

[Insert Table 4 and Table 5 about here]

Figure 1 shows plots of the impulse response functions of the return on the market due to sentiment measures. The impulse responses are plotted for increasing lag lengths for a push to the market return while Figure 2 plots the response impulses for the sentiment measure of Fear.

[Insert Figures 1 and 2 about here]

Overall, some of our results are surprising in contrast with the previous studies, we find that some measures of sentiment have strong predictive powers. Out of the four measures of sentiment (Fear, Joy, Gloom, and Stress), fear is significant at lags up to four to five days. This indicates that Fear Granger causes returns and should be exploitable in predicting future market returns up to five days. In advance, this effect is bi-directional and runs from this sentiment measure to stock returns and from the returns to this sentiment measure (Fear). In the next section we investigate the effects of sentiment measures on mean return and volatility.

ii). Investor Sentiment and Returns Volatility in Futures Markets

Table 6 presents the TGARCH (1,1), model (2) and (3), estimates with four emotion measures at levels as exogenous variables. All the sentiment variables have the expected signs and Joy and Gloom are statistically significant at the one percent level. The coefficient for Stress is significant at the 1% level. The coefficient for Fear has the correct sign but it is not statistically significant. The coefficients for the conditional volatility are all highly statistically significant. The asymmetric parameters are positive and significant. The results support strong leverage effects, where negative shocks have larger effect on volatility of S&P 500 returns (leverage effects). When ε_{t-1} is negative, the total effects are given by $(\psi + \beta)\ \varepsilon^2_{t-1}$. So, one would expect β to be positive for bad news, to have larger impacts. Since $\psi > 1$, this implies that the conditional volatility is increased more by the negative shocks than by the positive shocks of an equal size.

[Insert Table 6 about here]

Table 7 shows the TGARCH (1,1) parameter estimates with change in our emotion measures. The model fits very well as all the coefficients for the model are highly significant. Among the sentiment measures in the model, cMP_Fear has the largest impact with coefficient of -74.9378 that is statistically significant at the 1% level. The negative sign indicates that changes in fear are associated with drops in the market return. cMP_Joy has the second largest coefficient of 43.0263 which is also statistically significant at the 1% level. The coefficient has a positive sign implying that increases in joy are associated with increases in the market return. Gloom and stress coefficients have the “correct” sign (negative) and are statistically significant the at 1% level. The coefficients for TARCH are statistically significant and imply that negative shocks to the market return have almost three times impact on the conditional volatility compared to positive shocks 0.1187 vs. 0.0422).

[Insert Table 7 about here]

In summary, our TGARCH (1,1) model with emotional measures fit the data very well. We find that the fear among investors has a major and lasting effect on the market return and conditionally volatility. The findings in this section regarding market return and conditional volatility confirm our findings from the VAR(5) model – that the fear in the market place causes a larger volatility that lasts up to four days. This sentiment measure could be used to predict market return and volatility.

ROBUSTNESS CHECK

i). Fear Effect with VIX

To confirm the robustness of our main findings in the previous sections that investors' fears affect market return and volatility, we include an alternative measure of fear (VIX) known as "fear index" in our TGARCH model. We are interested in knowing whether our results are sensitive to inclusion of this variable in our model.

The Implied Volatility Index (VIX) is calculated by COBE and represents the implied volatility of an at-the money option (both calls and puts) on the S&P 500 stock index option prices with more than 23 days and less than 37 days to expiration. The VIX is considered to be the world's premier barometer of investor sentiment and market volatility. We estimate the following TGARCH (1,1) model

(4) $R_{S\&P,\,t} = \alpha_0 + \alpha_1 R_{S\&P\ t-1} + \alpha_2 VIX_t + \alpha_3 Fear_t + \varepsilon_t$

(5) $H_t = \omega + (\psi + \beta,\ 1_{\{\varepsilon t\ -1<0\}})\ \varepsilon^2_{t-1} + \gamma_1 H_{t-1}$

where VIX is the COBE Volatility Index and fear is change in the fear sentiment.

Table 8 reports the estimates for the TGARCH (1,1) model of the above specification. The coefficients of interest are α_2 and α_3 in (4). Both coefficients are statistically significant at the 1% level. Inclusion of the "fear index" (VIX) in our model did not change the significance of the sentiment measure of fear. This suggests that, if anything, the sentiment measure of fear used in this paper has a major effect on the return and conditional volatility of the market.

[Insert Table 8 about here]

INVESTOR EMOTIONS IN PREDICTING STOCK INDEX AND TREASURY FUTURES RETURN COMOVEMENTS

INTRODUCTION

Futures market has been recognized for its economic importance in the global marketplace. It provides with an efficient mechanism to determine prices based on actual and estimated amounts of supply and demand, as much as with a liquid marketplace for corporates and institutions to hedge various types of financial risks. The economic efficiency of the market can be fulfilled in conditions of investors' rational reaction to market information and news. However, the investors' rationality can be sensitive to the ebbs and flows of news and rumor, and their emotional reactions to such information have additional effects on price movements to the informational effect itself (Engelberg, and Parsons, 2011; Engelberg, Sasseville, and Williams, 2013; Peterson, 2013). An accurate detection of investor emotions in the market will be beneficial for predicating financial futures price movement, increasing the efficacy of the futures risk hedging and improving the security pricing efficiency.

Experimental financial research has documented that individual investors' emotional states influence their risk taking behaviors (Kuhnen and Knutson, 2011), as well as their trading performances (Lo, Repin and Steembarger, 2005). Valence-based approach and appraisal-based approach are two main theories that dominate human emotion studies. Valence in discussing emotion refers to the effects of positive versus negative feeling states (Barrett, 2006). Kuhnen and Knutson (2011) found that investors in positive emotional states take relatively higher risk-seeking strategies by holding riskier portfolios compared to those in negative emotional states. The new development of neurological analysis technologies, such as voice analysis, facial expression recognition, and functional magnetic resonance imaging (fMRI), allow neural financial analysts to quantify investors' cognitive and emotional activities into measurements. Mayew and Venkatachalam (2012) and Price, Seiler and Shen (2016), in two separate studies, quantified managers' voices from their earnings conference call audios into informational cues by running through vocal emotion analysis software. Those managers' emotional vocal cues have been found to be useful to predict the cumulative abnormal returns around the companies' earnings conference calls. While the valence-based approach offers explanatory power on the extent of emotional affection on investors' risk taking behaviors, it fails to account for the differences between behaviors driven by emotions of similar level of valences, such as shame, fear and anger (Lerner and Keltner, 2000; Lerner and Keltner, 2001; Tiedens and Linton, 2001; Watson, and Spence, 2007). Appraisal theorists contend that emotions can be distinguished at a more fine-grained level as a person's appraisal or cognitive response to a specific situation change (Lerner and Keltner, 2000; Tiedens and Linton, 2001). With different appraisals of certainty and control found between fear and anger, it leads to sharply contrasting perceptions of risk attached to those two different emotions even in the same level of valence. Fear promotes pessimistic risk estimates and risk-averse choice; on the other hand, anger encourages optimistic risk estimates and risk-seeking choices (Lerner, Goldberg and Tetlock, 1998; Lerner and Keltner, 2000; Lerner and Keltner, 2001; Tiedens and Linton, 2001). To apply appraisal approach explanation of emotions in investment, a financial analyst may infer from an investor's distinct emotion to evaluate the investor's affective and cognitive state, and predict the investor's response to a current market event. Since individuals combine to form the financial market, all investors' collective emotions observed in public media can reveal a significant part of market behaviors (Peterson, 2003). In the first essay of this dissertation, the empirical results suggest that the distinct emotions appeared in public media, such as fear, gloom, joy and stress have predictability power on stock returns at daily base. Nowadays, it becomes a goal for researchers to quantify media-based investor emotions with robust methodologies, and then to analyze the effects of investor emotions on asset prices.

There have been no significant findings documented on investor emotions in futures markets. However, researchers found that the investors' behavioral attitudes have certain influences in the use of futures contracts. Pennings and Leuthold (2000) showed that farmers' heterogeneous psychological attitude toward market orientation, risk exposure, market performance, and entrepreneurial behavior play important roles in their use of futures contracts. Currently, the most widely adopted measurement of investors' attitude is investor sentiment. Earlier literatures have documented the investor sentiment effects in forecasting futures market returns. Simon and Wiggins (2001) examined whether market-based sentiment indicators, as measured by the volatility index, the put—call ratio, and the trading index, can provide predictive power for subsequent returns on S&P 500 futures contracts over 10-day, 20-day, and 30-day horizons. The empirical results demonstrated that high degree of market fear and skepticism leads to subsequent strong S&P futures' performance, which is consistent with the contrarian paradigm. Wang (2003) investigated whether actual trader position-based sentiment index is useful for predicting returns in the S&P 500 index futures market. The results supported that large speculator sentiment as a price continuation indicator is correlated with an increase in returns, whereas large hedger sentiment as a contrary indicator is associated with a decrease in returns on the S&P 500 futures. Wang (2001) also studied whether a trader position-based sentiment index has predictive power in agricultural futures markets. The results indicated that large speculator sentiment predicts price continuations, whereas large hedger sentiment forecasts price reversals. Kurov (2008) tested whether positive feedback trading in futures market is related to investor sentiment by using high frequency price and order flow data. He found that positive feedback trading appears to be active in periods of high investor sentiment, which is consistent with the noise trading hypothesis that the order flow contains less information when investor sentiment is high. Gao and Suss (2015) present a model of investor sentiment impact on commodity futures returns. The authors constructed a market sentiment index by Partial Least Squares regressions (PLS) with higher moments of the option implied return distribution and other established sentiment proxies. The constructed sentiment index explained up to 19% of the commodity futures returns variations by controlling macroeconomic effects, the linkage to stock market returns, and the commodity-related factors. The authors further identified that the interdependence between sentiment and commodity futures returns increased after 2003. Moskowitz, Ooi, and Pedersen (2011) documented a significant time series momentum effect across nearly five dozen futures contracts in equity index, currency, commodity, and bond futures markets. They found that persistence in returns for 1 to 12 months following a partial reversal over longer horizons, consistent with sentiment theories of initial under-reaction and delayed over-reaction.

Stock and bond correlation has important implications for asset allocation and risk management. Those early years' studies suggested a positive correlation between changes in stock prices and bond returns before 1990. This positive relationship can be explained by common discount rate effect (Shiller and Baltratti, 1992; Campell and Ammer, 1993). Recent works have shown that bond-stock co-movements changes in a time varying pattern, driven by the variations across economic and market conditions (Christiansen and Ranaldo, 2006). Financial economists investigated the stock and bond market co-movements during economic expansions and recessions. They argued that the cash flow effect may dominate during contractions, while the discount rate effect may be more important during expansions. Their empirical evidences supported the hypothesis that stock-bond correlation is shown to be positive during economic expansions, whereas this relationship turned to be negative during economic recession (Boyd, Hu, Jagannathan, 2005; Andersen, Bollerslev, Diebold, and Vega, 2007; Yang, Zhou, and Wang, 2009). Connolly, Stivers, and Sun (2005) posited that the time varying pattern of stock-bond correlations can be explained by changes in stock market uncertainty. They suggested that stock-bond correlation decreases with increasing stock market uncertainty, measured by option-implied stock market volatility. At the same time, there are an increasing number of studies to investigate stock and bond correlations in futures market. Chui and Yang (2012) argued that the use of futures market data to study the matter can be beneficial: 1) to avoid the notable nonsynchronous trading problem for daily stock index data; 2) to gauge the active traders' behaviors, such as speculators, with a lower transaction costs in futures trading. Najand and Yung (1997) modeled the price dynamics among exchange rates, stock index, and treasury bonds in futures markets. They found that returns on foreign currency futures are positively correlated with returns on US stock index futures and negatively correlated with returns on Treasury bond futures. Christiansen and Ranaldo (2007) documented a time-varying realized bond-stock correlation conditional on macroeconomic conditions by using a high-frequency dataset on SP500 index and 10-year treasury notes futures contracts. Bansal, Connolly, and Stivers (2010) investigated US stock index and Treasury notes returns in a bivariate regime-switching model. They found that a low stock-bond correlation, a high stock volatility and a high mean bond return exist during a high stock market stress. Chui and Yang (2012) also studied the time-varying correlations between stock and bond futures markets. They found that stock market uncertainty affects the stock-bond futures correlations when the market is in bearish states.

A variety of multivariate GARCH processes have been applied by academic researchers in exploring inter-market correlations. Bhar (2001) proposed a bivariate E-GARCH model to test the linkages between the equity market and the index futures market in Australia. The diagnostic tests suggested that bivariate E-GARCH specification captures the dynamic behavior of the joint spot equity and index futures return-generating process, and fit the data well. De Goeij and Marquering (2004) employed a multivariate process to estimate the intertemporal interaction between the stock and bond returns. The empirical findings indicated that both variances and covariances between stock and bond returns exhibit significant asymmetries. Cappiello, Engle and Sheppard (2006) developed a new GARCH process, the asymmetric generalized dynamic conditional correlation (AG-DCC) model in studying the correlations of equity and bond returns in global markets. AG-DCC model builds new advantages on GARCH models in adding series-specific news impact and smoothing parameters and capturing conditional asymmetries in correlation dynamics. Recently, a branch of copula-based GARCH models has applied in exploring the volatility and dependence structures of stock and bond returns (Wu and Lin, 2014). Copula-based model is considered to be more efficient, because it allows for skewness in the distribution of security returns and asymmetry in the dependence structure between the returns.

There is voluminous amount of research about the interdependence between bond and stock market, and methodologies in exploring such an interdependence; yet only a few papers start to investigate bond-stock return comovements from the investor sentiment and emotion perspective. Recent researches have proposed that investors' risk attitudes are highly influenced by their moods and emotions (Kuhnen and Knutson, 2011; Bassi, Colacito, and Fulghieri, 2013).

The changes in investors' emotions may have an impact on the investors' cross market diversification behaviors. In accordance with "flight-to-quality" pattern, when there is an extreme fear dominated in the market, investors tend to make risk-averse choices of investments. In that manner, investors will ride on safer investment portfolios by leveraging a higher portion of their asset allocations on bond market. Kamstra, Kramer, and Levi (2014) identified a seasonal pattern of variations in bond returns, due to the changes in investors' moods and their risk attitudes across seasons, which is consistent with the above hypothesis. The market uncertainties on economics sources are identified as the major determinants for stock and bond return comovements (Baele, Bekaert and Inghelbrecht, 2010); at the same time, there is a need to investigate on the effects of investor sentiment and emotion on stock and bond return comovements.

Sentiment and emotion driven noise trading could cause large price movements and excess volatilities in the short run. Da, Engelberg and Gao (2014) established a FEARS (Financial and Economic Attitudes Revealed by Search) index based on aggregated volume of household internet search on certain financial words. They found that FEARS index can be a useful predictor for short-term return reversals and temporary increases in volatilities. They also examined the predictive power of FEARS index on the mutual fund flows between equity and intermediate Treasury bonds. The documented evidence supported that mutual fund investors shift their investments from equities to bonds after a spike in FEARS, which is consistent with "flight to safety" hypothesis. Sun, Najand and Shen (2016) used a high frequency sentiment dataset from Thomson Reuters MarketPsych Indices (TRMI) to predict short run stock returns in granularity of half hours. The empirical evidence suggested that intraday S&P 500 index returns are predictable using lagged half-hour investor sentiment, and this return predictability is related to noise trading activities. Yet there is not a significant study to delineate how investor emotions can be useful for predicting stock index and Treasury futures returns, and comovements between those two futures markets.

The purpose of this study is three fold: First, we investigate the extent of usefulness of informational content of our sentiment measures in predicting stock futures and treasures futures returns using daily data for different measures of emotional sentiments. Second, we investigate whether emotion sentiments affect financial futures returns and volatilities. Third, we explore the role of emotion sentiment factors in volatility transmission in financial futures markets. To the best of our knowledge, this is the first study that extensively explores the role of investors' sentiment in the most liquid contracts (S&P 500 futures and 10-year Treasury notes) in futures markets.

In our Vector Auto-Regressive predictive models, we find that fear can predict SP500 index futures return up to four days, while joy and optimism can forecast Treasury notes futures return up to two or four days. Furthermore, by conducting a Multivariate GARCH model to test volatility interdependence between the two futures markets, we document that both Fear and Optimism have impact on the stock market futures returns and volatility. The above findings interestingly coincide with emotion driven noise trading hypothesis that noise traders shift to the bond market during a spike of fear in the stock market, in order to vacuum noise trading out from the stock market. So the following days' stock return reversals can be predicted by informed investors. On the other hand, when the optimistic expectations fill up the market, noise traders switch back to the stock market to seek risk investment that eliminate most parts of confounding signals in the bond market, followed by a short run reversal in the bond market. The empirical evidences in this paper align with Da, Engelberg and Gao's (2014) findings that individual investors switch from equity funds to bond funds when negative sentiment is high.

The rest of the paper is organized as follows. The next section summarizes the previous investor sentiment and emotion literature. A subsequent section describes the data and empirical methodology. Then the following section explains the empirical results based on Vector Auto-Regressive, Threshold-GARCH, VARMA-GARCH models, and a robustness check. The paper concludes with a list of several main contributions.

LITERATURE REVIEW ON SENTIMENT AND EMOTIONS

Investor sentiment research received a large amount of attention from academic research in the last two decades. The main stream sentiment indicators can be categories in three groups: economic-based sentiment, survey-based sentiment, and media-based sentiment. The traditional economic-based sentiment indices include: closed-end fund discount (Zweig, 1973; Neal and Wheatley, 1998), trading volume (Baker and Stein, 2004), and composite sentiment index based on the first principal component of common sentiment proxies (Baker and Wurgler, 2006; Gao and Suss, 2012). There are two main survey-based sentiment measurements: 1) sentiment survey from American Association of Individual Investors (AAII) and 2) sentiment survey from Investor's Intelligence (II) sentiment survey (Brown and Cliff, 2004, 2005). Along with the development of computer enabled content analysis, media-based sentiment indicators from textual analysis of news stories and social media blogs have been adopted for sentiment research. The most common content analysis methods in textual sentiment analysis are dictionary-based approach and machine learning (Kearney and Liu, 2014). The most popular programs for built-in dictionaries in English language are General Inquirer (GI) and DICTION. Tetlock (2007) implemented Harvard IV-4 dictionary in GI to run textual analysis in daily news from the *Wall Street Journal*. Loughran and McDonald (2011) later developed a financial context based dictionary incorporating six financial meaningful word classifications. Jegadeesh and Wu (2013) proposed a content analysis model employing a more appropriate term weighting scheme suitable for finance applications. Sentiment analysis in machine learning mainly relies on statistical techniques, such as Support Vector Machine (SVM), Naïve Bayes Classifier, and Maximum Entropy, to classify texts into positive or negative categories (Li, 2010). Huang, Zang and Zheng (2014) applied the Naïve Bayes Classifier algorithm to classify textual information from a large sample of financial analyst reports. The advanced computer programs and content analysis methodologies also provide opportunities for financial analyst and institutional investors to measure market emotions through public media contents.

With recent launches of several powerful news analytics database, researchers have investigated the news media sentiment's impacts on commodity futures market. Borovkova (2011), Borovkova and Mahakena (2013), and Smales (2014) sequentially studied the price dynamics of crude oil, natural gas, gold futures conditional on news sentiments, as measured by the Thomson Reuters News Analytics. They found that news sentiments and news events have significant impacts on commodity futures returns, and this sentiment-return relationship appears to be asymmetric, where negative news sentiment provokes a greater response in returns of commodity futures than positive news sentiment. Thomson Reuters MarketPsych Indices (TRMI) included market level emotion indictors that can be useful to study stock index and Treasury futures returns, conditional volatility, and the change of correlations between stock index and Treasury futures returns.

The investors’ psychological biases in their information processing and financial decision making have been found highly related to investor emotions or mood. Hirshleifer and Shumway (2003) confirm the sunlight effect that the happy mood, induced by morning sunshine in the city of a country's leading stock exchange, is significantly correlated with daily market index returns across 26 countries. Goetzmann, Kim, Kumar, and Wang (2014) introduced weather-based indicators of mood, and showed that investor optimism, associated with lower values of deseaonalized cloud cover, is significantly correlated with investors’ propensities to buy, stock overpricing, stock return comovement. Additionally, Edmans, Garcia, and Norli (2007) documented that the negative mood, affected by a soccer game loss, could lead a significant market decline.

Fear, gloom, joy, and optimism were studied separately in previous studies to document their effects on investors’ evaluation of risks. The most commonly documented emotion in the existing finance research is fear. Financial crisis often injected a lot of fear into the future market movement, and that effect usually slow down the financial recovery process, or even create more turmoil in the market. The implied volatility indices are often used as proxies for market fear. High levels in the implied volatility indicate that investors are fearful about market future prospect, so previous research adopted the implied volatility indices (VIX among others) to forecast forward looking stock returns and other financial security returns (Rubbaniy, Asmerom, Rizvi and Naqvi, 2014; Esqueda, Luo and Jackson, 2015). Da, Engelberg and Gao (2015) established a daily fear index based internet search volume from millions of households. They further found that the internet search based fear index can predict asset prices, volatility and mutual fund flows. Investors tend to lose their faith and hope in stock market after experiencing a long-lasting recession. The gloomy stage of market downturn may take years to recover, because investors are more sensitive to the fragile market (Lauricella, 2011). Azzi and Bird (2005) found that market boom or gloom state affect analysts' recommendation tendency, where analysts' recommendations favor more towards high momentum growth stocks during the boom years than during the gloom years. On the other hand, a recent paper proved that investments made on hotels during booms underperform for a few years (Povel, Sertsios, Kosova, Kumar, 2015). Researchers speculate that people's happiness is highly correlated with their personal income, although the causal relationship between the two may be bilateral (Di Tella, MacCulloch and Oswald, 2003). Finance researchers often regard sunshine and temperature as indicators of investors' joy or happiness. Hirshleifer and Shumway (2003) confirmed that stock market perform better during sunny days rather than cloudy days. This documented "sunlight effect" attributes to investors' joyful mood to sunshine rather than to long-term value growth. Karabulut (2013) adopted Facebook's Gross National Happiness (GNH) as a measure of investors' happiness manifested on social media. He further found that "an increase of one standard deviation in GNH is associated with an increase of 11:23 basis points in market returns over the next day." Financial optimism is defined as the overestimation of the future financial outcome, so it sometimes causes the investors' overconfidence and the assets' overpricing in the market (Balasuriya, Muradoglu and Ayton, 2010). Kaya (2012) employed the subjective stock market expectation responses from Health and Retirement Survey as a proxy for investors' optimism. She further confirmed Balasuriya, Muradoglu and Ayton' earlier research that optimistic investors tend to invest more in risky assets in their financial portfolios and take a higher debt borrowing position. Additionally, Ciccone (2003) reported that firms with overly optimistic expectations earn lower returns than those with pessimistic expectations.

Based on the TRMI market level emotion indicators, and the documented investor emotion literatures, we explore the predictive power of emotion measurements, such as fear, gloom, joy, and optimism, on stock index and Treasury returns in last two decades. At the same time, we are also interested to test whether investor emotions can be reliable substitutes or complements in explaining the change of correlations between stock index and Treasury returns.

DATA AND METHODOLOGY

We obtain data for our analysis from MarketPsych of Thomson Reuters. The Thomson Reuters MarketPsych Indices (TRMI) are updated every minute and derived from a collection of premium news, global internet news coverage, and a broad group of social media (Peterson, 2013). TRMI utilizes contents derived both from news and social media to reflect sentiments from both professional and individual investors. For the first category, MarketPsych sources of text include *The New York Times*, *The Wall Street Journal*, *Financial Times*, *Seeking Alpha* and dozens more sources available to professional investors. Less formal news sources are obtained from Yahoo! and Google News. For the second category, TRMI utilizes over 2 million social media sites including StockTwits, Yahoo! Finance, Blogger, chat rooms and other sources. MarketPsych employs lexical analysis to extract sentiment indices by scrapping all sources minutely, which includes over 2 million news articles and posts every day. Each sentiment index is a combined news and social medial content and each minute value is a simple average of the past 24 hours (1440 minutes) of information (Peterson, 2013). Thus, the TRMI represent an unmatched collection of premium news and a broad range of social media.

i). Emotion Sentiment Variables

In the first step of our empirical analysis, we start out with 24 TRMI sentiment measure that represent different emotions of investors in the market place. We perform stepwise regresssions to select the sentiments that have the highest stastical signifcance in explaining stock index futures returns. Four sentiment measures that were selected by stepwise regressions are: cMP_FEAR, MP_GLOOM, cMP_JOY, MP_OPTIMSM.[2]

Each sentiment index is 24 hour rolling average score of references in news and/or social media to that particular measure. All the measures range from 0 to 1, except for volume. TRMI sentiment ranges from -1 to 1 which reflect overall positive reference net of negative references. Our data set is daily data from January 1, 1998 through December 31, 2014. For financial futures variables, we obtain stock index futures and 10-year Treasury notes futures for near-by contracts, the most liquid futures contracts, from Global Finance database.

Table 9 provides descriptive statistics and correlation matrix for our variables (emotion sentiment changes, stock index futures returns, and Treasury Notes futures returns) used in this study. The stock index futures return (Fspr) is positively correlated with changes in joy and optimism and negatively correlated with changes in fear, and gloom. Treasury Notes futures contract return (TNFR) is positively correlated with fear and gloom and negative correlated with joy and optimism.

[Insert Table 9 about here]

2 The results are not reported here but available upon request from the author.

ii). VAR Analysis of Sentiment and Returns

Predictive power of sentiment has always been as source of great interest to researchers. Brown and Cliff (2004, 2005) examine the usefulness of sentiment in predicting stock returns. They find that stock returns Granger-cause sentiment, while sentiment is not helpful in predicting stock returns. Verma et al. (2008), on the other hand, find some predictive power of sentiment when they decompose the sentiment into rational and irrational components. Thus, the extent of usefulness of sentiment in predicting returns beyond the informational content of past returns has been controversial. There are a few studies that investigate the role of sentiment in predicting stock index returns in the futures markets. Kurov (2008) examines the order flow of traders in stock index futures and its effect on price changes. The author finds evidence consistent with positive feed-back trading and concludes that sentiment-driven noise trading affect price changes. Simon and Wiggins (2001) investigates the predictive power of market-based sentiment measures (volatility index, the put–call ratio, and the trading index) for subsequent S&P 500 index returns for different horizons. The authors conclude that these variables, over a variety of horizons, have statistically and economically significant forecasting power. Gao and Suss (2015) find a strong presence of sentiment exposure in commodity futures returns. They find that their sentiment measure provides explanatory power for comovement among commodity futures beyond the macro- and equity-related sentiment measures and conclude that "represents a distinct source of premia."

The purpose of this study is three fold: First, we investigate the extent of usefulness of informational content of our sentiment measures in predicting stock futures and treasures futures returns using daily data for different measures of emotional sentiments. Second, we investigate whether emotion sentiments affect financial futures returns and volatilities. Third, we explore the role of emotion sentiment factors in volatility transmission in financial futures markets. To the best of our knowledge, this is the first study that extensively explores the role of investors' sentiment in the most liquid contracts (S&P 500 futures and 10-year Treasury notes) in futures markets.

We employ a VAR model that in which market returns and different measures of sentiment act as a system with the goal of identifying causality between sentiment and market in a similar manner to Brown and Cliff (2004). The model we propose is

$$\text{(6)} \qquad Yt = \lambda + \sum_{i=1}^{5} \psi Yt - i + \mathcal{E}\, t$$

where Y_t is a vector that contains market returns and different measure of sentiment (Fear, Joy, Gloom, Optimism, and Volume). We include trading volume in our models since divergence of opinions leads to rising volume. Gao and Suss (2015) argue that in period of high market sentiment, optimism leads higher liquidity and trading volume.

We estimate VAR models of up to 5 days, based on selection metrics such as AIC and BIC, to investigate the causal structures and forecasting capabilities of sentiment measures.

iii). Sentiment Measures and Stock Futures Returns Volatility

The effect of sentiment on stock returns and volatility is not very clear. Some researchers find that sentiment affects both mean and variance of stock returns (Lee et. al, 2002; Verma & Verma, 2007). However, Wang et al. (2006) find that the forecasting power of sentiment for volaitlity disappears if lagged returns are included in the models. We utltize a TGARCH model to investigate the effect of semtiment measures on stock meand return and volatility. TGARCH model incorporates the leverage effect since it has a certain term for negative return innovations (see Zakoian, 1994). We employ the following TGARCH (1,1) model to investigate the effects of sentiment measures on the market returns volatility

(7) $R_{i,t} = \alpha_0 + \alpha_1 R_{i,t-1} + \alpha_2 Fear_t + \alpha_3 Joy_t + \alpha_4 Gloom_t + \alpha_5 Optimism_t + \varepsilon_t$

(8) $H_t = \omega + (\psi + \beta, 1_{\{\varepsilon t-1<0\}})\, \varepsilon^2_{t-1} + \gamma_1 H_{t-1}$

In the TGARCH model above, the coefficient to the lagged square error in a GARCH model is allowed to attain different values, depending on the sign of lagged error term. In this TGARCH model, the indicator function is 1 if $\varepsilon_{t-1} <0$, and 0 otherwise. In this model, for positive lagged errors, the coefficient is just ψ parameter, while the coefficient for negative error terms is $\psi + \beta$.

EMPIRICAL RESULTS

i). Sentiment Measures and Return Predictability

Stock Index Futures

Table 10 presents the estimated daily parameters for the VAR (5) model with five sentiment level measures (Fear, Joy, Gloom, Optimism, and Volume). Out of the five measures of sentiments, only Fear is significant and capable of predicting the stock index futures returns up to four days. The coefficient for Fear where the market return is the dependent variable is significant at lag two and has a t-statistics of 2.43, which is statistically significant at the1% level. The coefficient for Fear at lag four has a t-statistics of 2.08, which is also statistically significant at the 5% level. We find that other investor sentiment measures have no predictability power for the stock index futures returns. We also find that volume has no significant power to predict returns in futures markets. We also find a statistically significant autocorrelation at lag 5 for stock index futures. Thus, stock index futures returns seem to be predictable up to four days by sentiment index of Fear only. Our results seem to be consistent with Da et al. (2014) for the spot market. The authors construct a measure that aggregates queries like “recession,” “bankruptcy,” and “depression.” They call this measure FEARS (Financial and Economic Attitudes Revealed by Search) index. They show that this FEARS index predicts aggregate market returns in short-horizon (one day).

When Fear is the dependent variable, we find that lagged values of Fear and stock index futures return influence this sentiment measure. The stock index futures return at lag one has a t-statistics of -7.40 and is statistically significant at the 1% level.

The sentiment measure Joy is influenced by the lag of the stock index futures return and optimism at lag of one day, past values of Fear (lags 1 and 5); gloom (lag 1). Joy is related to its past values up to three days. The sentiment measure Optimism is influenced by the previous day index futures return, Fear, and Gloom. Volume is influenced by the index futures return and Optimism at lag 1, Joy at lags 3 and 5 days and surprising, volume is not related to Fear.

[Insert Table 10 and Table 11 about here]

Figure 3 shows plots of the impulse response functions of the return on the stock index futures due to sentiment measures. The impulse responses are plotted for increasing lag lengths for a shock to the market return.

[Inset Figures 3 about here]

Treasury Notes Futures

Table 12 shows the results for estimating the VAR (5) system when the return on 10-year Treasury Notes included in the model. The results indicate that treasury notes return is not related to its past values, Fear and Gloom. However, it seems to be influenced by Joy and trading volume at lag 2, and Optimism at lag 4. The sentiment measure of Fear is influenced by the treasury return and Optimism at lag one; and Gloom and Joy at lag of three days. The results for other measures of sentiment resemble those reported in Figure 5, i.e., the sentiments do not seem affect the treasury returns in the futures markets and in turn, not influenced by it. This result is in contrast with the findings in the previous section where we found bi-directional causal relationship between the sentiment measure of Fear and the stock index futures return.

Overall, our results regarding stock index futures returns are consistent with recent findings of Da et al. (2014) in the spot market and Gao and Suss (2015) in commodity futures markets. However, we fail to document any causal relation between treasury futures return and investor sentiment.

We find that some measures of sentiment have strong predictability power. Out of the four measures of sentiment (Fear, Joy, Gloom, and Optimism) -- fear is significant at lags up to four days. This indicates that Fear causes returns and should be exploitable to predict future market returns up to four days. This effect is bi-directional and runs from this sentiment measure to futures stock returns and from the returns to this sentiment measure (Fear). In the next section we investigate the effects of sentiment measures on mean return and volatility in futures markets.

[Insert Table 12 and Table 13 about here]

Figure 4 shows plots of the impulse response functions of the return on the Treasury Notes futures due to sentiment measures. The impulse responses are plotted for increasing lag lengths for a shock to the Treasury Notes futures return while Figure 5 plots the response impulses for the sentiment measure of Fear.

[Inset Figures 4 and Figure 5 about here] *ii) Investor Sentiment and Returns Volatility in Futures Markets*

Stock Index Futures

Table 14 Panel A presents TGARCH (1,1), model (7) and (8), estimates with four emotion measures as exogenous variables. All the sentiment variables have the correct signs all the coefficients for our model are highly significant at the one percent level. Among the sentiment measures in the model, cMp_Fear has the largest impact with coefficient of -78.9843 that is statistically significant at the 1% level. The negative sign indicates that changes in fear are associated with drops in the futures S&P 500 index return.

The coefficient for Gloom (cMP_Gloom) is also negative and highly significant. Our results are here consistent with Da et.al (2015) findings for the spot market. The authors find that their measure of negative sentiment (FEARS) is highly correlated with the aggregate market return.

We have two measures of positive sentiments in our TGARCH (1,1) model, Joy and Optimism. The coefficient for Joy (cMP_Joy) is positive and highly significant. This coefficient is the second largest coefficient in the model (41.6085) and has the correct sign. The coefficient for the second measure of positive sentiment (cMP_Optimism) is also statistically and economically significant. Taken together, these positive sentiments imply that increases in these sentiments are associated with increases in the market return.

The coefficients for TARCH are statistically significant and imply that negative shocks to the stock index futures return have almost twice impact on the conditional volatility compares to positive shocks (0.1093 vs. 0.0575).

In summary, our TGARCH (1,1) model with emotional sentiment measures fit the data very well. We find that the fear among investors has major and lasting effect on the market return and conditionally volatility in the futures market. Consistent with Da et al. (2015) findings for the spot market, we find that our negative sentiment measurers (Fear and Gloom) strongly reflect return and conditional volatility in futures market. We also document the effect of positive sentiments (Joy and Optimism) on the return and volatility in futures market.

The findings in this section regarding the stock index futures return and conditional volatility confirm our findings on VAR(5) model -- the fear in the market place causes large volatility that lasts up to four days. This sentiment measure could be used to predict return and volatility in the futures markets.

Treasury Notes Futures

Table 14 Panel B reports the results for out TGARCH model specifications for Treasury Notes futures returns. We find that our measure of negative sentiments (Fear) is positive and significant at the 5% level. The sentiment measure, Gloom, has the correct sign but is not statistically significant. Our result here is consistent with Da et al. (2015) finding for the spot market, increases in the Fear index causes movements of funds from the risky assets to safe assets (flight to quality) which consistent with "noise trading" hypothesis. Additionally, we also further documented that there is a negative correlation between Optimism and Treasury Notes futures returns. This can interpreted as that when there is increase of optimism in the market, investors switch their interests from investing in Treasury Notes to those relatively risker assets. The coefficient for asymmetric volatility is not statistically significant (TARCHB1) implying that positive returns and negative returns have the same impact in the Treasury futures markets.

[Insert Table 14 about here]

ROBUSTNESS CHECK

i). Fear Effect with VIX

To confirm robustness of our main finding in the previous sections, investors fear affect market return and volatility in futures markets, we include an alternative measure of fear (VIX) known as "fear index" in our TGARCH model. We are interested in knowing whether our results are sensitive to inclusion of this variable in our model.

The Implied Volatility Index (VIX) is calculated by COBE and represents the implied volatility of an at-the money option (both calls and puts) on the S&P 500 stock index option prices with more than 23 days and less than 37 days to expiration. VIX is considered to be the world's premier barometer of investor sentiment and market volatility. We estimate the following TGARCH (1,1) model

(9) $R_{S\&P\ Futures,\ t} = \alpha_0 + \alpha_1 R_{S\&P\ Futures,\ t-1} + \alpha_2 VIX_t + \alpha_3 Fear_t + \varepsilon_t$

(10) $H_t = \omega + (\psi + \beta, 1_{\{\varepsilon t\ -1<0\}})\ \varepsilon^2_{t-1} + \gamma_1 H_{t-1}$

where VIX is the COBE Volatility Index and fear is change in the fear sentiment.

Table 15 reports the estimates for the TGARCH (1,1) model of the above specification. The coefficients of interest are α_2 and α_3 in (9). We find the coefficient for VIX (α_2) not statistically in the presence of our Fear index. However, the coefficient for Fear sentiment is highly significant. Interesting, Da et al. (2015) report very similar results for the spot market. Our sentiment measure of Fear remains a strong predictor of futures return even after controlling for VIX. Inclusion of the "fear index" (VIX) in our model did not change the significance of the sentiment measure of fear. In fact, the magnitude of the coefficient for this negative sentiment increased by almost 30%. This suggests that, if anything, the sentiment measure of fear used in this paper has a major effect on the return and conditional volatility of the market.

[Insert Table 15 about here]

ii) Fear, Optimism and Volatility Transmission in Futures Markets

In this section we explore the interdependence of stock equity futures volatility and treasury notes futures volatility and the effects of investor sentiments on their returns in futures markets. Many studies have examined the interdependence of equity markets and shocks to the volatility using GARCH framework, for example Hamao et al. (1990) Koutmos and Booth (1995), Bekaret and Wu (2000), among others. However, few studies have focused on volatility dependence in financial futures markets. In previous section we showed that SP& 500 futures and treasury notes futures are influenced by investor sentiments. In this section we turn our attention to volatility interdependence in futures market and how they may have been influenced by investor sentiment. We employ the following multivariate VARMA-GARCH (1,1) (DCC) model of Engle (2002) to perform our empirical investigation of volatility interaction in financial futures markets.

(11) $R_{i,\,t} = \alpha_0 + \alpha_1\, R_{i,\,t-1} + \alpha_2\, Fear_t + \alpha_3\, Optimism_t + \varepsilon_t$

(12) $H_t = D_t R D_t$, where $D_t = \mathrm{diag}\{\sqrt{h_{i,t}}\}$

where $R_{i,t}$ is daily return on the S&P 500 futures index and 10-year treasury notes futures, H_t conditional volatility, R_t dynamic conditional correlation (DCC), and $D_t = \mathrm{diag}\{\sqrt{h_{i,t}}\}$. Engle (2002) compares the performance of several multivariate GARCH specifications and shows that DCC model outperforms the other models.

Table 16 presents parameter estimates for our VARMA-GARCH (1,1) model. We find that positive and negative sentiments affect the stock market futures returns (Fspr). The coefficients for Fear and Optimism are highly significant and signs are as expected. The coefficient for Fear is negative, indicating that change in fear is associated with market decline while the coefficient for Optimism is positive, indicating that increase in optimism is associated with increase in the stock index futures returns. The results also shows that there is no lead and lag relations between S&P 500 futures return and Treasury Notes futures returns, the coefficients for TNFR(t-1) is statistically insignificant. The Treasury Notes futures return is influenced by fear and optimism and is not affected by the lag of the index futures returns, Fspr(t-1). The positive sign for change in Fear indicates that increase in fear would lead to higher prices for treasury notes (flight to safety). The negative sign for Optimism indicates that increases in optimism leads lower treasury futures returns. The coefficients in the volatility equations are all highly statistically significant.

[Insert Table 16 about here]

CONCLUSIONS

Essay One explores the interaction between US media content and the US stock market returns and volatility. We utilize propriety investor sentiment measures developed by Thompson Reuters MarketPsych. The data is comprehensive commercial textual analysis that provides 24-hour rolling average score of references in news and social media by counting overall positive references net of negative references. We select four measures of investor sentiment that reflect both pessimism and optimism of small investors. These measures are Fear, Gloom, Joy and Stress. Our objective is two-fold: First, we examine the ability of these sentiment measures to predict market returns. For this purpose, we use dynamic VAR models. Second, we are interested in exploring the effects of these sentiment measures on the market returns and volatility. For this purpose, we utilize a TGARCH model.

We explore the ability of sentiment measure to predict the market return both in the level and in the change as suggested by Brown and Cliff (2004). In our VAR models we use five trading days (a calendar week) and find that some measures of sentiment have strong predictive power, in contrast to previous studies. Out of the four measures of sentiment (Fear, Joy, Gloom, and Stress), Fear is significant at lags up to four to five days. This indicates that Fear Granger causes returns and should be exploitable to predict future market returns up to five days. This effect is bi-directional and runs from this sentiment measure to stock returns, up to five days, and from the stock returns to Fear, up to two days. The sentiment measure of Stress has a small effect on the market return for one-day lag. The other two sentiment measures, Gloom and Joy, seem to play no role in predicting market returns.

To investigate the relations between sentiment measures and market return and volatility, we employ a TGARCH (1,1) model. We find that our TGARCH (1,1) model with emotional measures fits the data very well. We find that the fear among investors has major and lasting effects on the market returns and conditionally volatility. The findings regarding market return and conditional volatility confirm our findings in VAR(5) model -- fear in the market place causes high volatility that lasts up to four days. This sentiment measure could be used to predict both the stock market return and volatility.

To check the robustness of our results, we use an alternative measure of Fear known as the “fear index’ (VIX). We find that inclusion of the “fear index” (VIX) in our model did not change the significance of the sentiment measure of Fear. In fact, the magnitude of the coefficient for this negative sentiment increased by almost 39%. This suggests that, if anything, the sentiment measure of Fear used in this paper has a major effect on the return and conditional volatility of the market.

Essay two investigates the effect of investor emotions in financial futures markets by using Thompson Reuters MarketPsych indices. The data is commercial strength comprehensive textual analysis that provides 24 hour rolling average score of total references in news and social media by counting overall positive references net of negative reference. We select four measures of investor sentiment that reflect both pessimism and optimism of small investors. These measures are Fear, Gloom, Joy and Optimism.

The purpose of this study is three fold: First, we investigate the extent of usefulness of informational content of our sentiment measures in predicting stock futures and treasures futures returns using daily data for different measures of emotional sentiments. Second, we investigate whether emotion sentiments affect financial futures returns and volatilities. Third, we explore the role of emotion sentiment factors in volatility transmission in financial futures markets. To the best of our knowledge, this is the first study that extensively explores the role of investors’ sentiment in the most liquid contracts (S&P 500 futures and 10-year Treasury notes) in futures markets.

We explore the ability of sentiment measure in predicting the S&P 500 futures return and 10 year Treasury Notes futures returns. In our VAR models we use 5 trading days (a calendar week) and find that some measures of sentiment have strong predictability power, in contrast to previous studies. We find that some measures of sentiment have strong predictability power. Out of the four measures of sentiment (Fear, Joy, Gloom, and Optimism) -- Fear is significant at lags up to four days. This indicates that Fear causes returns and should be exploitable to predict future market returns up to four days. This effect is bi-directional and runs from this sentiment measure to futures stock returns and from the returns to this sentiment measure (Fear). However, we cannot find any causal relation between treasury futures return and investor sentiment.

We find that the fear among investors has major and lasting effect on the market return and conditionally volatility in the futures market. Consistent with Da et al. (2015) findings for the spot market, we find that our negative sentiment measurers (Fear and Gloom) strongly reflect return and conditional volatility in futures market. We also document the effect of positive sentiments (Joy and Optimism) on the return and volatility in equity futures market.

We also find that there is significant volatility interdependence in financial futures markets. We find that positive and negative sentiments affect the stock market futures returns and volatility. The coefficient for Fear is negative, indicating that change is Fear is associated with market decline while the coefficient for Optimism is positive, indicating that increase in Optimism is associated with increase in the stock index futures returns. The results also shows that there is no lead and lag relations between S&P 500 futures return and Treasury Notes futures returns. The Treasury Notes futures return is influenced by Fear and Optimism and is not affected by the lag of the index futures returns. The positive sign for change in Fear indicates that increase in fear would lead to higher prices for treasury notes (flight to safety). The negative sign for Optimism indicates that increases in optimism leads lower treasury futures returns. The coefficients in the volatility equations are all highly statistically significant.

Our empirical results show that sentiment is a systematic risk that is priced. Returns in futures markets are contemporaneously positively correlated with shifts in sentiment. Moreover, the magnitude of bullish (bearish) changes in sentiment leads to downward (upward) revisions in volatility and higher (lower) future excess returns.

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Table 1. Descriptive Statistics and Correlations

Panel A	cMP_FEAR	cMP_GLOOM	cMP_JOY	cMP_STRESS	LogVolume	Spr
N	2450	2450	2450	2450	2450	2450
Mean	0.0000799	0.0005890	0.0001152	0.0004651	19.37287	0.01851
Std Dev	0.00123	0.00379	0.00153	0.00443	0.82122	1.22663
Sum	0.19574	1.44828	0.28230	1.13960	47464	45.34929
Minimum	-0.00492	-0.01617	-0.00681	-0.01807	17.02138	-9.45954
Maximum	0.00775	0.02309	0.00889	0.02102	20.72292	6.70488

Panel B	cMP_FEAR	cMP_GLOOM	cMP_JOY	cMP_STRESS	LogVolume	Spr
cMP_FEAR	1.00000					
cMP_GLOOM	0.16254 ***	1.00000				
	(<.0001)					
cMP_JOY	-0.10137 ***	-0.17455 ***	1.00000			
	(<.0001)	(<.0001)				
cMP_STRESS	0.19786 ***	0.25235 ***	-0.23859 ***	1.00000		
	(<.0001)	(<.0001)	(<.0001)			
LogVolume	-0.00323 ***	-0.02987 ***	-0.00828 ***	-0.02943 ***	1.00000	
	(0.8729)	(0.1394)	(0.6822)	(0.1453)		
Spr	-0.12226 ***	-0.09745 ***	0.11590 ***	-0.13535 ***	0.03661 ***	1.00000
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0700)	

This table provides summary statistics (Panel A) and correlation coefficients (Panel B) for the full sample of 2450 daily observations from January 1, 1998, to December 31, 2014. The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the stock return data in the table come from Global Finance database. Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_JOY is the daily change of market-level joy; cMP_GLOOM is the daily change of market-level gloom; cMP_STRESS is the daily change of market-level stress; LogVolume is the log of the daily NYSE trading volume; and Spr is the log of the daily SP500 index returns. In Panel B, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1%

Table 2. Predicting S&P 500 Returns Using Sentiment Level Measures

	S&P 500 Returns					
Emotional Indicators	MP_FEAR	MP_GLOOM	MP_JOY	MP_STRESS	LogVolume	Spr
Investor Emotions$_{t-1}$	7.24535	-2.05990	11.98361	-6.28205	-0.07598	-0.01406
	(0.32)	(0.32)	(0.68)	(-0.99)	(-0.67)	(-0.68)
Investor Emotions$_{t-2}$	42.76968*	-8.76807	-4.70875	6.04609	0.09381	0.02229
	(1.78)	(-1.13)	(-0.25)	(0.88)	(0.78)	(1.04)
Investor Emotions$_{t-3}$	-28.43230	13.14652*	24.54766	6.46966	0.05688	-0.00873
	(-1.19)	(1.71)	(1.29)	(0.95)	(0.47)	(-0.41)
Investor Emotions$_{t-4}$	41.18187*	-1.14285	-3.56170	-6.19283	0.05689	0.03772*
	(1.72)	(-0.15)	(-0.19)	(-0.90)	(0.47)	(1.78)
Investor Emotions$_{t-5}$	-46.63145**	-8.99388	-7.61670	-8.62348	-0.08393	0.03782*
	(-2.08)	(-1.26)	(-0.44)	(-1.37)	(-0.73)	(1.80)

This table provides Vector Autoregressive (VAR) Model Parameter Estimates of the SP500 stock returns on investor sentiment measures to its five day lag. The sample period comprised 2450 trading days from January 1, 1998, to December 31, 2014.The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the stock return data in the table come from Global Finance database. Among the variables, MP_FEAR is the daily market-level fear; MP_JOY is the daily market-level joy; MP_GLOOM is the daily market-level gloom; MP_STRESS is the daily market-level stress; LogVolume is the log of the daily NYSE trading volume; and Spr is the log of the daily SP500 index returns. In the table, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 3. Feedback Effects of S&P 500 Returns on Sentiment Level Measures

Emotional Indicators	MP_FEAR	MP_GLOOM	MP_JOY	MP_STRESS	LogVolume
S&P 500 Returns$_{t-1}$	-0.00020***	-0.00045***	0.00011***	-0.00039***	-0.02236***
	(-10.22)	(-7.39)	(4.57)	(-5.59)	(-6.06)
S&P 500 Returns$_{t-2}$	-0.00003*	-0.00000	-0.00004*	0.00001	-0.00762**
	(-1.73)	(-0.03)	(-1.68)	(0.17)	(-1.99)
S&P 500 Returns$_{t-3}$	-0.00001	0.00002	-0.00002	0.00004	-0.00332
	(-0.29)	(0.26)	(-0.82)	(0.57)	(-0.87)
S&P 500 Returns$_{t-4}$	0.00003	-0.00003	-0.00001	-0.00000	0.00395
	(1.40)	(-0.52)	(-0.40)	(-0.04)	(1.04)
S&P 500 Returns$_{t-5}$	0.00002	-0.00001	-0.00002	0.00010	0.00322
	(0.79)	(-0.19)	(-0.61)	(1.34)	(0.86)

This table provides Vector Autoregressive (VAR) Model Parameter Estimates of the SP500 stock returns on investor emotions to its five day lag. The sample period comprised 2450 trading days from January 1, 1998, to December 31, 2014.The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the stock return data in the table come from Global Finance database. Among the variables, MP_FEAR is the daily market-level fear; MP_JOY is the daily market-level joy; MP_GLOOM is the daily market-level gloom; MP_STRESS is the daily market-level stress; LogVolume is the log of the daily NYSE trading volume; and Spr is the log of the daily SP500 index returns. In the table, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 4. Predicting S&P 500 Returns Using Changes in Sentiment Measures

	S&P 500 Returns					
Emotional Indicators	cMP_FEAR	cMP_GLOOM	cMP_JOY	cMP_STRESS	LogVolume	Spr
Investor Emotions $_{t-1}$	-3.40856	3.74980	12.73912	-11.57809*	-0.10443	-0.01365
	(-0.16)	(0.53)	(0.72)	(-1.85)	(-0.93)	(-0.66)
Investor Emotions $_{t-2}$	49.19478**	-6.14296	10.91673	-8.07179	0.05331	0.01800
	(2.14)	(-0.85)	(0.60)	(-1.24)	(0.45)	(0.84)
Investor Emotions $_{t-3}$	9.18601	8.74953	15.36164	1.05858	0.04567	-0.01087
	(0.40)	(1.20)	(0.84)	(0.16)	(0.38)	(-0.51)
Investor Emotions $_{t-4}$	45.59842**	-3.08257	19.80056	3.88275	0.02626	0.03771*
	(1.99)	(-0.43)	(1.09)	(0.60)	(0.22)	(1.77)
Investor Emotions $_{t-5}$	-17.26032	-7.26326	21.48029	-8.15370	-0.12058	0.03096
	(-0.79)	(-1.03)	(1.23)	(-1.30)	(-1.06)	(1.46)

This table provides Vector Autoregressive (VAR) Model Parameter Estimates of the SP500 stock returns on investor emotions to its five day lag. The sample period comprised 2450 trading days from January 1, 1998, to December 31, 2014.The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the stock return data in the table come from Global Finance database. Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_JOY is the daily change of market-level joy; cMP_GLOOM is the daily change of market-level gloom; cMP_STRESS is the daily change of market-level stress; LogVolume is the log of the daily NYSE trading volume; and Spr is the log of the daily SP500 index returns. In the table, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 5. Feedback Effects of S&P 500 Returns on Changes in Sentiment Measures

Emotional Indicators	cMP_FEAR	cMP_GLOOM	cMP_JOY	cMP_STRESS	LogVolume
S&P 500 Returns$_{t-1}$	-0.00017***	-0.00035***	0.00011***	-0.00033***	-0.02440***
	(-8.44)	(-5.57)	(4.53)	(-4.50)	(-6.56)
S&P 500 Returns$_{t-2}$	-0.00002	0.00001	0.00001	0.00001	-0.00903**
	(-0.92)	(0.11)	(0.31)	(0.19)	(-2.36)
S&P 500 Returns$_{t-3}$	0.00000	0.00002	-0.00000	0.00001	-0.00485
	(0.07)	(0.26)	(-0.04)	(0.19)	(-1.27)
S&P 500 Returns$_{t-4}$	-0.00002	-0.00007	0.00000	-0.00012	0.00269
	(-0.75)	(-1.06)	(0.11)	(-1.58)	(0.71)
S&P 500 Returns$_{t-5}$	-0.00002	0.00002	0.00001	0.00001	0.00258
	(-1.08)	(0.39)	(0.23)	(0.14)	(0.68)

This table provides Vector Autoregressive (VAR) Model Parameter Estimates of the SP500 stock returns on investor emotions to its five day lag. The sample period comprised 2450 trading days from January 1, 1998, to December 31, 2014.The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the stock return data in the table come from Global Finance database. Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_JOY is the daily change of market-level joy; cMP_GLOOM is the daily change of market-level gloom; cMP_STRESS is the daily change of market-level stress; LogVolume is the log of the daily NYSE trading volume; and Spr is the log of the daily SP500 index returns. In the table, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 6. Stock Returns on Sentiment Level Measures

	INTERCEPT	cFEAR	cGLOOM	cJOY	cSTRESS	Lagged spr	TARCHA0	TARCHA1	TARCHB1	TGARCH1	R^2
FEAR EFFECT	0.2655**	-32.3873***				-0.0458***	0.0269***	0.0425***	0.1145***	0.8800***	0.0102
	(3.57)	(-3.38)				(-2.09)	(5.41)	(3.80)	(7.63)	(78.39)	
GLOOM EFFECT	0.3877***		-9.8992***			-0.0435***	0.0258***	0.0414***	0.1161***	0.8816***	0.0097
	(4.14)		(-3.98)			(-2.00)	(5.34)	(3.74)	(7.92)	(79.77)	
JOY EFFECT	-0.1650*			16.2062***		-0.0383**	0.0308***	0.0306***	0.1288***	0.8785***	0.0069
	(-2.14)			(2.78)		(-1.75)	(6.24)	(2.67)	(8.15)	(80.50)	
STRESS EFFECT	0.6923***				-9.2603***	-0.0436**	0.0275***	0.0407***	0.1180***	0.8793***	0.0132
	(3.93)				(-3.79)	(-1.99)	(5.50)	(3.57)	(7.82)	(77.54)	
MULTIPLE	0.5228***	-13.7909	-15.7167***	46.5798***	-5.9596***	-0.0626***	0.0256***	0.0417***	0.1205***	0.8794***	0.0312
EMOTIONS' EFFECT	(2.93)	(-1.07)	(-4.11)	(6.61)	(-1.90)	(-2.91)	(5.15)	(3.57)	(7.58)	(78.38)	

This table provides Threshold GARCH (TGARCH) Estimates of the SP500 stock returns on different models of the investor emotions. The sample period comprised 2450 trading days from January 1, 1998, to December 31, 2014. The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the stock return data in the table come from Global Finance database. Among the variables, MP_FEAR is the daily change of market-level fear; MP_GLOOM is the daily change of market-level gloom; MP_JOY is the daily change of market-level joy; MP_STRESS is the daily change of market-level stress; and Spr is the daily log-returns of the SP500. In the table, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 7. Stock Returns on Changes in Sentiment Measures

	INTERCEPT	cFEAR	cGLOOM	cJOY	cSTRESS	Lagged spr	TARCHA0	TARCHA1	TARCHB1	TGARCH1	R^2
FEAR EFFECT	0.0457**	-95.2792***				-0.0534***	0.0285***	0.0358***	0.1211***	0.8800***	0.0197
	(2.43)	(-6.73)				(-2.44)	(5.80)	(3.20)	(7.92)	(81.35)	
GLOOM EFFECT	0.0549***		-27.2520***			-0.0448***	0.0289***	0.0360***	0.1214***	0.8793***	0.0137
	(2.89)		(-5.64)			(-2.05)	(5.76)	(3.17)	(8.03)	(78.84)	
JOY EFFECT	0.0322*			62.1722***		-0.0412**	0.0303***	0.0377***	0.1212***	0.8764***	0.0156
	(1.69)			(5.45)		(-1.89)	(5.92)	(3.21)	(7.75)	(79.18)	
STRESS EFFECT	0.0503***				-26.6205***	-0.0436**	0.0288***	0.0375***	0.1205***	0.8780***	0.0208
	(2.67)				(-6.58)	(-2.03)	(5.84)	(3.30)	(8.02)	(78.91)	
MULTIPLE	0.0589***	-74.9378***	-17.8333***	43.0263***	-17.2930***	-0.0636***	0.0296***	0.0422***	0.1187***	0.8731***	0.0422
EMOTIONS' EFFECT	(3.09)	(-5.19)	(-3.55)	(3.61)	(-4.05)	(-2.95)	(5.67)	(3.37)	(7.48)	(73.98)	

This table provides Threshold GARCH (TGARCH) Estimates of the SP500 stock returns on different models of the investor emotions. The sample period comprised 2450 trading days from January 1, 1998, to December 31, 2014. The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the stock return data in the table come from Global Finance database. Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_GLOOM is the daily change of market-level gloom; cMP_JOY is the daily change of market-level joy; cMP_STRESS is the daily change of market-level stress; and Spr is the daily log-returns of the SP500. In the table, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 8. Robustness Check with VIX

	INTERCEPT	cFEAR	VIX	Lagged spr	TARCHA0	TARCHA1	TARCHB1	TGARCH1	R^2
AICMULTIPLE	0.3531***	-96.0859***	-0.0175***	-0.0661***	0.0180***	0.0521***	0.0927***	0.8925***	0.0485
EMOTIONS' EFFECT	(6.58)	(-6.90)	(-6.95)	(-3.09)	(3.94)	(4.75)	(6.73)	(82.07)	

This table provides Threshold GARCH (TGARCH) Estimates of the SP500 stock returns on different models of the investor emotions. The sample period comprised 2450 trading days from January 1, 1998, to December 31, 2014. The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the stock return data in the table come from Global Finance database. Among the variables, cMP_FEAR is the daily change of market-level fear; VIX is CBOE S&P 500 Volatility Index and Spr is the daily log-returns of the SP500. In the table, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 9. Descriptive Statistics and Correlations

Panel A	cMP_FEAR	cMP_GLOOM	cMP_JOY	cMP_OPTIMSM	Fspr	TNFR
N	2394	2394	2394	2394	2394	2394
Mean	0.0000828	0.0005796	0.0001209	-0.0005519	0.00662	0.00181
Std Dev	0.00123	0.00379	0.00152	0.00646	1.24110	0.41856
Sum	0.19824	1.38751	0.28934	-1.32135	15.84985	4.33180
Minimum	-0.00492	-0.01617	-0.00555	-0.03172	-10.39979	-2.17672
Maximum	0.00775	0.02309	0.00889	0.03041	6.15684	3.53665

Panel B	cMP_FEAR	cMP_GLOOM	cMP_JOY	cMP_OPTIMSM	Fspr	TNFR
cMP_FEAR	1.00000					
cMP_GLOOM	0.16501***	1.00000				
	(<.0001)					
cMP_JOY	-0.10139***	-0.17623***	1.00000			
	(<.0001)	(<.0001)				
cMP_OPTIMSM	-0.17634***	-0.38146***	0.25796***	1.00000		
	(<.0001)	(<.0001)	(<.0001)			
Fspr	-0.11989***	-0.09135***	0.10785***	0.12936***	1.00000	
	(0.8729)	(0.1394)	(0.6822)	(<.0001)		
TNFR	0.08149***	0.06338***	-0.03733*	-0.09520***	-0.20821***	1.00000
	(<.0001)	(0.0019)	(0.0678)	(<.0001)	(<.0001)	

This table provides summary statistics (Panel A) and correlation coefficients (Panel B) for the full sample of 2394 daily observations from January 1, 1998, to December 31, 2014. The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the SP500 index futures returns in the table are calculated based on SP500 index futures last price data from Global Finance database. Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_GLOOM is the daily change of market-level gloom; cMP_JOY is the daily change of market-level joy; cMP_OPTIMSM is the daily change of market-level optimism; FSpr is the log of the daily SP500 index futures returns, and TNFR is the log of the daily 10 yr T Notes futures returns. In Panel B, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 10. Predicting S&P 500 Index Futures Returns Using Sentiment Measures

	S&P 500 Index Futures Returns					
Emotional Indicators	cMP_FEAR	cMP_GLOOM	cMP_JOY	cMP_OPTIMSM	SPFvol	Fspr
Investor Emotions$_{t-1}$	-16.08740	-0.44477	14.54922	-6.72777	-0.09480	0.01976
	(-0.72)	(-0.06)	(0.80)	(-1.47)	(-1.31)	(0.94)
Investor Emotions$_{t-2}$	56.38718**	0.43488	15.73524	3.83487	0.07915	0.02393
	(2.43)	(0.06)	(0.84)	(0.81)	(0.89)	(1.12)
Investor Emotions$_{t-3}$	30.86324	5.52049	22.05897	1.59606	-0.02500	0.00114
	(1.32)	(0.71)	(1.17)	(0.34)	(-0.28)	(0.05)
Investor Emotions$_{t-4}$	48.22703**	-6.37450	9.37863	0.45064	0.04419	0.03332
	(2.08)	(-0.82)	(0.50)	(0.10)	(0.49)	(1.56)
Investor Emotions$_{t-5}$	-35.69400	-9.80402	15.65306	-2.64639	-0.03239	0.04673**
	(-1.61)	(-1.30)	(0.87)	(-0.58)	(-0.44)	(2.20)

This table provides Vector Autoregressive (VAR) Model Parameter Estimates of the SP500 index futures returns on investor sentiment measures to its five day lag. The sample period comprised 2394 trading days from January 1, 1998, to December 31, 2014. The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the SP500 index futures returns and volume in the table are calculated based on SP500 index futures last price and trading volume data from Global Finance database. Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_GLOOM is the daily change of market-level gloom; cMP_JOY is the daily change of market-level joy; cMP_OPTIMSM is the daily change of market-level optimism; SPFvol is the log of the daily SP500 index futures trading volume; and FSpr is the log of the daily SP500 index futures returns. In the table, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 11. Feedback Effects of S&P 500 Index Futures Returns on Sentiment Measures

Emotional Indicators	cMP_FEAR	cMP_GLOOM	cMP_JOY	cMP_OPTIMISM	SPFVolume
S&P 500 Futures Returns $_{t-1}$	-0.00015***	-0.00035***	0.00010***	0.00036***	-0.02147***
	(-7.40)	(-5.59)	(3.89)	(3.40)	(-3.60)
S&P 500 Futures Returns $_{t-2}$	-0.00003	-0.00004	0.00000	0.00016	0.00333**
	(-1.43)	(-0.63)	(0.11)	(1.48)	(0.55)
S&P 500 Futures Returns $_{t-3}$	-0.00001	-0.00004	0.00002	0.00020*	0.00085
	(-0.43)	(-0.58)	(0.98)	(1.83)	(0.14)
S&P 500 Futures Returns $_{t-4}$	-0.00001	-0.00009	-0.00001	0.00021*	0.00138
	(-0.42)	(-1.50)	(-0.57)	(1.95)	(0.23)
S&P 500 Futures Returns $_{t-5}$	-0.00001	-0.00003	0.00003	-0.00003	-0.00010
	(-0.27)	(-0.42)	(1.34)	(-0.29)	(-0.02)

This table provides Vector Autoregressive (VAR) Model Parameter Estimates of the SP500 index futures returns on investor sentiment measures to its five day lag. The sample period comprised 2394 trading days from January 1, 1998, to December 31, 2014. The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the SP500 index futures returns and volume in the table are calculated based on SP500 index futures last price and trading volume data from Global Finance database. Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_GLOOM is the daily change of market-level gloom; cMP_JOY is the daily change of market-level joy; cMP_OPTIMSM is the daily change of market-level optimism; SPFvol is the log of the daily SP500 index futures trading volume; and FSpr is the log of the daily SP500 index futures returns. In the table, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 12. Predicting 10 Year Treasury Notes Futures Returns Using Sentiment Measures

	10 Year Treasury Notes Futures Returns					
Emotional Indicators	cMP_FEAR	cMP_GLOOM	cMP_JOY	cMP_OPTIMSM	TNFvol	TNFR
Investor Emotions$_{t-1}$	-10.37938	-0.36189	-2.13693	2.37263	0.00457	0.00955
	(-1.40)	(-0.14)	(-0.35)	(1.54)	(0.44)	(0.46)
Investor Emotions$_{t-2}$	4.40126	-2.18343	-13.47598**	0.09963	0.02241*	0.00980
	(0.57)	(-0.84)	(-2.14)	(0.06)	(1.66)	(0.47)
Investor Emotions$_{t-3}$	7.39857	1.17567	1.87669	0.72535	-0.00368	-0.02349
	(0.96)	(0.45)	(0.30)	(0.45)	(-0.27)	(-1.13)
Investor Emotions$_{t-4}$	-1.84538	3.75788	1.22194	2.91810*	-0.01108	0.03287
	(-0.24)	(1.44)	(0.20)	(1.83)	(-0.82)	(1.58)
Investor Emotions$_{t-5}$	3.44923	-0.23499	-4.80600	0.39160	0.00088	0.02657
	(0.46)	(-0.09)	(-0.79)	(0.25)	(0.08)	(1.29)

This table provides Vector Autoregressive (VAR) Model Parameter Estimates of the 10 year Treasury Notes futures returns on investor sentiment measures to its five day lag. The sample period comprised 2394 trading days from January 1, 1998, to December 31, 2014. The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the 10 year Treasury Notes futures returns and volume in the table are calculated based on 10 year Treasury Notes futures last price and trading volume data from Global Finance database. Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_GLOOM is the daily change of market-level gloom; cMP_JOY is the daily change of market-level joy; cMP_OPTIMSM is the daily change of market-level optimism; TNFvol is the log of the daily 10 year Treasury Notes futures trading volume; and TNFR is the log of the daily 10 year Treasury Notes futures returns. In the table, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 13. Feedback Effects of 10 Year Treasury Notes Futures Returns Using Sentiment Measures

Emotional Indicators	cMP_FEAR	cMP_GLOOM	cMP_JOY	cMP_OPTIMISM	TNFVolume
10 Year Treasury Futures Returns$_{t-1}$	0.00011*	0.00026	-0.00002	-0.00032	0.01912
	(1.84)	(1.39)	(-0.23)	(-1.03)	(0.46)
10 Year Treasury Futures Returns$_{t-2}$	-0.00005	-0.00014	-0.00000	-0.00047	0.04140
	(-0.84)	(-0.78)	(-0.06)	(-1.49)	(0.99)
10 Year Treasury Futures Returns$_{t-3}$	0.00005	-0.00005	0.00007	0.00016	0.04406
	(0.81)	(-0.30)	(1.00)	(0.50)	(1.06)
10 Year Treasury Futures Returns$_{t-4}$	-0.00003	-0.00012	0.00003	0.00006	-0.03904
	(-0.48)	(-0.65)	(0.39)	(0.20)	(-0.94)
10 Year Treasury Futures Returns$_{t-5}$	0.00002	0.00014	0.00000	-0.00023	-0.04896
	(0.28)	(0.79)	(0.00)	(-0.74)	(-1.19)

This table provides Vector Autoregressive (VAR) Model Parameter Estimates of the 10 year Treasury Notes futures returns on investor sentiment measures to its five day lag. The sample period comprised 2394 trading days from January 1, 1998, to December 31, 2014. The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the 10 year Treasury Notes futures returns and volume in the table are calculated based on 10 year Treasury Notes futures last price and trading volume data from Global Finance database. Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_GLOOM is the daily change of market-level gloom; cMP_JOY is the daily change of market-level joy; cMP_OPTIMSM is the daily change of market-level optimism; TNFvol is the log of the daily 10 year Treasury Notes futures trading volume; and TNFR is the log of the daily 10 year Treasury Notes futures returns. In the table, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 14. Investor Emotions and Futures Returns

Panel A. S&P 500 Index Futures Returns

INTERCEPT	cFEAR	cGLOOM	cJOY	cOPTIMSM	SPFVol	Fspr(-1)	TARCHA0	TARCHA1	TARCHB1	TGARCH1
0.4876**	-78.9843***	-14.6736***	36.8816***	10.8474***	-0.0429*	-0.0455**	0.0293***	0.0575***	0.1093***	0.8666***
(2.01)	(-5.35)	(-2.69)	(2.93)	(3.31)	(-1.88)	(-2.11)	(5.13)	(4.30)	(6.37)	(67.80)
R-Square: 0.0367	AIC: 6932.54058	Normality Test: 170.4579	Pr > ChiSq: <.0001							

Panel B. 10 Yr Treasury Notes Futures Returns

INTERCEPT	cFEAR	cGLOOM	cJOY	cOPTIMSM	TNFVol	TNFR (-1)	TARCHA0	TARCHA1	TARCHB1	TGARCH1
0.005203	13.3370**	3.1609	2.8726	-4.5367***	-0.000822	0.0224	0.001604***	0.0504***	-0.0128	0.9480***
(0.08)	(2.07)	(1.40)	(0.55)	(-3.46)	(-0.17)	(1.22)	(4.49)	(5.93)	(-1.42)	(147.09)
R-Square: 0.0136	AIC: 2384.50476	Normality Test: 619.9079	Pr > ChiSq: <.0001							

This table provides Threshold GARCH (TGARCH) Estimates of the SP500 index futures returns and 10 Year Treasury Notes Futures Returns on the investor emotions separately. The sample period comprised 2394 trading days from January 1, 1998, to December 31, 2014. Panel A provide an investor emotion model SP500 index futures returns. The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), the SP500 index futures returns and volume in the table are calculated based on SP500 index futures last price and trading volume data from Global Finance database, and the 10 year Treasury Notes futures returns and volume in the table are calculated based on 10 year Treasury Notes futures last price and trading volume data from Global Finance database. Panel A shows correlations between market emotion indicators and SP500 index futures returns in a T-GARCH Model. Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_GLOOM is the daily change of market-level gloom; cMP_JOY is the daily change of market-level joy; cMP_OPTIMSM is the daily change of market-level optimism; SPFvol is the log of the daily SP500 index futures trading volume; and FSpr is the log of the daily SP500 index futures returns. Panel B shows correlations between market emotion indicators and 10 year Treasury Notes futures returns in a T-GARCH Model. Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_GLOOM is the daily change of market-level gloom; cMP_JOY is the daily change of market-level joy; cMP_OPTIMSM is the daily change of market-level optimism; TNFvol is the log of the daily 10 year Treasury Notes futures trading volume; and TNFR is the log of the daily 10 year Treasury Notes futures returns. In the table, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 15. Robustness Check with VIX

Panel A. S&P 500 Index Futures Returns

INTERCEPT	cFEAR	VIX	Fspr(-1)	TARCHA0	TARCHA1	TARCHB1	TGARCH1
0.3291***	-95.2309***	-0.0169***	-0.0481**	0.0184***	0.0609***	0.0830***	0.8891***
(5.86)	(-6.69)	(-6.34)	(-2.30)	(3.82)	(5.12)	(5.97)	(77.90)
	R-Square: 0.0449	AIC: 6940.28188	Normality Test: 114.5527		Pr > ChiSq: <.0001		

Panel B. 10 Yr Treasury Notes Futures Returns

INTERCEPT	cFEAR	VIX	TNFR (-1)	TARCHA0	TARCHA1	TARCHB1	TGARCH1
-0.0389**	18.8123***	0.001881**	0.0221	0.001557***	0.0415***	0.000981	0.9498***
(-2.14)	(2.97)	(2.53)	(1.21)	(4.59)	(5.29)	(0.11)	(157.00)
	R-Square: 0.0074	AIC: 2394.80662	Normality Test: 582.5651		Pr > ChiSq: <.0001		

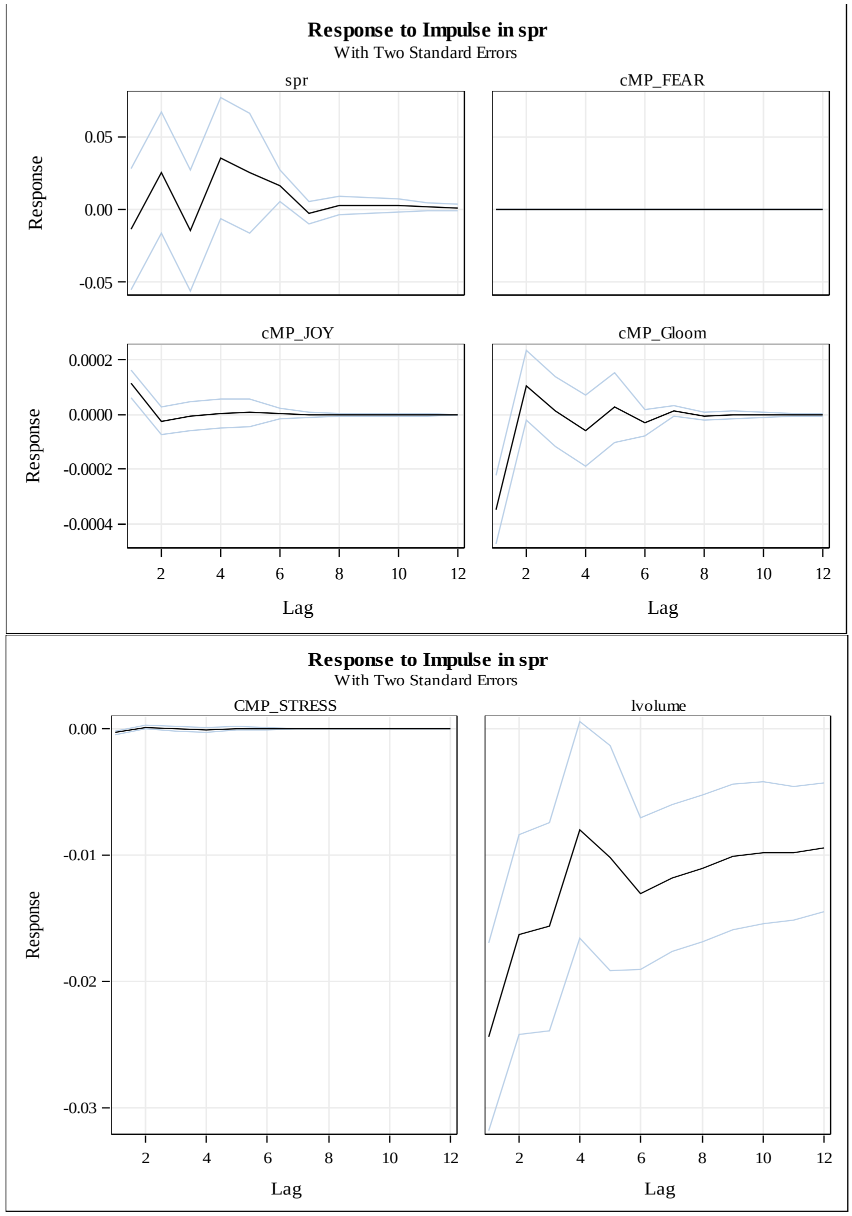
This table provides Threshold GARCH (TGARCH) Estimates of the SP500 index futures returns and 10 Year Treasury Notes Futures Returns on the alternative measures of investor emotions separately as robustness check. The sample period comprised 2394 trading days from January 1, 1998, to December 31, 2014. Panel A provide an investor emotion model SP500 index futures returns. The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), the SP500 index futures returns and 10 year Treasury Notes futures returns calculated based on the SP500 index futures and 10 year Treasury Notes futures last prices and VIX data in the table come from Global Finance database. Panel A shows correlations between market emotion indicators and SP500 index futures returns in a T-GARCH Model. Among the variables, cMP_FEAR is the daily change of market-level fear; VIX is CBOE S&P 500 Volatility Index; and FSpr is the log of the daily SP500 index futures returns. Panel B shows correlations between market emotion indicators and 10 year Treasury Notes futures returns in a T-GARCH Model. Among the variables, cMP_FEAR is the daily change of market-level fear; VIX is CBOE S&P 500 Volatility Index; and TNFR is the log of the daily 10 year Treasury Notes futures returns. In the table, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 16. Fear, Optimism and Volatility Transmission in Futures Markets

Fspr					TNFR				
CONST1	cFEAR(t)	cMP_OPTIMSM(t)	Fspr(t-1)	TNFR(t-1)	CONST2	cFEAR(t)	cMP_OPTIMSM(t)	Fspr(t-1)	TNFR(t-1)
0.06214***	-98.92317***	14.51096***	0.02561	-0.03608	-0.00931	22.43430***	-3.90169***	0.00544	0.00412
(3.48)	(-6.25)	(5.01)	(1.20)	(-0.75)	(-1.26)	(3.57)	(-3.32)	(0.78)	(0.20)
VARMA-GARCH (1,1) Parameter Estimates									
DCCA	DCCB	GCHC1_1	GCHC2_2	ACH1_1_1	ACH1_2_2	GCH1_1_1	GCH1_2_2		
0.03769***	0.94728***	0.02805***	0.00157	0.12304***	0.04050***	0.86060***	0.95113***		
(5.28)	(86.37)	(4.06)	(n/a)	(8.34)	(5.15)	(52.86)	(99.04)		
AIC: -1.36207	HQC: -1.35504								

This table provides VARMA-GARCH (1,1) Estimates of investor emotions and volatility transmission between the SP500 index and 10 Year Treasury Notes Futures. The sample period comprised 2394 trading days from January 1, 1998, to December 31, 2014. The change of fear and change of optimism in the table are calculated based on fear index and optimism index from the Thomson Reuters MarketPsych Indices (TRMI), the SP500 index futures returns and 10 year Treasury Notes futures returns in the table are calculated based on the SP500 index futures last price and 10 year Treasury Notes futures last price from Global Finance database. Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_OPTIMSM is the daily change of market-level optimism; FSpr is the log of the daily SP500 index futures returns; and TNFR is the log of the daily 10 year Treasury Notes futures returns. In the table, * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Figure 1. Impulse Response Functions of the Stock Return



This figure provides response to impulse of the SP500 stock returns and investor emotions to its five day lag. The sample period comprised 2453 trading days from January 1, 1998, to December 31, 2014.The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the stock return data in the table come from Global Finance database. Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_GLOOM is the daily change of market-level gloom; cMP_JOY is the daily change of market-level joy; cMP_STRESS is the daily change of market-level stress; LVolume is the log of the daily NYSE trading volume; and Spr is the daily log-returns of the SP500.

Figure 2. Impulse Response Functions of the Market Fears

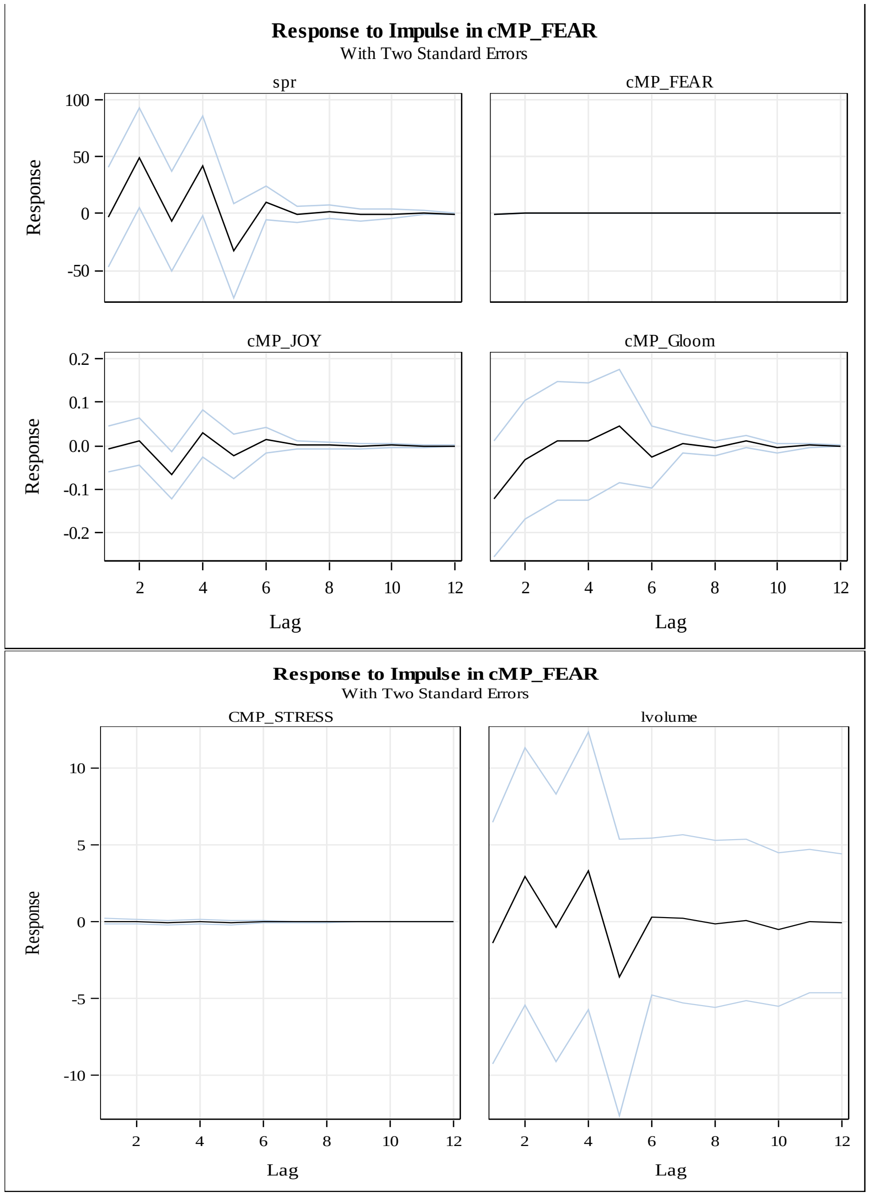


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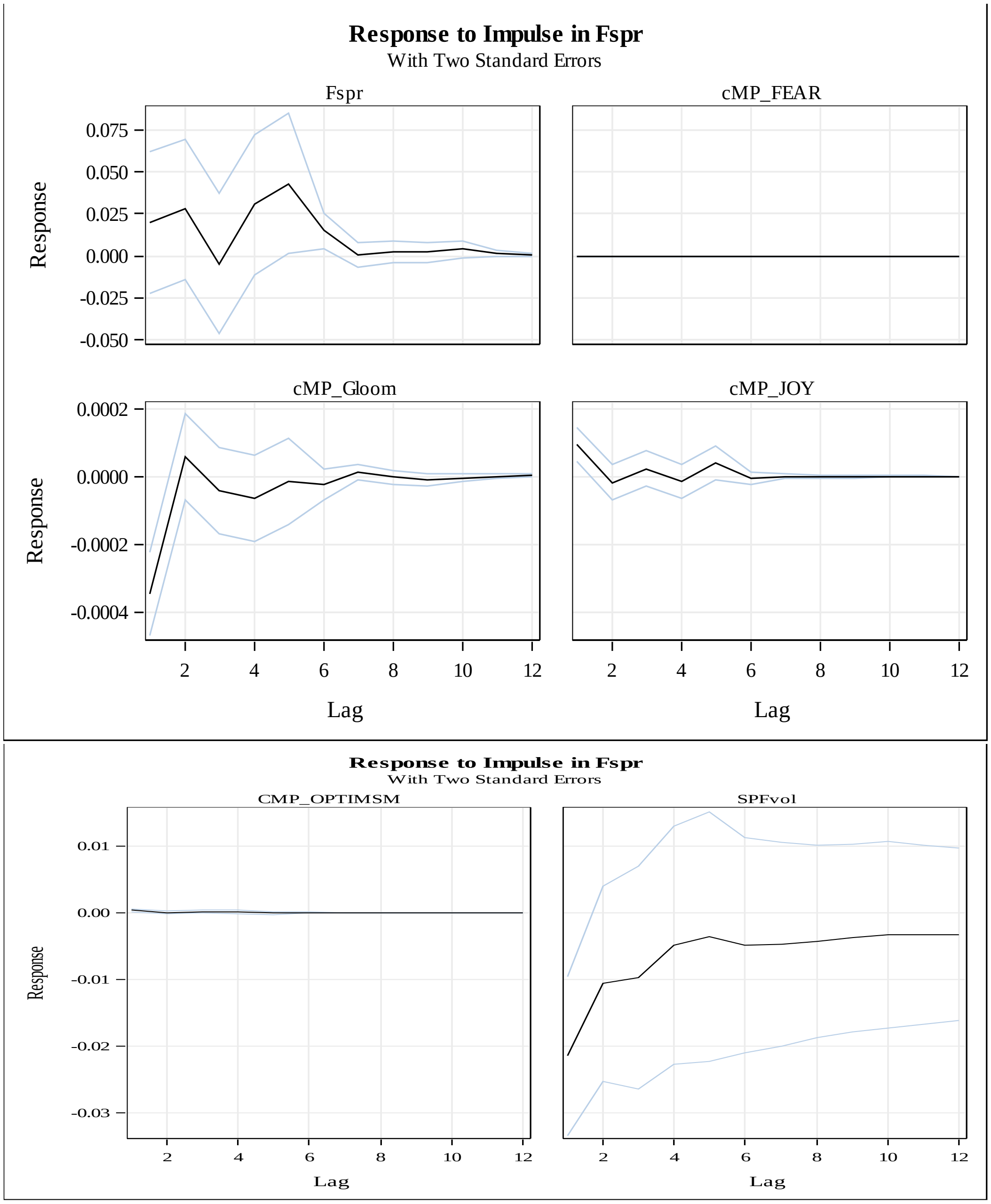
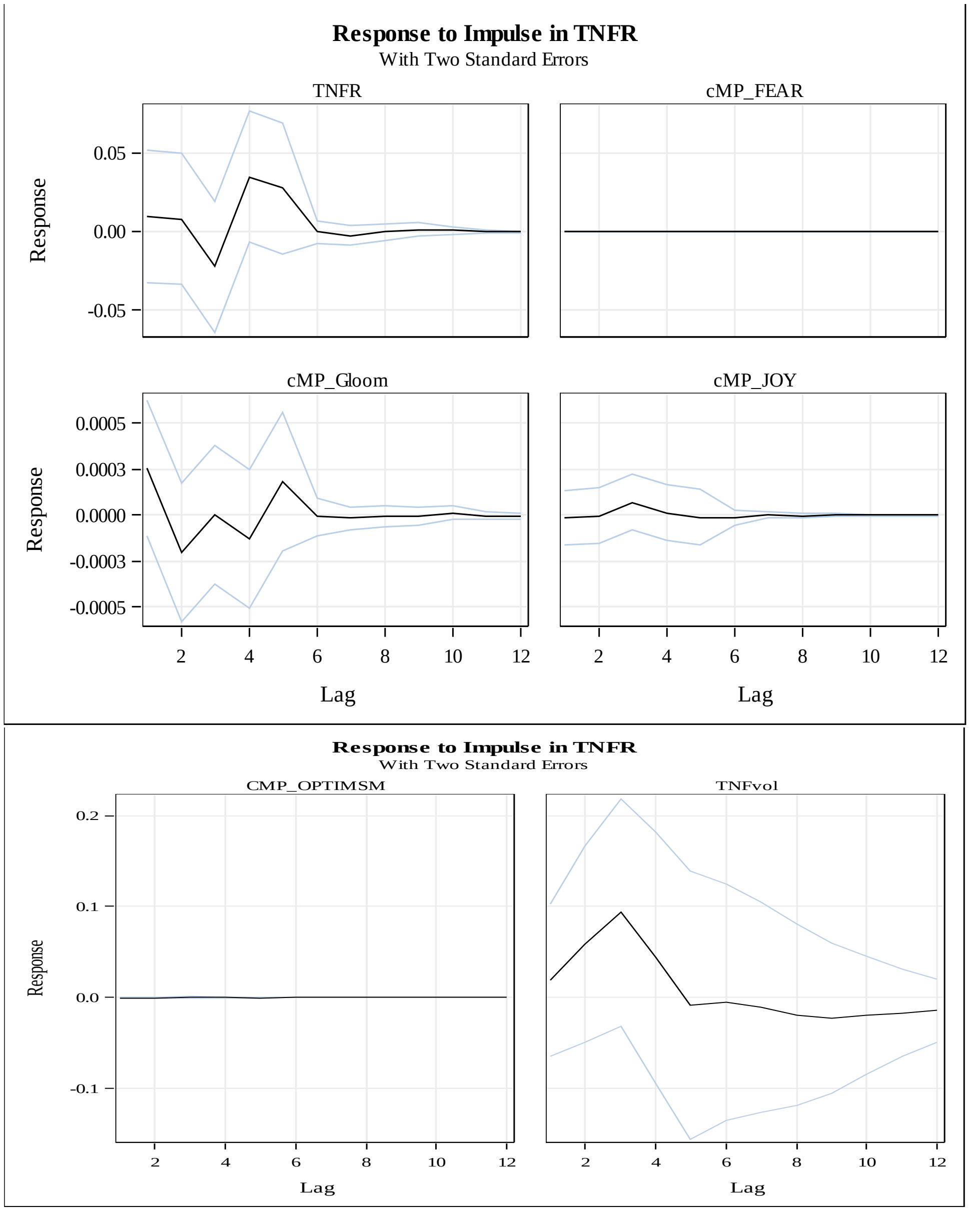
Figure 3. Response to Impulse in SP500 index futures returns



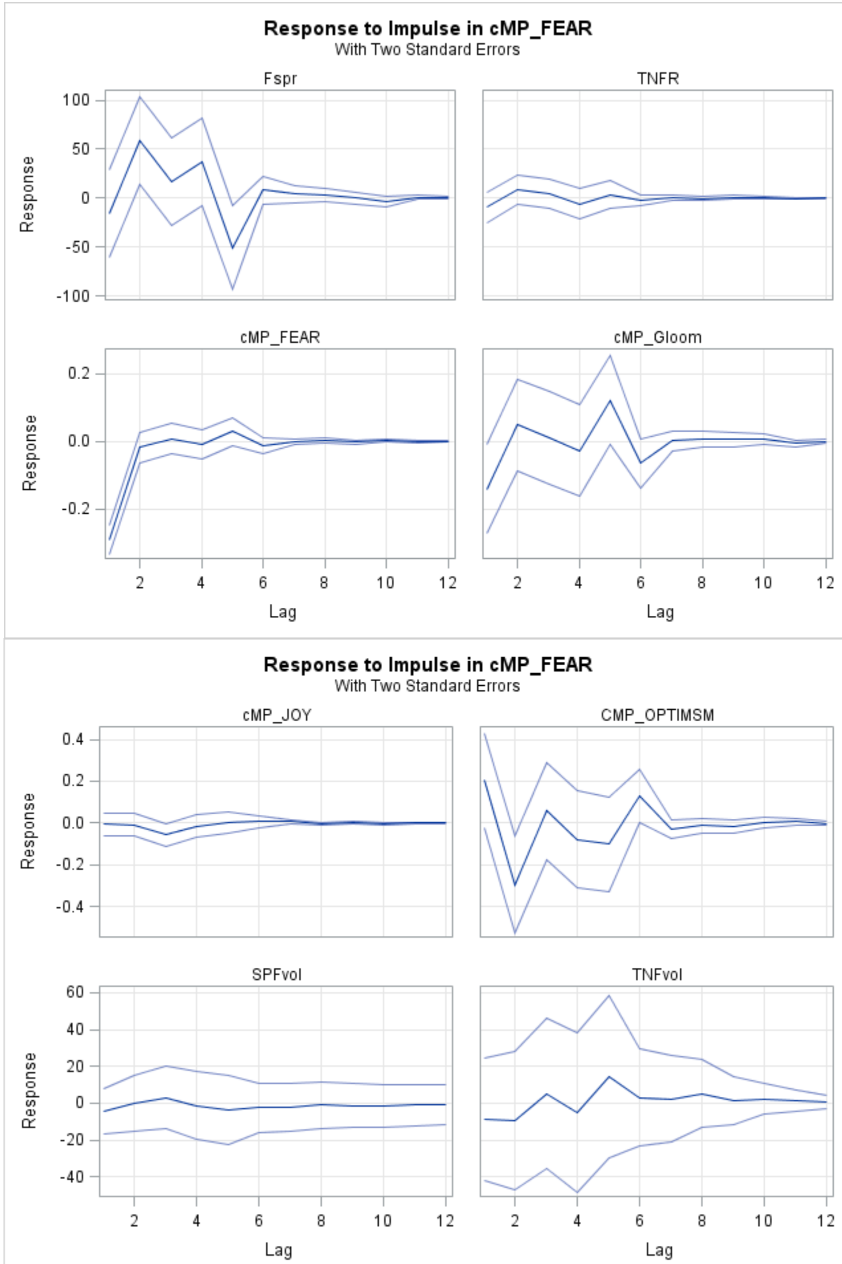
This figure provides response to impulse in SP500 index futures returns its twelve day lag. The sample period comprised 2394 trading days from January 1, 1998, to December 31, 2014. The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the SP500 index futures returns and volume in the table are calculated based on SP500 index futures last price and trading volume data from Global Finance database. Among the variables, Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_GLOOM is the daily change of market-level gloom; cMP_JOY is the daily change of market-level joy; cMP_OPTIMSM is the daily change of market-level optimism; SPFvol is the log of the daily SP500 index futures trading volume; and FSpr is the log of the daily SP500 index futures returns.

Figure 4. Response to Impulse in 10 Year Treasury Notes Futures Returns



This figure provides response to impulse in 10 Year Treasury Notes Futures Returns its twelve day lag. The sample period comprised 2394 trading days from January 1, 1998, to December 31, 2014. The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the 10 Year Treasury Notes Futures Returns and volume in the table are calculated based on 10 Year Treasury Notes Futures last price and trading volume data from Global Finance database. Among the variables, Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_GLOOM is the daily change of market-level gloom; cMP_JOY is the daily change of market-level joy; cMP_OPTIMSM is the daily change of market-level optimism; TNFvol is the log of the daily 10 year Treasury Notes futures trading volume; and TNFR is the log of the daily 10 year Treasury Notes futures returns.

Figure 5. Impulse Response Functions of the Market Fears



This figure provides response to impulse in SP500 index futures returns its twelve day lag. The sample period comprised 2394 trading days from January 1, 1998, to December 31, 2014. The emotion indicators' data in the table come from the Thomson Reuters MarketPsych Indices (TRMI), and the SP500 index futures returns and volume in the table are calculated based on SP500 index futures last price and trading volume data from Global Finance database. Among the variables, Among the variables, cMP_FEAR is the daily change of market-level fear; cMP_GLOOM is the daily change of market-level gloom; cMP_JOY is the daily change of market-level joy; cMP_OPTIMSM is the daily change of market-level optimism; SPFvol is the log of the daily SP500 index futures trading volume; FSpr is the log of the daily SP500 index futures returns; TNFvol is the log of the daily 10 year Treasury Notes futures trading volume; and TNFR is the log of the daily 10 year Treasury Notes futures returns.

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RESEARCH PAPERS

- "Do Investors Infer Vocal Cues from CEOs During Quarterly REIT Conference Calls?" with S. Price, M. Seiler, *Journal of Real Estate Finance & Economics*, Forthcoming.
- "Stock Return Predictability and Investor Sentiment: A High Frequency Perspective" with L. Sun, M. Najand, *revise and resubmit at Journal of Banking & Finance.*
- "Emotion at Work on Big Data Analytics: Using Media-Based Emotion for Predicting Commodity Price." with F. Dong, W. He, *under review at Journal of Business Research.*
- "The Interdependence between the US and China: Do US Business Cycles Have a Significant Impact on Chinese Business Cycles?" with D. Selover, *under revision.*
- "Social Media-Based Forecasting: A Case Study of Tweets and Stock Prices in the Financial Services Industry." with W. He, L. Guo, V. Akula, *Journal of Organizational & End User Computing,* Forthcoming.
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