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Positive Feedback Trading and Investor Sentiment

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Abstract

This article examines how investor sentiment affects positive feedback trading behavior. By analyzing the daily closing total return of CSI 300 index and its individual returns of stocks, we find that relatively high or low sentiment induces active positive feedback trading. With a specific indicator of sentiment, we explain the microstructure setting of the relationship between positive feedback trading and sentiment. We adopt the classical feedback model from Sentana and Wadhwani (1992) to measure positive feedback trading behavior. By adding sentiment factor to the model, we successfully explain how sentiment influences the behavior of both feedback traders and rational investors. The empirical findings suggest that positive feedback traders are more likely to trade when the prices of most securities move forward together. When the sentiment of feedback traders is at an intermediate level, the feedback trading behavior is insignificant.

Keywords: Investor sentiment; Positive feedback trading; Chinese stock market; GARCH-M
1. Introduction

Recent studies have provided a growing body of empirical evidence that the sentiment of market participants can significantly affect asset returns in real-world financial markets (Baker and Wurgler 2006, 2007; Baker, Wurgler, and Yuan 2012; Greenwood and Shleifer 2014; Smales 2014; Yu and Yuan 2011). Both academics and practitioners have been attracted to continually digging up the abnormal features of the cross-sectional variation of return (Kelly and Tetlock 2013; Yao, Ma, and He 2014) and searching for the perfect indicator of sentiment for the purpose of prediction (Baker and Stein 2004; Frazzini and Lamont 2008; Simon and Wiggins 2001; Stambaugh, Yu, and Yuan 2012).

Investor sentiment, defined broadly, is a belief or an expectation about the future discounted cash flow and risk that is not justified by the information at hand. In real financial markets, there are different types of traders, who may have different kinds of beliefs corresponding to different trading strategies and behaviors. Apparently, a general sense of sentiment can hardly explain the mechanism of various kinds of investors’ behavior unambiguously. However, little research has focused on the relationship between sentiment and one specific type of investor.

We examine whether investor sentiment is related to a specific kind of trading behavior: positive feedback trading. Feedback trading refers to trading based on historical data. Positive feedback trading is a trading strategy that implies buying when prices rise and selling when they fall. A large number of studies have documented the existence of positive feedback trading around the world in both developed and emerging markets. However, without considering
investor sentiment, their research is incomplete and debatable. More recently, Kurov (2008) finds that there is a positive relationship between investor sentiment and positive feedback trading and notes that this relationship may increase market liquidity by reducing the transitory price fluctuations. Yang and Zhou (2015) examine the combined roles of investor trading behavior and investor sentiment on asset prices and find that both investor trading behavior and investor sentiment have significant effects on excess return beyond the three factors of Fama and French (1993). Following Kurov's (2008) approach, Hu et al. (2015) examine feedback trading behavior in a microstructure setting and find that positive feedback trading appears to increase in periods of rising sentiment.

The approach of this article differs from the previous literature in a few ways. First, the model used in this paper follows Sentana and Wadhwani (1992) in examining the significance of feedback trading existence rather than using a vector autoregression (VAR) of returns and order flow to measure feedback trading as Kurov (2008) did. By adding sentiment factor to the original model, we argue that the modified model makes more economical sense. Second, we use an individual indicator for investor sentiment of feedback trading and directly examine the relationship between the behavior and sentiment rather than via a created index as in Baker and Wurgler (2006). The motivation is that the specific indicator functions at specific points in the market cycle and aggregating several indicators into an overall index could dilute or obscure their individual information content. Our empirical result shows that positive feedback traders are more likely to trade when sentiment is relatively high or low. However, when the sentiment is near the average level, positive feedback trading is not active.

Our study contributes to the literature on two fronts. First, few studies examine feedback
trading behavior in a microstructure setting, although investor sentiment itself has been explored quite often in microstructure literature. Our document is one of the first to study the relationship between feedback trading behavior and sentiment. Second, we modify the classical feedback model by adding sentiment factor and use this modified model to estimate. The new model eliminates the contradiction between the classical empirical model and statement of De Long et al. (1990a). De Long et al. (1990a) believe that the positions of rational traders should be influenced by the behavior and sentiment of noise traders, but the classical feedback model fails to reflect that.

2. Sentiment indicator for feedback trading

This section describes the sentiment indicator of feedback trading. We call the proxy for this particular sentiment SFR. This measure is the ratio of the difference between the number of advancing issues (ADV) and declining issues (DEC) to the sum of these two kinds of issues:

$$SFR_t = \frac{ADV_t - DEC_t}{ADV_t + DEC_t}$$

Clearly, the value of SFR is within the range from -1 to 1. When SFR is close to 1, most individual stocks rise; when it is close to -1, most stocks fall. As feedback traders are incompletely rational, they lack the specialized knowledge to evaluate individual stocks. They assume that fluctuation of prices comes from either noise or “real risk”, and the movement of price out of real risk will continue. However, positive feedback traders cannot tell the difference between these situations. Nonetheless, they believe that when systematic risk comes, most stocks would rise or fall simultaneously. This trick may be useful for them to distinguish between noise
and information because systematic risk, such as adjusting the interest rate, often causes most securities to rise or fall simultaneously. Therefore, positive feedback traders take SFR as an indicator for systematic risk and increase their position when SFR is close to 1 or -1. They also prefer to trade with an increase in systematic risk because systematic risk erases the risk of selecting one or several stocks from many ones.

To eliminate the possible effect of the common market return component, we perform the following regression and obtain the residuals.

\[ SFR_t = a_0 + a_1 \times \text{Market}_t + \varepsilon_t \]  

(1)

Here, \( \text{Market}_t \) denotes the return of CSI 300 stock index. The residual \( \varepsilon_t \) is used as the sentiment of feedback trading (sentiment\(_t\)).

### 3. Methodology

#### 3.1. A feedback model with two types of investors

The assumption underpinning the model developed by Sentana and Wadhwani (1992) is that there are two types of investors. The first type, called smart-money investors, includes expected utility maximizers; the second type comprises positive feedback investors. Smart-money investors rely on fundamentals related to shares, and their behavior is characterized by risk aversion. This group is therefore assumed to hold a fraction of shares of the market portfolio, as given by

\[ Y_{1,t} = \frac{(E_{t-1}(R_t) - \alpha)}{\theta \sigma_t^2} \]  

(2)
where $Y_{1,t}$ represents the fraction of shares demanded by smart-money investors at time $t-1$; $R_t$ is the ex post return at $t$; $E_{t-1}$ is the expectation as of time $t-1$; $\alpha$ is the rate of return on a risk-free asset; $\sigma_t^2$ is the conditional variance at $t$; and $\theta$ is a fixed coefficient of risk aversion. Assuming that is positive, the product is the required risk premium at time $t$. The second type of investors follow a positive feedback strategy; thus, they buy (sell) after the price increases (decreases). Their demand function is given by

$$Y_{2,t} = \rho R_{t-1}$$

(3)

where $\rho > 0$. $\rho$ represents the sensitivity of demand to price changes by positive feedback traders. In equilibrium, all shares must be held; i.e., $Y_{1,t} + Y_{2,t} = 1$. It follows from Eq. (2) and Eq. (3) that

$$R_t = \alpha + \theta \sigma_t^2 - \theta \rho \sigma_t^2 R_{t-1}$$

(4)

The term $-\theta \rho \sigma_t^2 R_{t-1}$ in Eq. (4) implies that positive feedback trading will induce a negative autocorrelation in returns if is positive and significant.

3.2. A modified model

The model developed by Sentana and Wadhwani (1992), which is described in section 3.1, is often used to test the significance of feedback trading behavior. If is positive and significant, then the presence of positive feedback trading is confirmed. According to De Long et al. (1990a, 1990b), noise traders, including positive feedback traders, can create a risk in the price of the
asset that deters rational arbitrageurs from aggressively betting against them. Thus, prices can diverge significantly from fundamental values, even in the absence of fundamental risk, which reflects in the term $-\theta \rho \sigma_t^2 R_{t-1}$ in Eq. (4). The position of smart-money investors can also be influenced by the behaviors and sentiment of positive feedback trading. However, Eq. (2) does not include any term about feedback trading. This failure makes the model mentioned above incomplete. Based on this argument, we modify the original model by adding a sentiment term to Eq. (2)

$$Y_{t-1} = \frac{(E_{t-1}(R_t) - \alpha)}{\theta \sigma_t^2} + \frac{\gamma|R_{t-1}|sentiment_{t-1}}{\theta \sigma_t^2}$$  \hspace{1cm} (5)$$

The term $\frac{\gamma|R_{t-1}|sentiment_{t-1}}{\theta \sigma_t^2}$ is the difference between Eq. (2) and Eq. (5). $|R_{t-1}|$ represents the position of feedback traders; $sentiment_{t-1}$ is the sentiment of feedback traders relative to risk of this asset; and $\gamma$ is the coefficient of this term and represents the sensitivity of rational investors to feedback trading. When $(E_{t-1}(R_t) - \alpha) \gamma|R_{t-1}|sentiment_{t-1} > 0$, rational investors in Eq. (5) should increase their positions relative to the original model. For instance, if $(E_{t-1}(R_t) - \alpha) > 0$, rational investors will take positive positions according to traditional theory, similar to Eq. (5); however, if $sentiment_{t-1} > 0$, rational investors could “ride the bubble” to obtain more profit, which means that they could relatively increase their positions. When $(E_{t-1}(R_t) - \alpha) \gamma|R_{t-1}|sentiment_{t-1} < 0$, rational investors will take lower positions than they will in the original model, whereas in an extreme situation, they will take the opposite positions. For example, when $(E_{t-1}(R_t) - \alpha) < 0$, according to the original model, rational investors should take positive positions; if $sentiment_{t-1} < 0$ and $(E_{t-1}(R_t) - \alpha) \gamma|R_{t-1}|sentiment_{t-1} > 0$, rational investors should take lower positions than in original model; and if $sentiment_{t-1} < 0$
and \((E_{t-1}(R_t) - \alpha) - \gamma |R_{t-1}|sentiment_{t-1} < 0\), rational investors will take negative positions because of negative sentiment. To test the significance of sensitivity of feedback trading to sentiment, we modify Eq. (3) to

\[ Y_{2t} = (\beta^L D^L + \beta^M D^M + \beta^H D^H)R_{t-1} \]  

where \(D^L\), \(D^M\) and \(D^H\) are dummy variables corresponding to low, middle and high sentiment, with coefficients \(\beta\) used to test the sensitivity of feedback trading to different levels of sentiment. Similarly, all shares must be held, i.e., \(Y_{1,t} + Y_{2,t} = 1\). It follows from Eq. (5) and Eq. (6) that

\[ E_{t-1}(R_t) = \alpha + \theta \sigma^2_t - \theta \sigma^2_{t-1}(\beta^L D^L + \beta^M D^M + \beta^H D^H) - \gamma |R_{t-1}|sentiment_{t-1} \] 

It is easy to convert Eq. (7) into a regression equation with a stochastic error term by setting \(R_t = E_{t-1}(R_t) + \epsilon_t\) and substituting into Eq. (7) to get

\[ R_t = \alpha + \theta \sigma^2_t - (\beta^L D^L + \beta^M D^M + \beta^H D^H)\sigma^2_{t-1} - \gamma |R_{t-1}|sentiment_{t-1} + \epsilon_t \] 

Eq. (8) does not allow autocorrelation due to nonsynchronous trading or market inefficiencies. To account for this possibility, the following empirical version of Eq. (8) is used in the estimation:

\[ R_t = \alpha + \theta \sigma^2_t + \delta R_{t-1} - (\beta^L D^L + \beta^M D^M + \beta^H D^H)\sigma^2_{t-1} - \gamma |R_{t-1}|sentiment_{t-1} + \epsilon_t \] 

\(\delta\) captures the impact of nonsynchronous trading effect or, perhaps, market inefficiencies and frictions. Obviously, it is not necessary that positive feedback trading will induce negative autocorrelation in returns because of existence of sentiment.

### 3.3. \textit{GARCH-M model}

Completing the model requires that the conditional variance be specified. Numerous studies have
shown that the stock returns are conditionally heteroscedastic. Furthermore, as shown in Eq. (9),
the model includes the conditional variance \( \sigma_t^2 \). Hence, we adopt the GARCH-M model. ARCH-
M models (Engle, Lilien, and Robins 1987) generalize the ARCH-M model by allowing a
function of the variance to enter the regression function itself. The most common form of this
function uses the variance itself as a regressor. In this article, we have two related terms \( \sigma_t^2 \)
in the mean model. Consequently, the conditional variance of the return is modelled as an
GARCH-M(1,1) process given by
\[
\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2
\]
where \( \sigma_t^2 \) is the conditional variance of the returns at time \( t \), \( \varepsilon_t \) is the innovation at time \( t \) and \( \alpha_0, \alpha_1 \) and \( \beta_1 \) are non-negative fixed parameters.

Several parametric specifications have been used in the literature for stock returns, the
most common of which is the standard normal distribution. However, the standardized residuals
obtained from GARCH models that assume normality appear to be leptokurtic, thereby rendering
standard t-tests unreliable. As such, distributions with flatter tails, such as Student’s t and the
generalized error distribution (GED), have been suggested. In this paper, we employ the GED.
Its density function is given by
\[
f(\mu_t, \sigma_t, \nu) = \frac{\nu}{2} \left[ \frac{\Gamma\left(\frac{3}{\nu}\right)}{\Gamma\left(\frac{1}{\nu}\right)} \right]^{\frac{1}{2}} \left[ \frac{\Gamma\left(\frac{1}{\nu}\right)}{\Gamma\left(\frac{3}{\nu}\right)} \right]^{\frac{1}{2}} \left( \frac{1}{\sigma_t} \right) \exp \left( -\left[ \frac{\Gamma\left(\frac{3}{\nu}\right)}{\Gamma\left(\frac{1}{\nu}\right)} \right]^{\frac{\nu}{2}} \frac{\nu}{\Gamma\left(\frac{1}{\nu}\right)} |\varepsilon_t/\sigma_t| \right)
\]
where \( \Gamma(.) \) is the gamma function and \( \nu \) is a scale parameter or degrees of freedom to be
estimated endogenously. For \( \nu=2 \), the GED yields a normal distribution, while for \( \nu=1 \), it yields a
Laplace or double exponential distribution.
Given the initial values for $\varepsilon_t$ and $\sigma_t^2$, the parameter vector for $\varepsilon_t$ and $\sigma_t^2$, the parameter vector can be estimated by maximizing the log-likelihood over the sample period, which can be expressed as

$$L(\Theta|k, p, q) = \sum log f(\mu_t, \sigma_t^2, \nu)$$

(12)

where $\Theta$, $\mu_t$, $\sigma_t$ and $\nu$ are the parameter vector, conditional mean, conditional variance and scale parameter or degrees of freedom, respectively. Since the log-likelihood function is highly nonlinear in the parameters, numerical maximization techniques are used to obtain estimates of the parameter vector.

4. Empirical findings

4.1. Data and descriptive statistics

The study uses the daily closing total return of the CSI 300 index and its individual returns of stocks. The CSI 300 index is the China Securities Index (CSI) 300 stock index, which is also called the HuShen (HS) 300 stock index. It was jointly launched by the Shanghai Stock Exchange and the Shenzhen Stock Exchange on April 8, 2005. This index is composed of the 300 stocks that are the most heavily traded in the Chinese A-share markets and represents approximately 70% of total market capitalization of both Shanghai and Shenzhen stock exchanges. It was designed as a performance benchmark and as a base for derivatives innovation and other functions. Currently, the CSI 300 index is widely accepted as an overall reflection of the general movements and trends of the Chinese A-share markets.
The daily data range from 1 January 2007 to 30 June 2016, yielding 2308 observations. All data were obtained from the Wind database. Daily market returns are calculated as the percent logarithmic differences in the daily stock price index, i.e., \( R_t = 100(\log P_t - \log P_{t-1}) \).

Descriptive statistics for the daily returns are provided in Table 1.

From Table 1, the Kurtosis and Jacque-Bera statistics indicate that the series of daily index return is not normally distributed. The rejection of normality may be partly attributed to temporal dependencies in the moments of series. The Ljung-Box Q test statistic at 12 lags is significant. This result, ARCH-LM test (ARCH(P)), provides evidence of temporary dependencies in the first moment of the distribution of returns. This temporal dependency is usually interpreted as evidence of the presence of ARCH effects in the conditional volatility. We obtain sentiment by regression and divide it into three parts. High sentiment is greater than 3Q(0.2210), low sentiment is less than 1Q(-0.2341) and the remainder comprises middle sentiment. These three parts correspond to the dummy variables \( D^H \), \( D^L \) and \( D^M \), respectively.

### 4.2. Empirical results

Table 2 reports the maximum likelihood estimates for the empirical version of the modified feedback model described by Equations (9) and (10). The coefficient \( \alpha_0 \), which describes the conditional variance process, is highly significant. The autocorrelation in volatility coefficient, \( \alpha_1 \), is statistically significant, which intuitively implies that current volatility is a function of the last period’s squared innovation from an equity index value; equivalently, the conditional variance is updated in light of the new information, and the weight given to the last squared
innovation is \( \alpha_1 \).

The parameters of most interest in this paper are those coefficients of dummy variables that govern the autocorrelation of the return, \( \beta^L \), \( \beta^M \) and \( \beta^H \). \( \beta^L \) and \( \beta^H \) are positive and statistically significant, but \( \beta^M \) is not statistically significant. This result demonstrates that positive feedback traders are more likely to trade when their sentiment is relatively high or low. Because of incomplete rationality, positive feedback traders cannot distinguish systematic risk from unsystematic risk, and they are inclined to trade on systematic risk to erase the risk of choosing one security from many. With our particular indicator of sentiment, this result illustrates that positive feedback traders are inclined to buy when most securities rise and to sell when most securities fall. They believe that most securities move in the same direction when systematic risk comes.

The estimated degrees of freedom parameter, \( v \), is well below two but is close to unity, indicating the GED yields a double-exponential or Laplace distribution for all returns. A conventional t test rejects the hypothesis that \( v=2 \).

The coefficient \( \gamma \), which represents the sensitivity of rational investors to feedback trading, is positive and statistically significant. This result demonstrates that rational investors’ behavior is influenced by feedback traders, although the influence is not great. Hence, positive feedback trading will not necessarily induce a negative autocorrelation in returns.

The validity of these empirical findings depends on the correct specification of the model. The minimum requirements are that the standardized residuals that follow an assumed distribution with a mean of zero and a constant variance are linearly and nonlinearly independent. As shown in Table 2, the mean of standardized residuals fulfills the first
requirement of zero. In terms of linear and nonlinear independence, the LB statistic values demonstrate that, up to 12 lags, standardized residuals and squared standardized residuals follow i.i.d. processes. There are various alternative methods of proxying for $\sigma_t^2$. We used three different models: the Exponential GARCH model, IGARCH and standard GARCH model. Since the results were quite similar, we only report the standard GARCH model. Thus, the modified feedback model with errors following GARCH(1,1) processes successfully accounts for all linear and non-linear dependencies in the returns. The appropriateness of the density function used is tested on the basis of the Kolmogorov-Smirnov statistic $D$, where the null hypotheses is now that the estimated standardized residuals follow the GED with $\nu$ estimated degrees of freedom. The estimated $D$ statistics are below their critical value, so the assumed density function is not rejected.

5. Restriction on short sales and robust test

Unrestricted short sales with full use of the proceeds is a crucial assumption underlying both arbitrage and equilibrium models of capital asset prices. However, in Chinese equity markets, short sales were not allowed until 2010. On 31 March 2010, Chinese regulators launched a pilot program that allowed short sales and margin trading for 50 Shanghai Stock Exchange and 40 Shenzhen Stock Exchange stocks. On 16 April 2010, Shanghai and Shenzhen 300 stock index (CSI 300) futures were introduced into Chinese equity markets. The purpose of regulators is to help incorporate information into stock prices more efficiently, but the stock market crash of 2015 spurred China Securities Regulatory Commission (CSRC) to lift the bans on short selling and margin trading. It seems that policy makers consider short sellers to behave
as positive feedback traders. In this section, we break our sample into two subsamples: 1/4/2007 through 3/30/2010 (2007-2010 for short, or sample A), where short sales were completely banned, and 4/16/2010 through 6/30/2016 (2010-2016 for short, or sample B). The modified model is used to compare the difference of activities of positive feedback trading between these periods through empirical work, which will indicate whether short sales aggregate positive feedback trading to amplify deviations from fundamental values and give a robust test based on different ranges of data. Table 3 reports the maximum likelihood estimates for the two subsamples. For each of the sample periods, the coefficients of all parameters and their significance levels are shown. The remarkable fact is that $\beta^e$ and $\beta^H$ in sample B are larger than those in sample A, which means that short sales intensify the activity of positive feedback traders. The term $|R_{t-1}|sentiment_{t-1}$ measures the behavior of “riding the bubble” of rational investors who are forced to adjust their positions due to noise trader risk. The fact that $\gamma$ is larger in sample B implies that rational investors are more sensitive to noise trader risk because noise traders, including positive feedback traders, are allowed to perform short sales and margin trading.

Two subsamples show the same pattern as the overall sample: when investor sentiment is relatively high or low, positive feedback traders are more active. The other parameters also indicate that the modified model in this article is robust.

6. Conclusion

This paper has examined the autocorrelation pattern of the returns, assuming that some traders
follow positive feedback trading strategies. By modifying the model of Sentana and Wadhwani (1992), we find that positive feedback traders are more likely to trade when their sentiment are relatively high or low. Unlike previous papers, which used a created index as the sentiment proxy, we use a specific indicator to explain the mechanism of the relationship between sentiment and feedback trading. Positive feedback traders are found to select the moment when most securities move together. In contrast to prior researchers, we adopt Sentana and Wadhwani’s model to qualify the relationship between feedback trading and sentiment instead of VAR. We argue that the modified feedback model makes more sense. Our finding reveals a new pattern of feedback traders’ behavior such that feedback traders do not trade on every fluctuation of security price. Although feedback traders are a kind of noise trader who lacks complete rationality, they use a “rule of thumb” to trade. The effect of this trick of feedback traders is not the content of our article, but it may be useful. We also test the different activities of positive feedback trading with and without restrictions on sales. Short sales are found to intensify the activity of positive feedback traders. This result makes temporary bans on short selling and margin trading reasonable.

Notes

1 If \( \rho < 0 \), then there is negative feedback trading (see also Sentana and Wadhwani (1992).

2 \( \theta \sigma^2_i \) and \( \theta \sigma^2_i R_{t-1}(\beta^L D^L + \beta^M D^M + \beta^H D^H) \).

3 The Chinese A-share markets are only available for Chinese domestic investors.

References


Finance Trade 51 (Sup1):S111–S120. doi:10.1080/1540496x.2014.998914.


Table 1. Sample statistics.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std.Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>JB</th>
<th>LB(12)</th>
<th>LB2(12)</th>
<th>ARCH(P)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(A) Daily index return (1/1/2007-6/30/2016)</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>0</td>
<td>0.02</td>
<td>-0.53</td>
<td>2.84</td>
<td>886.25**</td>
<td>34.322**</td>
<td>58.992**</td>
<td>20.043**</td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>1Q</td>
<td>Media</td>
<td>3Q</td>
<td>Max</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>(B) SFR</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Description: $SFR_t = (ADV_t - DEC_t)/(ADV_t + DEC_t)$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>-1</td>
<td>-0.4739</td>
<td>-0.0214</td>
<td>-0.5610</td>
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<td>(C) Sentiment</td>
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</tr>
<tr>
<td>Description: $Sentiment_t = SFR_t - a_0 - a_1 * Market_t$</td>
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<td>0.2210</td>
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</table>

Asterisk (**) denotes significance at the 5% level. LB(12) and LB2(12) is Ljung–Box Q-statistic at lag 12 for the standardized residuals and squared standardize residuals, respectively. JB is the
Jarque–Bera test statistic. ARCH(p) is the Engle (1982) test for ARCH up to lag order 1.
Table 2. Maximum likelihood estimates of the modified feedback model.

<table>
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<th></th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t-Statistic</th>
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<td>91.46347***</td>
</tr>
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<td>0.002537290</td>
<td>305.01416***</td>
</tr>
<tr>
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<td>0.005037249</td>
<td>227.67251***</td>
</tr>
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<td>---</td>
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<td>---</td>
</tr>
<tr>
<td>Model diagnostics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( E(\varepsilon_t / \sigma_t) )</td>
<td>0.0042</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LB(12) for ( \varepsilon_t )</td>
<td>10.0620</td>
<td></td>
<td></td>
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<tr>
<td>LB2(12) for ( \varepsilon_t^2 )</td>
<td>9.8977</td>
<td></td>
<td></td>
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<tr>
<td>( D )</td>
<td>0.0242</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\[
R_t = \alpha + \theta \sigma_t^2 + \delta R_{t-1} - (\beta^L D^L + \beta^M D^M + \beta^H D^H) \sigma_t^2 R_{t-1} - \gamma |R_{t-1}| \text{sentiment}_{t-1} + \varepsilon_t
\]

\[
\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 \sigma_{t-1}^2
\]

***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. \( D \) is the Kolmogorov-Smirnov statistic testing the GED with the estimated scale parameter \( \nu \).
Table 3. Maximum likelihood estimates of the modified feedback model for subsamples.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Sample A</th>
<th>Sample B</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>-0.000148294***</td>
<td>-0.000004138</td>
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<tr>
<td>$\theta$</td>
<td>1.11152226***</td>
<td>-1.41717352***</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.044752882***</td>
<td>0.073829921***</td>
</tr>
<tr>
<td>$\beta^L$</td>
<td>1.828578539***</td>
<td>2.812587067***</td>
</tr>
<tr>
<td>$\beta^M$</td>
<td>-0.181243086</td>
<td>0.808238895</td>
</tr>
<tr>
<td>$\beta^H$</td>
<td>1.824685884***</td>
<td>2.786449857***</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.086672325***</td>
<td>0.156232312***</td>
</tr>
<tr>
<td>$\alpha_0$</td>
<td>0.000000984***</td>
<td>0.000000309***</td>
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<tr>
<td>$\alpha_1$</td>
<td>0.055382028***</td>
<td>0.054659398***</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.769179746***</td>
<td>0.770376110***</td>
</tr>
<tr>
<td>---------</td>
<td>----------------</td>
<td>----------------</td>
</tr>
<tr>
<td>$\nu$</td>
<td>1.145041363***</td>
<td>1.140791981***</td>
</tr>
</tbody>
</table>

***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.