2. PREDICTIVE ABILITY OF INVESTOR SENTIMENT FOR THE STOCK MARKET[1]

Karam KIM[2]
Doojin RYU[2,3]

Abstract

This study investigates investor sentiment's ability to forecast future stock returns in the short and long terms. We run predictive regressions to examine whether investor sentiment and macroeconomic variables predict stock returns. Investor sentiment forecasts stock returns for at least one month, but it loses its predictive ability after two months. Stock prices overvalued by investor sentiment revert to their intrinsic values after one month. The term spread negatively predicts stock prices, and this predictive ability persists in the long term. The results of an out-of-sample test show that investor sentiment generally has greater predictive power than a set of macroeconomic variables, indicating that investor sentiment can be a key factor in forecasting stock returns.

Keywords: Investor sentiment, Macroeconomic variables, Predictive ability, Return reversal, Short-term effect, Stock returns
JEL Classification: G12, G17, G41

1. Introduction

Classical financial theories assume that markets are efficient and their participants are rational. In contrast, behavioral finance studies show that stock prices often deviate from their fundamental and intrinsic values in financial markets. These studies claim that such mispricing is induced by uninformed, noisy, and irrational investors' trades (Chung, Hung, and Yeh, 2012; Gao and Liu, 2020; Reis and Pinho, forthcoming). Daniel, Hirshleifer, and Subrahmanyam (1998) suggest that uninformed investors, who are also called sentiment traders, tend to overreact to their beliefs and underreact to public information. In other words, they base their trading strategies on their expectations, beliefs, or moods regarding stocks rather than on public information, such as earnings announcements, analyst reports, or macroeconomic announcements, under short-sale constraints and limits-to-arbitrage (Antoniou, Doukas, and Subrahmanyam, 2013; Kim and Ryu, forthcoming; Seok, Cho, and

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[2] *College of Economics, Sungkyunkwan University, Seoul, Republic of Korea*
[3] *Corresponding Author (Doojin Ryu). E-mail: sharpjin@skku.edu*

Ryu, 2019a; Stambaugh, Yu, and Yuan, 2012; Walther and Willis, 2013). Mian and Sankaraguruswamy (2012) find that stock returns react more strongly to good (bad) earnings news when investor sentiment is high (low). Chen and Lien (2017) show that investor sentiment has a significantly positive effect on the excess returns around macroeconomic news. Considering that investors' trading based on their beliefs about stocks positively influences stock returns in real-time, stock prices may become overvalued as a result of investor overconfidence and sentiment (Chuang and Susmel, 2011; Kim, Ryu, and Yang, 2019; Wang, 2001).

One strand of the literature focuses on the predictive ability of sentiment indices. Baker and Wurgler (2007) find that investor sentiment has a significantly positive (negative) effect on current (future) stock returns. They suggest that investor sentiment generates return reversals because stock prices temporarily overvalued by investor sentiment converge back to their intrinsic values (Brown and Cliff, 2004; Coqueret, 2020; Dergiades, 2012; Sun, Najand, and Shen, 2016). Moreover, Chung, Hung, and Yeh (2012) show that investor sentiment's predictive power for stock returns is asymmetric and depends on the market state. Specifically, they find that investor sentiment's predictive power is greater when the market is bullish. Xu and Zhou (2018) find that a weekly sentiment index predicts the near-term future returns of diverse types of portfolios, especially for portfolios constructed based on small firms. This study improves upon many previous studies that investigate investor sentiment's ability to forecast stock returns in the short term (Huang, Jiang, Tu, and Zhou, 2015; Lee, Jiang, and Indro, 2002; Renault, 2017; Ruan, Wang, Zhou, and Lv, 2020) by examining the sentiment index's predictive performance in both the short and long terms and focusing on how long this predictive ability persists.

Our study aims to determine whether investor sentiment can predict stock returns in the short (i.e., less than a month) and long terms (i.e., greater than a month). To answer this research question, we first construct a bottom-up market-level daily sentiment index weighted by the market capitalizations of individual firms using the method suggested by Baker and Wurgler (2006). Then, we estimate predictive models to analyze whether investor sentiment can forecast near-term stock returns. Lastly, we test the out-of-sample performance of the predictive model with the sentiment index relative to a model without the index using the proportional reduction in the benchmark squared forecast error, following Huang, Jiang, Tu, and Zhou (2015).

This study has the following results. First, investor sentiment has explanatory power for current stock returns, implying that stock price dynamics include sentiment traders' overreactions. When investor sentiment is optimistic (pessimistic), stock prices are overvalued (undervalued). This finding, therefore, indicates that the stock market is inefficient and that some investors are irrational. Second, the effect of investor sentiment on future stock returns remains significantly negative until one month has passed. This result implies that investor sentiment predicts stock returns in the short term and generates a return reversal for one month. Third, the term spread, a countercyclical macroeconomic variable classified as a measure of the business cycle, only predicts stock returns in the long term, indicating that the term spread leads to the dynamics of stock returns (Shen, Yu, and Zhao, 2017). Finally, the stock return predictions using investor sentiment outperform those using macroeconomic variables, providing evidence that investor sentiment is a key factor for predicting short-term stock returns. This study has contributed to finding that investor sentiment's ability to predict stock returns lasts for one month and that the predictions using investor sentiment are more accurate than those using a set of macroeconomic variables.

The remainder of this paper is structured as follows. Section 2 reviews the literature. Section 3 describes the sample data and methodology. Section 4 interprets the empirical findings. Section 5 concludes.

2. Literature Review

Investor sentiment is defined as investors' emotions or beliefs regarding individual stocks or the stock market. Previous studies find that investor sentiment affects stock prices and that this sentiment effect in financial markets is not temporary (Berger and Turtle, 2012; Daniel, Hirshleifer, and Subrahmanyam, 1998; De Long, Shleifer, Summers, and Waldmann, 1990; Smales, 2017). Chau, Deesomsak, and Koutmos (2016) find that sentiment-driven trading impacts stock price dynamics and suggest that investor sentiment is a determinant of investors' trading behavior and individual stock prices. Li (forthcoming) shows that investor sentiment has greater explanatory power over stock returns than firm size and the book-to-market ratio have, implying that the sentiment effect can be included along with the size, value, and momentum effects as a market factor.

Recent studies focus on proposing various sentiment measures to further understand the degree of irrationality (Bandopadhyaya and Jones, 2008; Han, 2008; Ruan, Wang, Zhou, and Lv, 2020). Kumar and Lee (2006) propose individual investors' net buying as a proxy for investor sentiment because individual investors, unlike institutional investors, are considered to be sentiment traders. Individual investors are likely to be uninformed and inexperienced (Chang, Hsieh, and Wang, 2015; Yang, Ryu, and Ryu, 2017). Smales (2014) shows that news sentiment is highly correlated with the implied volatility index (i.e., the VIX), and some studies use the VIX to measure investor sentiment (Bandopadhyaya and Jones, 2008; Qadan and Yagil, 2012). Whereas some studies propose a single variable as a proxy for investor sentiment (Baker and Stein, 2004; Kumar and Lee, 2006; Lemmon and Portniaguina, 2006), Baker and Wurgler (2006) suggest various sentiment measures and construct a sentiment index (henceforth, BW index) by combining these measures using the principal component analysis (PCA). Following this approach, many studies extend the sentiment index to demonstrate the role and importance of investor sentiment in financial markets (Chen, Chong and She, 2014; Kim, Ryu, and Seo, 2014). Huang, Jiang, Tu, and Zhou (2015) recommend using the partial least squares (PLS) method, as they show that a sentiment index constructed with this methodology has greater explanatory power for stock returns than the BW index (Kim, Ryu, and Yu, forthcoming). Recent research suggests constructing a sentiment index by performing textual analysis using data from social networks, such as Facebook, Instagram, and Twitter (Naughton, Wang, and Yeung, 2019; Siganos, Vagenas-Nanos, and Verwijmeren, 2014).

Few studies specifically explore the sentiment effect in emerging markets even though individual investors, who are classified as uninformed and sentiment traders, participate much more frequently in emerging markets than in developed markets (Ryu, Kim, and Yang, 2017; Xu and Zhou, 2018). Yang and Gao (2014) suggest a market-wide sentiment index using the PCA methodology in the context of the Chinese stock market. Ryu, Kim, and Yang (2017) and Seok, Cho, and Ryu (2019b) propose a firm-specific sentiment index on a daily basis for the Korean stock market. These sentiment indexes have advantages in that the sentiment proxies are easily constructed and are available at high frequencies relative to the BW index. We also construct a bottom-up sentiment index by modifying and extending prior studies that develop sentiment indexes in emerging markets (Seok, Cho, Park, and Ryu, 2019; Yang and Gao, 2014). We focus on the Korean stock market, a leading emerging market, because some of its features make it very appropriate for this analysis (Chun, Cho, and Ryu, 2020; Kim, Cho, and Ryu, 2018; Seo, Kim, and Ryu, 2019; Shim, Kim, and Ryu, 2017; Ryu, Webb, and Yu, 2020; Ryu and Yu, 2020; Yang, Kim, Kim, and Ryu, 2018; Yu and Ryu, 2019, 2020). The Korean stock market is considered relatively inefficient and has more information asymmetry among participants compared to developed markets. The Korean market is characterized by the active participation of individual investors, also known as noise traders (Ahn, Kang, and Ryu, 2008; Ryu, 2012, 2013, 2015; Ryu, Ryu, and Yang, 2021; Ryu and Yang, 2018, 2019, 2020; Lee and Ryu, 2019; Yang, Ahn, Kim, and Ryu, 2017; Yang, Kutan, and Ryu, 2019).

3. Sample Data and Methodology

3.1 Investor Sentiment Index

This study constructs the bottom-up daily sentiment indicator by employing financial data from individual firms listed on the Korea Composite Stock Price Index (KOSPI) market from 2010 to 2019. The transaction data are obtained from FnGuide. We exclude firms whose stocks have been suspended from transactions or warned by the Korea Exchange (KRX). Yang and Gao (2014) suggest a suitable sentiment index for individual firms in the context of the emerging market, and many studies utilize this index to investigate investor sentiment's role in the stock market (Ryu, Ryu, and Yang, 2020). Our study also modifies and adopts Yang and Gao's (2014) sentiment index. We employ five sentiment proxies for an individual firm f at time t, as follows: the relative strength index (*STR*), the psychological line index (*PSY*), the logarithm of the trading volume (*LVOL*), the adjusted turnover ratio (*TOR*), and the individual net buying volume (*INB*). *STR* and *PSY* are related to price dynamics, and *LVOL*, *TOR*, and *INB* are related to trading volume dynamics. We use a weighted combination of individual firms (w_f) based on their market capitalizations at time *t* to construct the above five sentiment proxies.

In Equation (1), STR_t is the ratio of the number of days on which stock prices increase to the number of days on which stock prices decrease over the last 14 trading days. $RS_{f,t}$ and $P_{f,t}$ denote the relative strength and the stock price, respectively, of firm f at time t. PSY_t is the average number of days with positive stock returns over the last 12 trading days and is calculated as in Equation (2). The values of *STR* and *PSY* are multiplied by a scaling factor (100) and range from zero to one hundred. $LVOL_t$ indicates the logarithm of the trading volume of firm f at time t, as shown in Equation (3). $VOL_{f,t}$ denotes the stock's trading volume. In Equation (4), TOR_t is constructed by multiplying the turnover ratios by the signs of the firm's stock returns, $Stocks_{f,t}$ denotes the total number of stocks that each firm issues. In Equation (5), INB_t indicates the imbalance between individual investors' buy and sell volumes for individual firms. $IBV_{f,t}$ and $ISV_{f,t}$ denote the buy and sell volumes, respectively.

$$STR_t = \sum_{f=1}^{N}\left(w_f \times \frac{RS_{f,t}}{1+RS_{f,t}}\right) \times 100, \text{ where } RS_{f,t} = \frac{\sum_{k=0}^{13} max(P_{f,t-k}-P_{f,t-1-k},\ 0)}{\sum_{k=0}^{13} max(P_{f,t-1-k}-P_{f,t-k},\ 0)}, \quad (1)$$

$$PSY_t = \sum_{f=1}^{N}\left(w_f \times \sum_{k=0}^{11} \frac{max(P_{f,t-k}-P_{f,t-1-k},\ 0)}{P_{f,t-k}-P_{f,t-1-k}} \times \frac{1}{12} \times 100\right), \quad (2)$$

$$LVOL_t = \sum_{f=1}^{N}\left(w_f \times ln(VOL_{f,t})\right), \quad (3)$$

$$TOR_t = \sum_{f=1}^{N}\left(w_f \times \frac{VOL_{f,t}}{Stocks_{f,t}} \times 100 \times \frac{R_{f,t}}{|R_{f,t}|}\right), \quad (4)$$

$$INB_t = \sum_{f=1}^{N}\left(w_f \times \frac{IBV_{f,t}-ISV_{f,t}}{IBV_{f,t}+ISV_{f,t}}\right). \quad (5)$$

Then, using these sentiment proxies, we apply the PCA method to construct the sentiment index (Baker and Wurgler, 2006). We estimate the first principal components for the current terms of these five sentiment proxies and construct the sentiment index ($Sent_t$) by linear combining the estimated first principal components and the proxies, as shown in Equation (6).

$$Sent_t = 0.569 \cdot STR_t^{\perp} + 0.583 \cdot PSY_t^{\perp} - 0.023 \cdot LVOL_t^{\perp} + 0.403 \cdot TOR_t^{\perp} - 0.416 \cdot INB_t^{\perp}. \quad (6)$$

Here, we use orthogonal ($\perp$) sentiment proxies controlled for macroeconomic effects. The first principal components explain about 45.07% of the common components of the five sentiment proxies. The first principal components of LVOL and INB are negative, implying sentiment traders are likely to sell (buy) stocks when their expectations are optimistic (pessimistic). This result indicates that sentiment traders are noisy and uninformed. We standardize the estimated investor sentiment index so that its mean and standard deviations are zero and one, respectively.

The sentiment proxies are then adjusted to control for a set of major macroeconomic variables, including the implied volatility (*Vkospi*), the term spread (*Term*), the exchange rate (*Exch*), the credit spread (*Credit*), and the risk-free rate (*Rf*), and they are standardized using the sample mean and variance. In the context of the Korean financial market, the macroeconomic variables are defined as follows. *Vkospi* denotes the options-implied volatility index, also known as the VKOSPI, provided by the KRX. *Term* is calculated by subtracting the risk-free rate from the rate of return on five-year sovereign bonds. *Exch* is the USD/KRW exchange rate. *Credit* is calculated by subtracting the rate of return of AA-rated bonds from that of BBB- rated bonds. *Rf* denotes the risk-free rate, proxied by the 91-day certificate deposit rate of return.

In Table 1, Panel A shows the summary statistics of investor sentiment and its proxies, and Panel B shows the summary statistics of the macroeconomic variables. In Panel B of Table 1, *ΔVkospi* and *ΔRf* denote the first-differenced *Vkospi* and *Rf*, respectively, and are used for stationarity. The columns *Mean*, *Std*, *Min*, *Q1*, *Median*, *Q3*, and *Max* denote the mean, standard deviation, minimum, first quartile, median, third quartile, and maximum values, respectively, of each variable. All variables have means and standard deviations of zero and one, respectively, because they are all standardized. The columns *ADF(1)* and *ADF(2)* indicate the augmented Dickey-Fuller test statistics with AR(1) and AR(2) processes, respectively. The values of *ADF(1)* and *ADF(2)* are significant for all variables, implying that they are all stationary.

Table 1

Summary Statistics

Panel A. Investor Sentiment

	Mean	Std	Min	Q1	Median	Q3	Max	ADF(1)	ADF(2)
STR	0.000	1.000	-3.95	-0.657	0.049	0.693	3.079	-11.58***	-9.62***
PSY	0.000	1.000	-4.091	-0.628	0.021	0.646	3.343	-12.55***	-10.74***
LVOL	0.000	1.000	-3.183	-0.675	-0.045	0.577	3.959	-16.20***	-11.81***
TOR	0.000	1.000	-5.802	-0.509	0.019	0.551	3.937	-47.99***	-33.40***
INB	0.000	1.000	-3.610	-0.644	0.025	0.688	3.318	-35.55***	-25.64***
Sent	0.000	1.000	-4.230	-0.649	0.032	0.660	3.692	-12.55***	-10.74***

Panel B. Macroeconomic Variables

	Mean	Std.	Min	Q1	Median	Q3	Max	ADF(1)	ADF(2)
ΔVkospi	0.000	1.000	-7.833	-0.118	-0.028	0.050	31.030	-32.77***	-30.49***
Term	0.000	1.000	-1.409	-0.753	-0.181	0.375	3.163	-3.05**	-2.92**
Exch	0.000	1.000	-5.640	-0.607	0.001	0.561	7.056	-45.00***	-34.14***
Credit	0.000	1.000	-9.723	-0.005	-0.005	0.173	19.837	-37.51***	-26.34***
ΔRf	0.000	1.000	-18.087	0.037	0.037	0.037	13.674	-44.34***	-31.48***

*Note: *** and ** denote statistical significance at the 1% and 5% levels, respectively.*

3.2 Prediction Models

Cumulative stock returns are used to investigate the predictive power of investor sentiment for future stock returns. They are calculated as shown in Equation (7).

$$CR_{(t+1,t+H)} = \prod_{h=1}^{H}(1 + R_{t+h}) - 1, \tag{7}$$

where $CR_{(t+1,t+H)}$ denotes the cumulative stock return from time *t*+1 to time *t*+*H*. R_{t+h} denotes the market's daily rate of return at time *t*+*h*. This return is calculated using the weighted average stock prices based on the market capitalizations of individual firms.

We run a forecasting regression to investigate the predictive ability of investor sentiment as shown in Equation (8).

$$CR_{(t+1,t+H)} = \alpha + \beta \cdot Sent_t + \gamma \cdot Control_t + \epsilon_t, \tag{8}$$

where $Control_t$ is the set of macroeconomic control variables and γ denotes the vector of coefficients of the control variables. For the control variables, we use the five macroeconomic variables described in Section 2.1. If the coefficient β is significant, we can interpret that investor sentiment forecasts future stock returns.

3.3 Testing Out-of-Sample Forecasts

After estimating the predictive regression, we carry out an out-of-sample test to examine the forecasting power. The estimation period is from 2010 to 2014, and the evaluation period is from 2015 to 2019. R_{OS}^2 indicates the similarity between the predicted and actual stock returns, as shown in Equation (9). Following Huang, Jiang, Tu, and Zhou (2015) and Reschenhofer and Stark (2019), if R_{OS}^2 is positive, then investor sentiment is a better predictor of stock returns than the macroeconomic variables.

$$R_{OS}^2 = 1 - \frac{VDCR^{sent}}{VDCR^{macro}} = 1 - \frac{\sum_{t=p}^{T}(CR_{t+h} - PCR_{t+h}^{sent})^2}{\sum_{t=p}^{T}(CR_{t+h} - PCR_{t+h}^{macro})^2}, \tag{9}$$

where $VDCR^{sent}$ ($VDCR^{macro}$) denotes the volatility of the difference between the real and predicted stock returns by sentiment (macroeconomic variables). PCR_{t+h}^{sent} (PCR_{t+h}^{macro}) is the cumulative stock return predicted by investor sentiment (macroeconomic variables).

4. Empirical Findings

4.1 Sentiment Effect on Stock Returns

Before we examine investor sentiment's ability to predict stock returns, we display the time series of stock returns and investor sentiment in Figure 1. The solid (dotted) line shows the time series of investor sentiment (stock returns). In the figure, *Return* denotes stock returns, and *Sentiment* denotes investor sentiment. The right (left) vertical axis indicates the level of investor sentiment (stock returns). The figure roughly suggests that stock returns and investor sentiment move together (Chue, Gul, and Mian, 2019).

Figure 1

Time Series of Returns and Investor Sentiment.

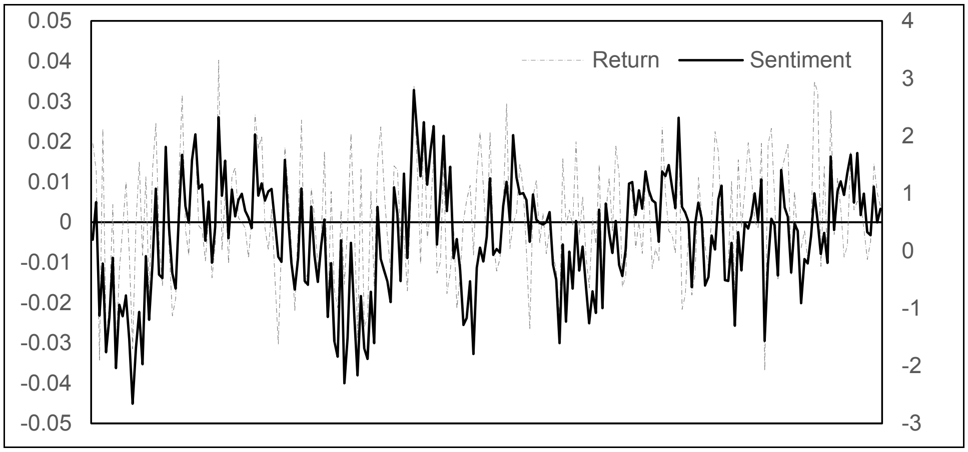

Table 2 shows the results of the regression examining whether investor sentiment impacts contemporaneous stock returns. The column labeled M1 shows the results when Sent is the only explanatory variable, and the column labeled M2 shows the results when Sent and the five macroeconomic variables, that is, *ΔVkospi*, *Exch*, *Credit*, *Term*, and *ΔRf*, are used to predict stock returns. The values in parentheses are *t*-statistics. *Adj*. R^2 is the adjusted R^2 value. The coefficient of *Sent* (0.714) and its *t*-statistic (9.85) indicate that investor sentiment has a significantly positive effect on current stock returns, consistent with Figure 1. The positive coefficient implies that sentiment traders, who are noisy, irrational, and uninformed, induce irrational stock return dynamics in real-time, causing stock prices to deviate from their fundamental values.

Table 2

Effects of Investor Sentiment and Macroeconomic Variables

	M1	M2
Sent	0.714*** (9.85)	0.713*** (9.79)
ΔVkospi		-0.013 (-0.18)
Term		-0.0837 (-1.13)
Exch		-0.055 (-0.75)
Credit		0.001 (0.01)
ΔRf		-0.004 (-0.05)
Adj.R^2	0.0377	0.0365

*Note: *** denotes statistical significance at the 1% level.*

Panels A and B of Table 3 show the abilities of investor sentiment and macroeconomic variables to predict stock returns in the short and long terms, respectively. Model M1 uses only Sent as the predictor for stock returns, and model M2 includes Sent and the five macroeconomic variables as predictors of stock returns. The results in Panel A of Table 3 show the impacts of investor sentiment on stock returns the next day ($CR_{(t+1,t+1)}$) and over the next week ($CR_{(t+1,t+5)}$), two weeks ($CR_{(t+1,t+10)}$), and one month ($CR_{(t+1,t+20)}$). The values in parentheses are t-statistics. Adj. R^2 is the adjusted R^2 value. Whereas investor sentiment positively affects stock returns in real time, the effect of investor sentiment on future stock returns is significantly negative in the short term. This result implies that the mispricing caused by uninformed traders reverts to the stock's intrinsic value and that this price discovery process takes one month. Specifically, the absolute value of the coefficient of investor sentiment increases gradually as the time frame changes from one day to one month. In other words, it takes one month for the stock mispricing to converge to the intrinsic value. This result is consistent with Coqueret's (2020) findings and suggests that the predictive power of investor sentiment stock returns reflects the feedback effect in the reverse direction.

Table 3

Predictive Abilities of Investor Sentiment and Macroeconomic Variables

Panel A. Predictive Abilities in the Short Term.

	$CR_{(t+1,t+1)}$		$CR_{(t+1,t+5)}$		$CR_{(t+1,t+10)}$		$CR_{(t+1,t+20)}$	
	M1	M2	M1	M2	M1	M2	M1	M2
Sent	-0.075^{**} (-2.05)	-0.075 (-1.53)	-0.462^{***} (-4.35)	-0.459^{***} (-4.31)	-0.582^{***} (-5.24)	-0.580^{***} (-3.94)	-0.721^{***} (-4.86)	-0.712^{***} (-4.73)
ΔVkospi		0.002 (0.03)		0.019 (0.18)		-0.006 (-0.04)		0.048 (0.23)
Term		-0.064 (-1.30)		-0.288^{***} (-2.67)		-0.538^{***} (-3.61)		-0.928^{***} (-5.42)
Exch		0.019 (0.39)		0.187^{*} (1.77)		0.136 (0.93)		0.250 (1.38)
Credit		-0.002 (-0.04)		0.023 (0.22)		0.029 (0.20)		0.187 (1.40)
ΔRf		0.003 (0.06)		-0.059 (-0.56)		0.033 (0.22)		-0.064 (-0.34)
Adj.R^2	0.001	-0.000	0.010	0.010	0.006	0.010	0.005	0.012

Panel B. Predictive Abilities in the Long Term.

	$CR_{(t+1,t+40)}$		$CR_{(t+1,t+60)}$		$CR_{(t+1,t+180)}$		$CR_{(t+1,t+240)}$	
	M1	M2	M1	M2	M1	M2	M1	M2
Sent	-0.445 (-1.94)	-0.412* (-1.78)	-0.038 (-0.11)	-0.015 (-0.05)	-0.076 (-0.12)	0.167 (0.27)	-0.683 (-0.90)	-0.133 (-0.17)
ΔVkospi		0.286 (0.78)		0.111 (0.27)		2.556 (1.81)		4.615 (2.90)
Term		-1.776*** (-7.25)		-2.850*** (-9.32)		-7.257*** (-11.21)		-8.353*** (-10.99)
Exch		0.349 (1.29)		0.377 (1.06)		0.863 (1.29)		0.789 (0.99)
Credit		0.363 (1.53)		0.613** (2.18)		-0.323 (-0.65)		-0.202 (-0.39)
ΔRf		0.172 (0.75)		0.016 (0.05)		-0.300 (-0.52)		0.609 (0.95)
Adj.R^2	0.001	0.015	-0.001	0.025	-0.001	0.050	-0.000	0.046

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

To determine the long-term effect of investor sentiment on stock returns, we investigate whether investor sentiment predicts stock returns over the next two ($CR_{(t+1,t+40)}$), three ($CR_{(t+1,t+60)}$), six ($CR_{(t+1,t+180)}$), and twelve months ($CR_{(t+1,t+240)}$) in Panel B of Table 3. The coefficients of *Sent* are insignificant in these regressions, implying that investor sentiment loses its ability to predict stock returns in the long term because stock prices overvalued by investor sentiment converge to their intrinsic values.

Conversely, we find that the macroeconomic variables have insignificant effects on current and future stock returns, with the exception of the term spread. If we examine whether macroeconomic variables predict stock returns after one year, they appear to significantly impact stock returns in the long term. Fama and French (1993) and Chordia and Shivakumar (2002) suggest that the term spread reflects the short-term business cycle. Thus, the term spread in a set of macroeconomic variables only predicts stock returns one week in the future. Moreover, the term spread negatively influences future stock returns, implying that it is countercyclical. The absolute value of the coefficient of the term spread increases gradually. These results indicate the importance of the interest rate structure.

In sum, investor sentiment is a better predictor of stock returns than macroeconomic variables are, but its role as a predictor of stock returns remains significant for only one month because overvalued stock prices converge to their fundamental value within one month

4.2. Out-of-sample test

For a robustness check, we perform an out-of-sample test. In Table 4, $VDCR^{sent}$($VDCR^{\mathrm{macro}}$) denotes the volatility of the difference between real stock returns and those predicted by investor sentiment (macroeconomic variables). R^2_{OS} is a measure of predictive ability. If its value is greater than zero, investor sentiment has greater predictive power than the macroeconomic variables. In the table, *1 day*, *5 days*, *10 days*, and *1 month* (*20 days*) indicate the volatility of the difference between real and predicted stock returns at times *t*+1, *t*+5, *t*+10, and *t*+20, respectively. The rows labeled *2 months*, *3 months*, *6 months*, and *1 year* show the predicted values at times *t*+40, *t*+60, *t*+180, and *t*+240, respectively. We find that R_{OS}^2 remains greater than zero until ten days have passed. Considering the results in Table 3, investor sentiment has greater forecasting power for stock returns than the macroeconomic variables in the short term. Investor sentiment's predictive power outperforms that of the macroeconomic variables by the greatest margin for stock returns five days in the future.

In the long term, R_{OS}^2 is positive over all time frames except two months in the future, but it is difficult to conclude that investor sentiment's ability to predict stock returns is greater than that of the macroeconomic variables in the long term. The values of $VDCR^{sent}$ and $VDCR^{\mathrm{macro}}$ are greater in the long term, implying that both investor sentiment and the macroeconomic variables have less predictive power in the long term than in the short term. Thus, investor sentiment and the macroeconomic variables lose their ability to predict stock returns after more time has passed. This result is consistent with those in Table 3.

Table 4

Out-of-Sample Forecastability

	$VDCR^{sent}$	$VDCR^{\mathrm{macro}}$	R_{OS}^2(%)
1 day	1.01607	1.01690	0.0798
5 days	4.9426	4.9703	0.5814
10 days	9.54422	9.5835	0.4096
1 month (20 days)	18.4306	18.4842	0.2903
2 months	36.8144	36.7501	-0.1750
3 months	52.6608	52.6845	0.0452
6 months	127.4230	127.7896	0.2868
1 year	175.9106	177.2513	0.7564

5. Conclusion

This study investigates whether investor sentiment predicts stock returns in the short and long terms using predictive regressions and an out-of-sample test. The main findings are as follows. First, investor sentiment affects simultaneous stock returns. We suggest that stock mispricing is likely to create investor sentiment. Stock prices are influenced by the overreactions of sentiment traders, whose trading strategies are based on their beliefs, expectations, or moods. Second, investor sentiment predicts stock returns until a month has passed, indicating that stocks overvalued by investor sentiment revert to their fundamental values over the next month. In other words, the mispricing induced by investor sentiment does not promptly revert to the fundamental values. Third, investor sentiment does not significantly predict stock returns after two months. This result means that investor sentiment loses its ability to predict stock returns after the return reversal has ended. Finally, investor sentiment has greater predictive ability than a set of macroeconomic variables. We, therefore, suggest that investor sentiment is a key factor in predicting stock prices.

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