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Stock Market's responses to intraday investor sentiment

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ABSTRACT

We investigate the effect of intraday sentiment on subsequent stock returns. Mispricing caused by intraday sentiment is not corrected immediately; rather, it lasts for about 30 min. After 30 min, however, investor sentiment negatively affects stock returns, suggesting that mispriced stocks are at least partially but not entirely adjusted back to their fundamental values. We also show that the effect of intraday sentiment depends on the degree of arbitrage. Intraday sentiment has little effect on firms that are easy to arbitrage. For these firms, the difference in the one-minute returns of firms with high and low sentiment is nearly zero, implying that any mispricing caused by intraday sentiment is immediately corrected for this group of firms. In contrast, among firms that are hard to arbitrage, the difference in the returns of firms with high and low sentiment lasts for about half an hour. This difference in the effect of intraday sentiment is not caused by the firms' liquidities.

1. Introduction

Traditional asset pricing models assume that investors are perfectly rational and markets are fully efficient. In these models, noise traders and their irrationality do not affect financial markets because market prices are determined only by fundamental values. Any slight mispricing caused by irrational investors is immediately absorbed by rational arbitrageurs. However, these classical models have limited ability to explain the movements of modern financial markets, and, thus, financial researchers focus on behavioral biases, such as overconfidence, self-attribution, confirmation bias, and investor sentiment. Particularly, many studies investigate investor sentiment, which measures investors' irrational optimism or pessimism regarding the market, in an effort to explain abnormal market movements. This study expands upon prior studies on sentiment and analyzes the effect of intraday sentiment on the stock market, to investigate the mispricing process caused by investors' behavioral biases. Specifically, we expand on Seok, Cho, and Ryu (2019a), Seok, Cho, and Ryu (2019b) daily measure by constructing a measure of firm-specific intraday investor sentiment using high-frequency transaction data.

Most prior studies on investor sentiment focus on its low-frequency effects on the stock market by analyzing monthly or annual investor sentiment (Antoniou, Doukas, & Subrahmanyam, 2016; Baker, Wurgler, & Yuan, 2012; Ben-Rephael, Kandel, & Wohl, 2012; Brown & Cliff, 2005; Cepni, Guney, Gupta, & Wohar, 2020; Cheema, Man, & Szulczyk, 2020; Chung, Hung, & Yeh, 2012; Fisher & Statman, 2000; Frazzini & Lamont, 2008; Kim, Ryu, & Seo, 2014; Kumar & Lee, 2006; Schmeling, 2009; Yu & Yuan, 2011). These

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analyses show that in the long term, periods of high sentiment are followed by low market performance, and similarly, periods of low sentiment are followed by high market performance. This result implies that over-valuations (under-valuations) in the stock market caused by excessive optimism (pessimism) are eventually corrected to fundamental values. However, analyses of long-term effects cannot capture rapid changes in investor sentiment and are unable to explain the mispricing process caused by such sentiment. Thus, researchers also try to examine the shorter-term or simultaneous effects of sentiment by estimating daily or weekly investor sentiment (Allen, McAleer, & Singh, 2019; Chen, Chong, & Duan, 2010; Coqueret, 2020; Da, Engelberg, & Gao, 2015; Joseph, Wintoki, & Zhang, 2011; Kim & Ryu, 2020, 2021a,b; Kim, Ryu, & Yang, 2019; Kim, Ryu, & Yu, 2021; Seok, Cho, Park, & Ryu, 2019; Yang & Zhou, 2016). These short-term analyses show that investor sentiment has a significantly positive effect on simultaneous and next-day returns, demonstrating the mispricing process caused by sentiment.

Recently, researchers have begun to investigate intraday sentiment using higher-frequency data. Gao and Liu (2020) argue that approximately 50% of equity trading in the U.S. market occurs on an intraday basis, and they emphasize the role of high-frequency intraday sentiment on subsequent market returns. They construct a measure of market-wide intraday sentiment and show that stock market sentiment strongly positively predicts subsequent returns. Zhang, Lin, and Zhang (2016) investigate intraday market movements and the subsequent intraday returns within the same day. They find that early intraday market movements affect retail investor sentiment, resulting in market movements in the same direction within the day. Similarly, Wan and Yang (2017) analyze high-frequency transaction data and find a positive feedback trading effect. Some researchers try to estimate intraday sentiment using alternatives to traditional financial data. Sun, Najand, and Shen (2016) use news and social media data to construct intraday sentiment and find that sentiment accumulated over half-hour significantly predicts S&P 500 index returns over the next half hour. Similarly, Renault (2017) constructs a half-hour sentiment index using text data from Twitter and finds that the change in sentiment over the first half-hour of the day significantly explains the return in the last half hour of the day. Broadstock and Zhang (2019) also extract sentiment from Twitter and find that both firm-specific and market-wide sentiment significantly affect intraday stock returns.

The abovementioned studies successfully construct intraday sentiment measures; however, their methodologies are usually limited to text analysis, making it difficult to apply them in non-English-speaking countries, including many emerging markets. It is also hard to construct firm-specific intraday sentiment using social media data. Furthermore, their results only hold for the last few hours of a day. To overcome these limitations, we construct a firm-specific intraday sentiment measure on a minute-by-minute basis using easily accessible data and a straightforward methodology. Our analyses based on the intraday measure of investor sentiment show that firms with higher sentiment at the minute level have better subsequent short-term stock performance. This better performance lasts for at least half an hour, indicating that the mispricing caused by changes in intraday sentiment is not immediately corrected on average; instead, the price pressure from irrational optimism (or pessimism) persists for some time. In this way, the high-frequency effect of intraday sentiment is superimposed on the market and forms daily sentiment. We also find that the effect of negative sentiment is more prominent and lasts longer than that of positive sentiment, suggesting that pessimism has a stronger effect on the stock market than optimism does. In contrast with the results of previous studies, these results hold for all trading hours and are especially strong in the first and last trading hours. Interestingly, the abovementioned effects are only observed for hard-to-arbitrage firms, that is, small firms, firms with low short sales and institutional trade ratios, and firms with high volatility. Among firms in the top size, short sales ratio, and institutional trade ratio deciles, and firms in the bottom volatility decile, the difference in the returns of firms with high and low sentiment is almost zero. We interpret that investor irrationality does not significantly affect the stock prices of easy-to-arbitrage firms because arbitrageurs immediately absorb the demand shock caused by irrational investors. This difference in the effect of the investor sentiment is not induced by the firms' liquidities.

Overall, we find that when intraday investor sentiment is high, a firm's short-term returns increase over the subsequent 30 min. Notably, negative sentiment has a stronger effect than positive sentiment. The positive effect of intraday sentiment on subsequent return is only observed in the case of hard-to-arbitrage firms, suggesting that these firms are dominated by sentiment traders. Our study contributes to the literature in two ways. First, we construct an intraday sentiment measure using high-frequency transaction data. Little research has been conducted on intraday sentiment, and existing studies only analyze textual data (Behrendt & Schmidt, 2018; Renault, 2017; Sun et al., 2016). Extending these studies' methods to non-English-speaking countries, such as many emerging markets, is difficult. In contrast, we create a measure that can be easily replicated using readily accessible transaction data. Second, our measure allows us to analyze the effect of intraday sentiment on stock market movements using abundant market data. Our sample consists of 65,984,869 data points, making it considerably larger than the samples used by other investor sentiment studies. This large sample supports the robustness of the results. For practitioners, we describe a potential intraday trading opportunity, especially for hard-to-arbitrage firms.

The remainder of the paper is structured as follows. Section 2 describes the data and the methodology for measuring intraday sentiment. Section 3 reports the empirical results of the study, and Section 4 presents the conclusion.

2. Data and methodology

2.1. Intraday investor sentiment

This study analyzes intraday transaction data for Korean manufacturing firms listed on the Korea Composite Stock Price Index (KOSPI) market in 2018. We collect per-minute transaction data from the Korea Securities Computing Corporation (KOSCOM) and match this data with other financial data from the FnGuide database. The KOSCOM database only provides data points for times when transactions take place. However, because we need continuous data observations to construct the sentiment index, we amend the KOSCOM database by assigning zero values for data points with no transactions and setting the price at those times equal to the previous price. The resulting sample includes 66,599,978 data points from 725 KOSPI manufacturing firms for 2018. We exclude data for after-hours trades (304,717) and data points during transaction suspensions (310,392) and ultimately analyze 65,984,869 data points, covering 725 firms, 244 trading days, and 390 min per day.

We improve upon Seok et al. (2019a), Seok et al. (2019b) investor sentiment measure by constructing an intraday investor sentiment measure. They measure firm-specific daily sentiment by performing a principal component analysis (PCA) of four sentiment proxies: the relative strength index (*RSI*), the psychological line index (*PLI*), the adjusted turnover ratio (*ATR*), and the logarithm of trading volume (*LTV*). Similarly, we calculate *RSI*, *PLI*, *ATR*, and *LTV* for each minute and then perform PCA. These four proxies are widely used in prior studies of daily or monthly investor sentiment (Ryu, Kim, & Yang, 2017). *RSI*, developed by Wilder (1978), captures the price pressure caused by irrational investors and is used to estimate investor sentiment (Chen et al., 2010; Hudson & Green, 2015; Yang & Yang, 2019). *PLI* estimates the psychological stability of noise traders, and Yang and Gao (2014), Yang and Chi (2021), and Zhou and Huang (2020) use it as a proxy for investor sentiment. The turnover ratio (i.e., *ATR*) and trading volume (i.e., *LTV*) reflect stock liquidity and also serve as proxies for investors' opinions (Baker & Stein, 2004; Debata, Dash, & Mahakud, 2018; Liao, Huang, & Wu, 2011). Yang and Zhou (2015, 2016) construct a daily sentiment index by conducting PCA using these four proxies; numerous other studies follow this methodology to estimate daily investor sentiment (Gao & Yang, 2018; Reis & Pinho, 2020; Ryu, Ryu, & Yang, 2020; Trichilli, Abbes, & Masmoudi, 2020). In particular, Kim, Ryu, and Yang (2021) argue that investor sentiment, which they measure using this methodology, still has a significant effect even after considering firm-level news. Thus, we conclude that the index constructed by performing PCA on these four proxies, appropriately measures investor sentiment. The detailed calculations are as follows.

We calculate *RSI*, which estimates whether stocks are oversold or overbought over the previous 15 min, following Eq. (1). Here, $P_{i,t}$ denotes the share price of stock i at minute t.

$$RSI_{i,t} = \left[\frac{RS_{i,t}}{1+RS_{i,t}}\right], \text{ where } RS_{i,t} = \frac{\sum_{k=0}^{14}\max\left(P_{i,t-k}-P_{i,t-k-1},0\right)}{\sum_{k=0}^{14}\max\left(P_{i,t-k-1}-P_{i,t-k},0\right)} \tag{1}$$

PLI, which reflects buying power relative to selling power over the previous 15 min, is defined in Eq. (2).

$$PLI_{i,t} = \left[\sum_{k=0}^{14}\left\{\frac{\max\left(P_{i,t-k}-P_{i,t-k-1},0\right)}{P_{i,t-k}-P_{i,t-k-1}}\right\}\Big/15\right] \tag{2}$$

The time-weighted average *ATR*, which is a measure of optimistic or pessimistic liquidity, is calculated as shown in Eq. (3). Here, $V_{i,t}$ and $S_{i,t}$ denote the trading volume and outstanding shares, respectively, of stock i at minute t, and $R_{i,t}$ is the return, calculated as $R_{i,t} = \left(\frac{P_{i,t}}{P_{i,t-1}}\right)-1$.

$$ATR_{i,t} = \sum_{k=0}^{14}\frac{15-k}{120}\times\frac{V_{i,t-k}}{S_{i,t-k}}\times\frac{R_{i,t-k}}{\left|R_{i,t-k}\right|} \tag{3}$$

We also use the equal-weighted average *ATR* over the previous 15 min instead of the time-weighted average *ATR*; however, the results are almost similar for the two measures. Finally, we use the logarithm of the trading volume over the previous 15 min to capture stock liquidity. This measure is calculated as in Eq. (4).

$$LTV_{i,t} = ln\left(\sum_{k=0}^{14}V_{i,t-k}\right) \tag{4}$$

We modify these proxies somewhat to estimate intraday sentiment at the minute level, as described in the above equations. We mitigate the common dependence of each proxy on the overall market by controlling for the effect of the market return. Additionally, we control for the effects of short-term volatility and price movement pressure on the proxies.[1] Specifically, we regress each of the four proxies on the minute-level market return, which is defined as the value-weighted minute-level return[2] of the sample firms, and the short-term volatility and the price momentum over the previous 15 min.[3] Finally, we use the residuals from these regressions to conduct PCA, and we develop a minute-level intraday sentiment index ($S_{i,t}$) using the first principal component (F_t) of each orthogonalized proxy. Eq. (5) presents the detailed calculation of this index. Here, $RSI^{\perp}$, $PLI^{\perp}$, $ATR^{\perp}$, and $LTV^{\perp}$ are the orthogonalized proxies

[1] As mentioned previously, all four proxies are widely used to estimate investor sentiment, but they also include the price movement pressure of a firm. We, therefore, mitigate the effects of price movement pressure on each proxy by controlling for short-term volatility and momentum. We thank an anonymous reviewer for raising this issue.

[2] Here, we construct the minute-by-minute market returns using market capitalization-based value weights. The results are the same when we use equal weighted returns.

[3] Seok, Cho, and Ryu (2019a, 2019b) also control for the term spread, the default spread, firm size, the book-to-market ratio, and the earnings-price ratio. However, data for these variables are not provided on an intraday basis. Additionally, Baker and Wurgler (2006) and Seok, Cho, and Ryu (2019a, 2019b) argue that adjusting for macroeconomic factors is not important, by showing that the results using unadjusted raw proxies are similar to those using adjusted proxies. Thus, we only control for the market return and short-term price movement pressure. We also use raw proxies to construct the sentiment index, and the results are almost the same.

Table 1

Summary Statistics. This table presents the summary statistics of the variables in this study. Panel A summarizes the intraday variables, such as the sentiment index and minute-level returns. Our sample includes 65,984,869 intraday data points; however, the first 15 data points for each day are used to calculate the sentiment proxies. As a result, we construct the sentiment index for 63,382,009 data points. The sentiment index is constructed by performing PCA for $RSI^{\perp}$, $PLI^{\perp}$, $LTV^{\perp}$, and $ATR^{\perp}$, where each component is an orthogonalized sentiment proxy. The last price data point for each day is used to calculate returns, and, thus, the sample includes 65,811,345 data points for minute-level returns. Panel B summarizes the daily firm characteristic variables for 2018. Firm size, *MV*, is calculated as the product of the daily closing price and outstanding shares. The short sales ratio, *SHORT*, and the institutional trade ratio, *INST*, are each defined as the ratio of the daily short sales volume to the total trading volume, and the ratio of the daily trading volume of foreign and institutional traders to the total trading volume, respectively. Stock volatility, *VOL*, is the standard deviation of minute-level returns over each day. N denotes the number of observations, MEAN is the average of each variable, and STD denotes the standard deviation. MAX and MIN represent the maximum and minimum values, respectively.

	N	MEAN	STD	MAX	MIN
Panel A. Intraday Variables					
Sentiment	63,382,009	0.0000	1.2886	60.5519	−86.1328
RSI	63,382,009	0.5428	0.2608	0.9953	0
PLI	63,382,009	0.1692	0.1280	1	0
LTV	63,382,009	7.1075	2.8491	17.9855	0
ATR	63,382,009	0.0000	0.0001	0.0214	−0.0150
$RSI^{\perp}$	63,382,009	0.0000	0.2039	2.4320	−1.8794
$PLI^{\perp}$	63,382,009	0.0000	0.1043	0.6820	−1.3260
$LTV^{\perp}$	63,382,009	0.0000	2.5152	13.3609	−21.3610
$ATR^{\perp}$	63,382,009	0.0000	0.0001	0.0155	−0.0101
Return	65,811,345	0.0000	0.0024	0.3000	−0.2999
Panel B. Daily Firm Characteristics					
MV	173,487	26.47	1.54	33.46	22.69
SHORT	173,487	0.0340	0.0569	0.8186	0.0000
INST	173,487	0.2934	0.2476	1.0000	0.0000
VOL	173,487	0.0030	0.0020	0.1146	0.0000

that represent the residuals from the regressions described above.

$$S_{i,t} = F_{t,RSI} \times RSI^{\perp}_{i,t} + F_{t,PLI} \times PLI^{\perp}_{i,t} + F_{t,ATR} \times ATR^{\perp}_{i,t} + F_{t,LTV} \times LTV^{\perp}_{i,t} \tag{5}$$

The first principal component contributes 42.29% of the variance on average, which is close to the value of 45% found by Seok et al. (2019b). The first 15 transactions on each date are used to calculate the sentiment proxies, and, thus, we ultimately construct the sentiment index for 63,382,009 data points, spanning 725 firms.

2.2. *Firm characteristics*

The financial data used in this study are taken from the FnGuide database. Baker and Wurgler (2006) use firm size, stock volatility, profitability, and growth opportunity to measure a firm's degree of arbitrage. Seok et al. (2019a), Seok et al. (2019b) further consider idiosyncratic volatility, leverage, bankruptcy probability, the institutional trade ratio, and the short sales ratio. Among these firm characteristics, we select firm size, the short sales ratio, the institutional trade ratio, and volatility, as they are the only variables that are available on a daily basis.[4] Other firm characteristics, such as profitability and leverage, are provided on a quarterly basis and are, thus, not suitable for analyzing the intraday effect of sentiment. The detailed definitions of each variable are as follows.

Firm size (i.e., *MV*) is calculated as the product of the daily closing price and outstanding shares, as shown in Eq. (6). The effect of sentiment is widely known to be more prominent for small firms because they are harder to value (Aboody, Even-Tov, Lehavy, & Trueman, 2018; Baker & Wurgler, 2006; Chen, Chou, & Lin, 2019; Kumar, 2009; Shen, Yu, & Zhao, 2017).

$$MV_{i,d} = P_{i,d} \times S_{i,d} \tag{6}$$

where $P_{i,d}$ and $S_{i,d}$ are the closing price and outstanding shares, respectively, of stock i on day d.

The short sales ratio (i.e., *SHORT*) and the institutional trade ratio (i.e., *INST*) are defined as the ratio of the daily short sales volume to the total trading volume (Eq. (7)), and the ratio of the daily trading volume for foreign and institutional traders to the total trading volume (Eq. (8)), respectively. Seok et al. (2019b) show that firms with high values of *SHORT* and *INST* are less affected by sentiment because foreign and institutional traders are usually sophisticated and informed (Engelberg, Reed, & Ringgenberg, 2012). Consequently, they offset the demand shocks caused by noise traders. Similarly, Yang, Ryu, and Ryu (2017) demonstrate that investor sentiment has a stronger effect on firms with high individual trade ratios.

$$SHORT_{i,d} = SV_{i,d}/V_{i,d} \tag{7}$$

[4] We also analyze idiosyncratic volatility, which is calculated as the standard deviation of the minute-level idiosyncratic return over a given day. However, the results using idiosyncratic volatility are identical to those using volatility, and, thus, are not presented here.

Table 2
Subsequent Returns According to Intraday Sentiment. This table shows minute-level returns for two equally weighted portfolios constructed according to the sign of firm sentiment. *POSI* is a portfolio of positive sentiment firms, and *NEGA* is a portfolio of negative sentiment firms. *DIFF* denotes the difference in the returns of these two portfolios. Panel A presents cumulative returns; that is, the returns over the first *k* minutes after portfolio construction. Panel B shows returns per minute; that is, portfolio returns from minute *k*-1 to minute *k*.

RET_k	1 M	15 M	30 M	45 M	60 M
Panel A. Cumulative Returns					
POSI (%)	0.0010	0.0075	0.0083	0.0079	0.0066
NEGA (%)	−0.0013	−0.0141	−0.0196	−0.0223	−0.0230
DIFF (%)	0.0023	0.0215	0.0279	0.0302	0.0296
Panel B. Returns per Minute					
POSI (%)	0.0010	0.0003	0.0002	0.0000	0.0002
NEGA (%)	−0.0013	−0.0004	−0.0001	0.0001	0.0003
DIFF (%)	0.0023	0.0006	0.0003	0.0000	−0.0002

where $SV_{i,d}$ and $V_{i,d}$ denote the short sales volume and the total transactions, respectively, of stock *i* on day *d*.

$$INST_{i,d} = (IBV_{i,d} + ISV_{i,d})/(TBV_{i,d} + TSV_{i,d}) \tag{8}$$

where $IBV_{i,d}$ ($ISV_{i,d}$) is the buying (selling) volume for institutional and foreign traders and $TBV_{i,d}$ ($TSV_{i,d}$) is the total buying (selling) volume. Stock volatility, *VOL*, is the standard deviation of the minute-level return over a given day, as shown in Eq. (9). Baker and Wurgler (2006), Chue, Gul, and Mian (2019), and Reis and Pinho (2020) show that highly volatile stocks are more exposed to the sentiment effect because they are difficult to arbitrage.

$$VOL_{i,d} = \sqrt{var(R_{i,t})} \tag{9}$$

where $R_{i,t}$ is the return of stock *i* at minute *t*.

Table 1 provides summary statistics for each variable. Panel A of Table 1 shows summary statistics for intraday variables, such as the sentiment index and minute-level returns, and Panel B provides summary statistics for daily firm characteristic variables.

3. Empirical results

3.1. Intraday investor sentiment and subsequent stock returns

To investigate the effect of intraday investor sentiment on subsequent minute-level returns, we conduct a simple sorting test. We construct two equally weighted portfolios based on the sign of sentiment every minute and then track each portfolio's excess return over the next 60 min. A portfolio's excess return is calculated as the difference between its return and the market return. Table 2 presents cumulative returns (Panel A) and returns per minute (Panel B) for 1, 15, 30, 45, and 60 min after investor sentiment is observed. The rows labeled *POSI* (*NEGA*) show returns after *k* minutes for portfolios of positive (negative) sentiment firms, and the rows labeled *DIFF* show the difference in the returns of the two portfolios.

Table 2 presents two interesting results. First, the *POSI* rows show that the cumulative return for firms with positive sentiment increases for 30 min and then decreases. The *NEGA* rows show that for firms with negative sentiment, the cumulative return decreases for an hour. Thus, firms with positive (negative) intraday sentiment have higher (lower) subsequent returns over the short term, followed by lower (higher) performance. Seok et al. (2019b) show that daily sentiment is positively related to short-term stock returns. They argue that the overpricing (underpricing) caused by high (low) sentiment is not corrected immediately owing to the KOSPI market's inefficiency. Thus, high (low) sentiment periods are followed by positive (negative) next-day returns. Additionally, they show that mispricing is eventually corrected and that, as a result, stock returns after three and four days are negatively related to daily sentiment. The findings in Table 2 support this claim with high-frequency intraday data. The mispricing caused by intraday sentiment persists for about 30 min but, subsequently, is partially corrected. These results are consistent with the findings of Sun et al. (2016). They show that investor sentiment over a given half-hour significantly positively affects returns over the next half hour. Gao and Liu (2020) also find that five-minute lagged sentiment is positively related to future market index returns. Our results support the findings of these studies using data at the individual firm level.

Second, negative sentiment has a more prominent effect on subsequent returns than positive sentiment, and its effect persists longer. Table 2 shows that half-hour returns for the negative sentiment group (-1.96 bp) are twice as large as those for the positive sentiment group (0.83 bp). Additionally, the mispricing caused by negative sentiment persists for longer (about 60 min) than that caused by positive sentiment (about 30 min). These results indicate that pessimism has a stronger impact on the stock market than optimism does. Lutz (2016) and Smales (2017) demonstrate that sentiment has a stronger effect on market returns during recessions or bear markets. Our results are, therefore, consistent with the previous findings, using intraday data.

Fig. 1 displays the results in Table 2 over 60 min in continuous time. Panel A presents the cumulative returns on high sentiment and low sentiment portfolios and the difference between them, and Panel B shows returns per minute for 60 min. Fig. 1 graphically demonstrates that positive (negative) sentiment is followed by short-term positive (negative) returns and that the return on a portfolio constructed with negative sentiment firms is greater in absolute terms. It also shows that the effect of negative sentiment persists for a

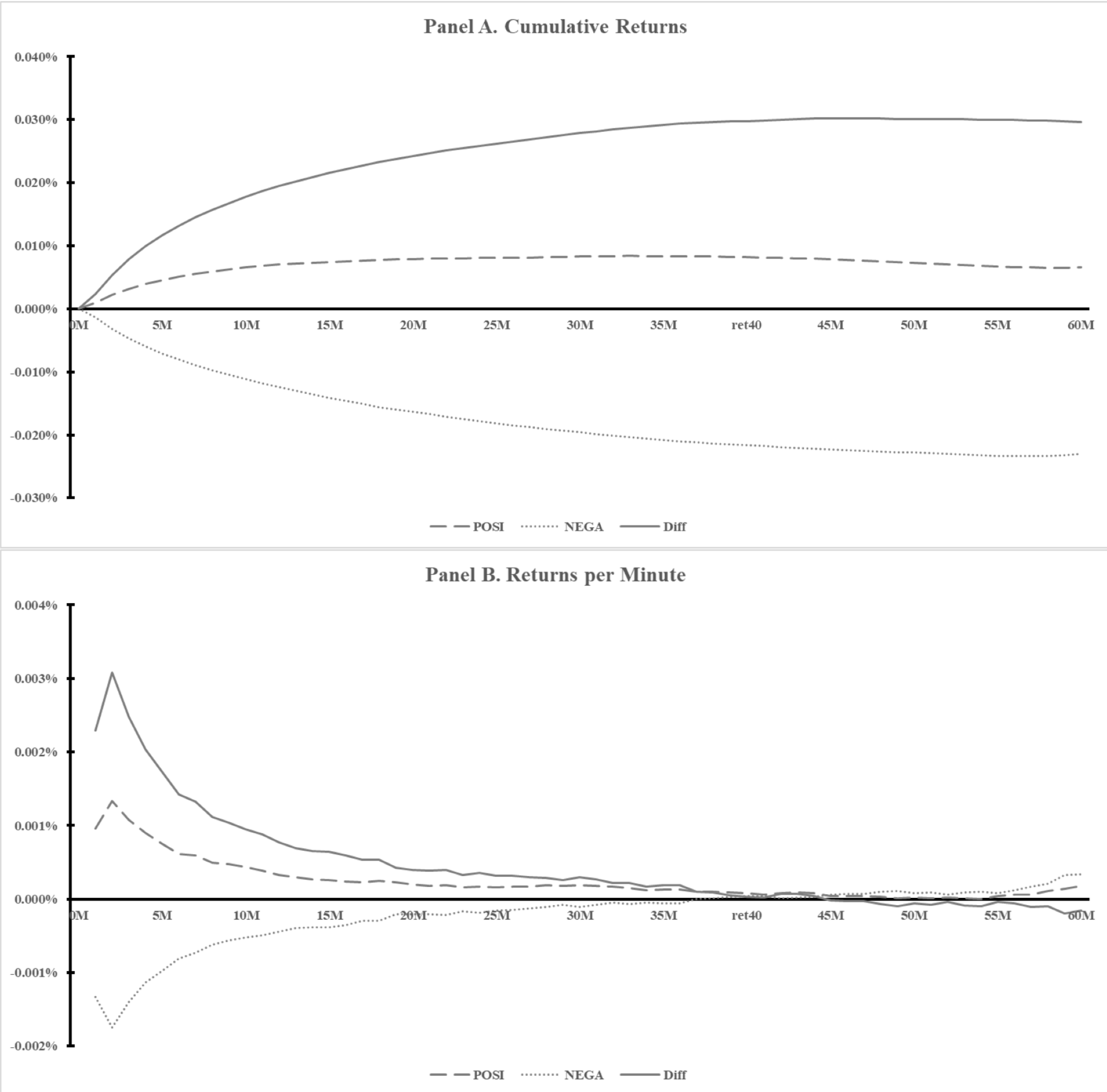

Fig. 1. Subsequent Returns According to Intraday Sentiment. This figure presents the minute-level returns of two equally weighted portfolios constructed according to the sign of firm sentiment. *POSI* is a portfolio of positive sentiment firms, and *NEGA* is a portfolio of negative sentiment firms. *DIFF* denotes the return difference between these two portfolios. The broad dotted line shows the return on *POSI*, and the tight dotted line shows the return on *NEGA*. The solid line shows the difference in the returns of the two portfolios. Panel A shows cumulative returns, that is, the return over the first *k* minutes after portfolio construction. Panel B shows returns per minute, that is, the portfolio return from minute *k*-1 to minute *k*. In each figure, the *x*-axis shows the minutes after portfolio construction, and the *y*-axis shows returns.

longer period.

A sorting test is very simple and intuitively shows the effect of intraday sentiment on minute-level returns; however, it may ignore some key factors affecting the results, and the statistical significance of the results cannot be determined. Thus, we also conduct long-short portfolio analysis and estimate Fama-MacBeth regressions to investigate the effects precisely. First, we sort all the firms in the full sample according to their sentiment every minute; we buy the stocks of firms in the top 30% and short those of firms in the bottom 30%. Then, we track the return and alpha of this long-short portfolio after 1, 15, 30, 45, and 60 min. Here, the portfolio alpha is obtained from Carhart's four-factor model, which we construct following Fama and French (1993) and Carhart (1997). More specifically, we define the market factor (*MKT*) as the value-weighted minute-level return of the sample (i.e., the 725 manufacturing firms). We divide the sample firms into *large* (top 50%) and *small* (bottom 50%) firms based on their market value at the end of June. We also divide them into *value* (top 30%), *neutral* (medium 40%), and *growth* (bottom 30%) groups based on the value of *BE/ME*, where *BE* is book equity at the end of the previous fiscal year and *ME* is the market value in December of the previous year. We then calculate

Table 3
Returns of Long-Short Portfolios Constructed Based on Intraday Sentiment. This table shows the minute-level returns and Carhart's four-factor alpha of a long-short portfolio constructed by buying the 30% of stocks with the highest sentiment and shorting the 30% stocks with the lowest sentiment. The first row (RET_k) shows the raw return from minute *k*-1 to minute *k*, and the second row ($ALPHA_k$ *(%)*)shows the portfolio alpha from minute *k*-1 to minute *k*. *t*-statistics are given in brackets. The superscripts ** and *** denote statistical significance at the 5% and 1% levels, respectively.

	1 M	15 M	30 M	45 M	60 M
RET_k (%)	0.0024***	0.0006***	0.0002**	−0.0003***	−0.0003***
	(23.50)	(6.22)	(2.07)	(-2.94)	(-3.41)
$ALPHA_k$ (%)	0.0024***	0.0006***	0.0002***	−0.0002***	−0.0003***
	(26.25)	(7.35)	(2.88)	(-2.62)	(-3.14)

Table 4
Effect of Intraday Sentiment on Subsequent Returns. This table shows the effect of intraday sentiment on subsequent minute-level returns. The first row (*Univariate*) shows the beta of sentiment, β_0, obtained from a univariate regression, that is, $R_{i,t+k} = \alpha_i + \beta_{i,0} \times S_{i,t} + \varepsilon_{i,t+k}$. Here, $R_{i,t+k}$ denotes the realized return of stock *i* at minute $t+k$, where *k* ranges from one to sixty, and $S_{i,t}$ represents the intraday sentiment of stock *i* at minute *t*. The second row (*FF4 Model*) shows the beta of sentiment, β_0, obtained from a Carhart four-factor regression, that is, $R_{i,t+k} = \alpha_i + \beta_{i,0} \times S_{i,t} + \beta_{i,1} \times MKT_{t+k} + \beta_{2,i} \times SMB_{t+k} + \beta_{3,i} \times HML_{t+k} + \beta_{4,i} \times MOM_{t+k} + \varepsilon_{i,t+k}$. Here, MKT_{t+k}, SMB_{t+k}, HML_{t+k}, and MOM_{t+k} are the factor returns at minute $t+k$. Newey and West *t*-statistics with three lags are given in brackets. The superscripts ** and *** denote statistical significance at the 5% and 1% levels, respectively.

	1 M	15 M	30 M	45 M	60 M
Univariate	0.0035***	0.0010***	0.0003**	−0.0002**	−0.0003***
	(14.38)	(8.82)	(2.96)	(-2.69)	(-6.00)
FF4 Model	0.0035***	0.0010***	0.0003**	−0.0002	−0.0003***
	(13.23)	(7.48)	(2.61)	(-1.65)	(-4.94)

the size factor (*SMB*) as the difference between the average minute-level return of the three small portfolios (*small & value*, *small & neutral*, and *small & growth*), and of the three large portfolios (*large & value*, *large & neutral*, and *large & growth*). Similarly, we define the value factor (*HML*) as the difference between the average minute-level return of the two value portfolios (*small & value* and *large & value*) and that of the two growth portfolios (*small & growth* and *large & growth*). Finally, we divide the sample firms into *large* (top 50%) and *small* (bottom 50%) firms based on their market values at the end of the month and into *winner* (top 30%), *neutral* (middle 40%), and *loser* (bottom 30%) firms based on their cumulative returns from month *t*-12 to month *t*-2. Subsequently, we calculate the momentum factor (*MOM*) as the difference between the average minute-level return of the two winner portfolios (*small & winner* and *large & winner*) and that of the two loser portfolios (*small & loser* and *large & loser*).[5] These factors are used throughout the analysis. Table 3 shows the returns and alphas for the long-short portfolio.

The portfolio return and alpha are both positive until 30 min; then, both of them become negative. Specifically, the return and alpha are significantly positive from the first to the thirtieth minute, indicating that intraday investor sentiment positively affects subsequent stock performance. However, this effect disappears after about 30 min, and after 45 min, the long-short portfolio's performance becomes significantly negative, suggesting that the mispricing caused by intraday sentiment is partially corrected within an hour. This result statistically supports the results shown in Table 2 and Fig. 1.

Finally, we construct Eq. (10) and estimate Fama-MacBeth regressions to directly investigate the effect of intraday sentiment on subsequent stock performance at the minute level. Here, $R_{i,t+k}$ denotes the realized return of stock *i* at minute $t+k$, where *k* ranges from one to sixty, and $S_{i,t}$ represents the intraday sentiment of stock *i* at minute *t*. MKT_{t+k}, SMB_{t+k}, HML_{t+k}, and MOM_{t+k} are the factor returns at minute $t+k$.

$$R_{i,t+k} = \alpha_i + \beta_{i,0} \times S_{i,t} + \beta_{i,1} \times MKT_{t+k} + \beta_{2,i} \times SMB_{t+k} + \beta_{3,i} \times HML_{t+k} + \beta_{4,i} \times MOM_{t+k} + \varepsilon_{i,t+k} \quad (10)$$

We perform two preprocessing steps before proceeding with the regression. First, we rescale the sentiment index ($S_{i,t}$) using min–max normalization so that it ranges from zero to one. Table 1 shows that the scale of the sentiment index is much larger than that of minute-level stock returns, and this imbalance renders the beta of sentiment too small. Note that rescaling an independent variable only increases the beta's magnitude and does not change its significance. Second, we drop data points without transactions. About one-third of the data points (20,622,568 of the 65,811,345 data points) have no transactions but include zero stock returns. These false zero returns may distort the beta of sentiment, and, thus, we exclude data points with no transactions. Table 4 shows the regression results. Only the beta of sentiment is presented because the effect of intraday sentiment on subsequent returns is the focus of this study. The results in Table 4 strongly support the previous results. Intraday investor sentiment affects stock returns positively for the next one to thirty minutes. After that, however, the effect decreases and becomes negative after 45 min. This negative effect persists significantly even after 60 min.

5 The detailed methodology is described on French's website(http://mba.tuck.dartmouth.edu/pages/faculth/ken.french).

Table 5
Subsequent Returns According to Intraday and Daily Sentiment. This table shows the cumulative returns after k minute (RET_k) of four equally weighted portfolios constructed according to the signs of intraday and daily sentiment. Panel A shows the cumulative returns, that is, the returns over the first k minutes after portfolio construction, of a portfolio of firms with positive intraday sentiment; Panel B shows cumulative returns of a portfolio of firms with negative intraday sentiment. *POSI* is a portfolio of firms with the positive daily sentiment, and *NEGA* is a portfolio of firms with the negative daily sentiment. *DIFF* denotes the difference in the returns of these two portfolios, and *t*-statistics are shown in brackets. The superscripts * and *** denote statistical significance at the 10% and 1% levels, respectively.

	1 M	15 M	30 M	45 M	60 M
Panel A. Positive Intraday Sentiment					
POSI (%)	0.0009	0.0087	0.0113	0.0126	0.0123
NEGA (%)	0.0013	0.0081	0.0093	0.0098	0.0101
DIFF (%)	−0.0003***	0.0006*	0.0020***	0.0029***	0.0022***
	(-2.69)	(1.65)	(4.50)	(5.35)	(3.60)
Panel B. Negative Intraday Sentiment					
POSI (%)	−0.0007	−0.0092	−0.0109	−0.0120	−0.0114
NEGA (%)	−0.0015	−0.0145	−0.0202	−0.0232	−0.0245
DIFF (%)	0.0009***	0.0053***	0.0093***	0.0112***	0.0131***
	(5.62)	(13.86)	(19.19)	(20.11)	(21.18)

Table 6
Effect of Intraday Sentiment on Subsequent Returns by Time. This table shows the effect of intraday sentiment by trading time. The first row (*RET)* shows minute-level returns for a portfolio constructed by buying stocks with high sentiment and shorting stocks with low sentiment. The second row (*Univariate*) shows the beta of sentiment obtained from a univariate regression. We define T1, T2, T3, T4, T5, and T6 as the periods from 9:31 to 10:30, 10:31 to 11:30, 11:31 to 12:30, 12:31 to 13:30, 13:31 to 14:30, and 14:31 to 15:30, respectively. Newey and West *t*-statistics with three lags are given in brackets. The superscript *** denotes statistical significance at the 1% level.

	T1	T2	T3	T4	T5	T6
RET (%)	0.0054***	0.0022***	0.0006***	0.0010***	0.0015***	0.0027***
	(19.31)	(9.06)	(3.09)	(4.95)	(6.74)	(9.47)
Univariate	0.0072***	0.0039***	0.0016***	0.0012***	0.0024***	0.0030***
	(6.96)	(9.92)	(5.00)	(9.79)	(10.10)	(8.15)

This subsection shows that the mispricing caused by intraday sentiment lasts for about half an hour. This result is consistent with the findings of previous studies that analyze daily sentiment. Yang and Zhou (2016) find a positive relation between daily investor sentiment and simultaneous stock returns; Seok et al. (2019b) also argue that the positive effect of daily investor sentiment lasts for one day. In other words, previous studies show that next-day returns are greater for firms with high sentiment than for firms with a low sentiment. If the stock market is perfectly efficient, then any mispricing caused by behavioral bias should be immediately corrected by arbitrageurs. The lasting impact of sentiment on short-term returns implies that the KOSPI market has some inefficiency. It is logical to ask how long the mispricing due to sentiment lasts. Baker and Wurgler (2006), Schmeling (2009), and Huang, Jiang, Tu, and Zhou (2015) argue that a high investor sentiment period is followed by lower stock market returns because an overpricing due to optimistic investors should ultimately return to the fundamental value. The results of this subsection support these studies by finding a negative effect of intraday sentiment on stock returns after half an hour has passed.

However, mispricing induced by intraday investor sentiment is not completely corrected within one hour. Instead, the price is only partially adjusted back to the stock's fundamental value. The results in Panel A of Table 2 and Panel A of Fig. 1 show that although the difference in the cumulative returns of firms with positive and negative sentiment decreases in size, it is still positive, even after one hour. This result implies that the residual effects of intraday sentiment accumulate to form daily sentiment. We conduct an additional analysis by combining the daily investor sentiment index of Seok et al. (2019b) with our intraday index, and investigate the effect of a trading day's intraday sentiment on that day's daily sentiment. The results show that if the intraday sentiment on a specific trading day is positive (negative) on average, the daily sentiment on that day is more likely to be positive (negative) as well.[6] We also investigate whether the effect of intraday investor sentiment is related to daily sentiment. Because intraday sentiment accumulates to form daily sentiment, the effect of positive (negative) intraday sentiment is expected to be stronger when daily sentiment is positive (negative). We divide the full sample of firms into two groups according to the daily investor sentiment index, that is, firms with high daily sentiment and firms with a low daily sentiment. We then analyze whether the effect of intraday sentiment differs across the two groups. Table 5 presents the results. We find that the effect of positive intraday investor sentiment on subsequent cumulative returns is more prominent when daily sentiment is positive. Regardless of the direction of daily sentiment, the subsequent returns increase when intraday sentiment is high. However, this increase is larger when daily sentiment is also high, and the difference is significant.

[6] More specifically, if the intraday sentiment on a specific trading day is positive on average, then the probability that the daily sentiment on that day is positive is 54.07%. Similarly, if the intraday sentiment on a given day is negative on average, then the probability that the daily sentiment is negative is 57.12%.

Table 7

Subsequent Returns According to Intraday Sentiment and Firm Characteristics. This table shows the difference in returns (%) for firms with positive and negative sentiment grouped by firm characteristics, that is, firm size (*MV*), the short sales ratio (*SHORT*), the institutional trade ratio (*INST*), and volatility (*VOL*). The *High* column denotes the group with high values of these characteristics, and the *Low* column denotes the group with low values of these characteristics. The rows labeled 1 M show returns after one minute, and the rows labeled 30 M and 60 M show returns (%) from 2 to 30 min and from 30 to 60 min, respectively.

	Low	2	3	4	5	6	7	8	9	High
Panel A. MV										
1 M	0.009	0.008	0.006	0.005	0.004	0.002	0.000	−0.003	−0.005	−0.016
30 M	0.061	0.047	0.035	0.035	0.026	0.014	0.010	0.004	−0.001	0.003
60 M	0.009	0.003	−0.001	0.000	−0.004	−0.011	−0.002	−0.005	−0.002	−0.002
Panel B. SHORT										
1 M	0.009	0.007	0.006	0.005	0.004	0.003	0.000	−0.001	−0.003	−0.006
30 M	0.061	0.047	0.037	0.030	0.033	0.024	0.013	0.010	0.005	0.002
60 M	0.015	0.003	−0.002	−0.005	0.001	−0.001	−0.004	−0.002	−0.002	−0.006
Panel C. INST										
1 M	0.003	0.006	0.007	0.007	0.005	0.003	0.000	−0.002	−0.006	−0.005
30 M	0.024	0.038	0.043	0.039	0.029	0.024	0.012	0.005	0.001	0.001
60 M	−0.015	0.002	0.001	−0.002	−0.002	0.001	−0.009	−0.007	−0.007	0.000
Panel D. VOL										
1 M	0.001	0.002	0.002	0.001	0.001	0.002	0.002	0.004	0.006	0.006
30 M	0.006	0.006	0.020	0.015	0.025	0.025	0.026	0.033	0.043	0.056
60 M	−0.001	−0.008	−0.003	−0.001	0.000	0.001	−0.002	−0.007	−0.002	0.006

Similarly, negative intraday sentiment has a stronger effect when daily sentiment is low.

Finally, we investigate the effect of intraday sentiment according to the time of day. Sun et al. (2016) show that market-wide changes in intraday investor sentiment, as measured by textual data, can predict market returns over the next half hour. This effect is particularly strong in the last two hours of the trading day. Similarly, Renault (2017) argues that changes in investor sentiment in the first half-hour of the trading day predict returns in the last half hour of the trading day. To confirm these results, we group trading times by hour from 9:31 to 15:30. Then, we investigate the long-short portfolio returns and the beta of sentiment according to trading time. Table 6 shows the results of this analysis. The first row of Table 6 shows minute-level long-short portfolio returns, and the second row shows the Fama-MacBeth univariate regression coefficients of sentiment. Here, we only present raw returns and betas from univariate regressions because controlling for other factors does not change the results in per-minute terms.

Table 6 shows that intraday sentiment has a significantly positive effect throughout the trading day, which is consistent with the findings of Sun et al. (2016), except for the first trading hour. Additionally, the effect of intraday sentiment is particularly strong in the first and last trading hours. Thus, the effect of intraday sentiment on subsequent returns exhibits a *U*-shaped pattern over time; that is, the effect is larger for the first and last trading hours and is smaller in the middle of the day. Interestingly, this pattern is completely consistent with that of the intraday trading volume. In our sample data, the average number of total transactions is greatest during the first trading hour (67,286,006), and it subsequently decreases until the middle of the day (31,689,651 at T3 and 34,427,122 at T4). It then increases again to 46,766,334 during the last trading hour (T6). Combined with the results of Table 6, this finding implies that high trading volumes partially induce the mispricing caused by sentiment.

3.2. *Intraday sentiment effect across firm characteristics*

Previous studies argue that mispricing due to sentiment arises because arbitrageurs have limited ability to absorb the demand shocks caused by sentiment (e.g., Yang et al., 2017). Thus, studies show that the effect of sentiment is more prominent for firms that are hard to arbitrage. In this subsection, we investigate whether this result still holds on an intraday basis using high-frequency data.

First, we divide the full sample of firms into ten decile groups, according to the firm characteristics defined in subsection 2.2. We average each daily characteristic over one month to stably maintain the distribution across deciles. Then, we match each firm's decile rank in month *t*-1 with intraday sentiment and minute-level returns in month *t*. For example, intraday sentiment and returns in February are matched with the decile rank for firm size in January. Then, we subdivide each decile group according to the sign of sentiment at every minute. As a result, we form 20 groups at each minute, including, for example, the lowest firm characteristic decile with negative sentiment, the lowest firm characteristic decile with positive sentiment, the highest firm characteristic decile with negative sentiment, and the highest firm characteristic decile with positive sentiment. Then, we track the stock returns of each group over the next 60 min. Table 7 shows the difference in returns for the positive and negative sentiment groups within each decile for each

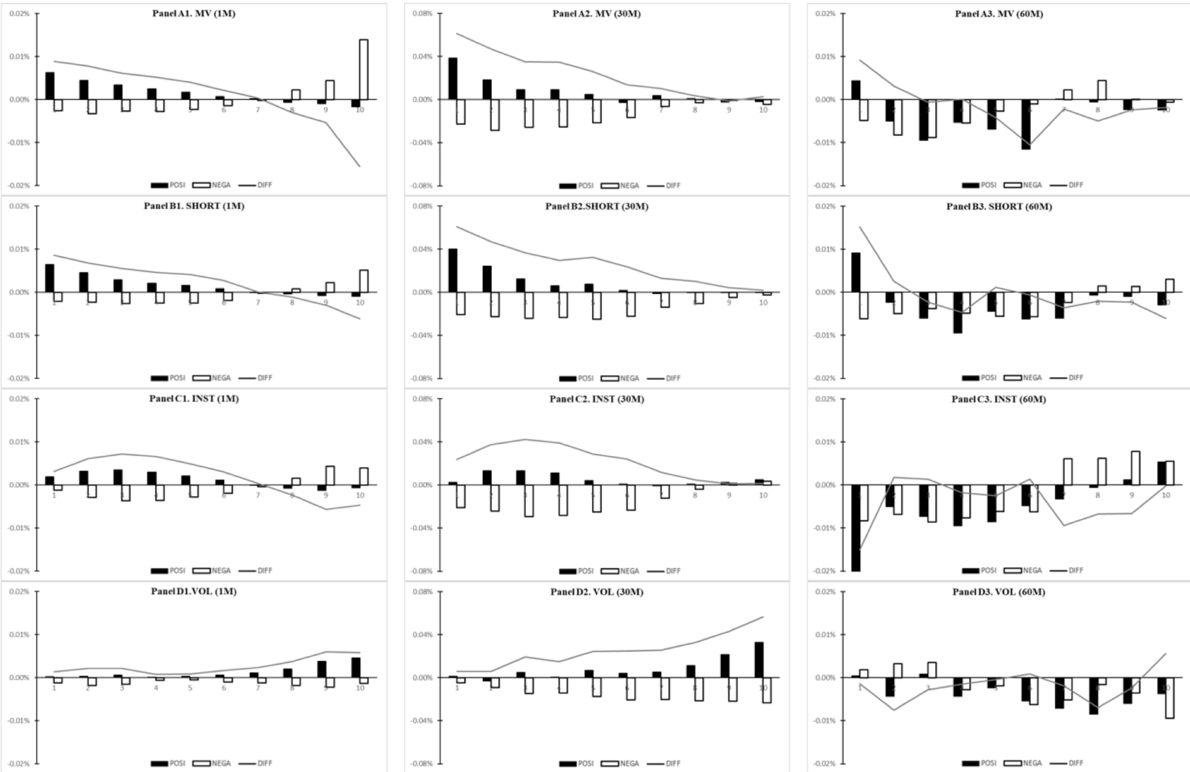

Fig. 2. Subsequent Returns According to Intraday Sentiment and Firm Characteristics. This figure shows the excess returns of firms with positive sentiment and firms with negative sentiment grouped by firm characteristics, that is, firm size (*MV*), the short sales ratio (*SHORT*), the institutional trade ratio (*INST*), and volatility (*VOL*). Each graph also shows the difference in the returns. In each graph, the values of the firm characteristics increase toward the right. The solid bars denote the average excess returns of firms with positive sentiment, and the clear bars denote those of firms with negative sentiment. The solid lines are the difference in returns. The graphs labeled “1M” show returns after one minute, and the graphs labeled “30 M” and “60 M” show returns from 2 to 30 min and from 30 to 60 min, respectively.

characteristic. Owing to space limitations, we only present the results for minute 1, minutes 2 to 30, and minutes 31 to 60.[7] The rows labeled “1M” show returns after one minute, the rows labeled “30 M” show returns from two to thirty minutes, and the rows labeled “60 M” show returns from thirty to sixty minutes.

Panel A of Table 7 shows that the one-minute return difference across firms with positive and negative sentiment decreases as firm size increases. Similarly, the one-minute return difference decreases as the short sales and institutional trade ratios increase, and it increases as volatility increases. This result shows that the mispricing effect of sentiment over one minute is stronger for firms with smaller *MV*, lower *SHORT* and *INST*, and higher *VOL*, that is, hard-to-arbitrage firms. We observe similar patterns in the results for two to thirty minutes. Thus, the more difficult arbitrage, the longer the mispricing effect of sentiment persists. However, the results for 31 to 60 min do not show the same pattern, indicating that the different effects of intraday sentiment for firms with different characteristics do not persist after 30 min. Fig. 2 graphically presents the results in Table 7.

Fig. 2 intuitively shows the differing effects of intraday sentiment on subsequent returns according to firm characteristics. On the rightmost side of Panel A1, returns do not differ by sentiment, meaning that sentiment does not affect returns after one minute for large firms. Conversely, for the smallest firms (the leftmost side of Panel A1), the solid and transparent bars are significantly different. Positive sentiment is followed by higher per minute returns, and negative sentiment is followed by lower per minute returns. Panel A2 shows a similar pattern to Panel A1, but we observe no such pattern in Panel A3. Thus, we conclude that intraday sentiment has a more pronounced effect on small firms over 30 min. The results for the other firm characteristics show a similar pattern; the return difference is only significantly positive on the left sides of Panels B and C and on the right side of Panel D. In other words, the effect of sentiment is stronger for firms with lower short sales and institutional trade ratios, and firms with higher volatility. These patterns last for 30 min (i. e., the middle panels labeled “30 M”) and then disappear (i.e., the right panels labeled “60 M”).

[7] We also analyze more segmented returns, that is, returns from 2 to 15 min, 15 to 30 min, 30 to 45 min, and 45 to 60 min. However, this further segmentation does not significantly affect the results. The results for returns from 2 to 15 min and from 15 to 30 min are almost the same as the results for returns from 2 to 30 min, and the results for returns from 30 to 45 min and from 45 to 60 min show a similar pattern to the results for returns from 30 to 60 min.

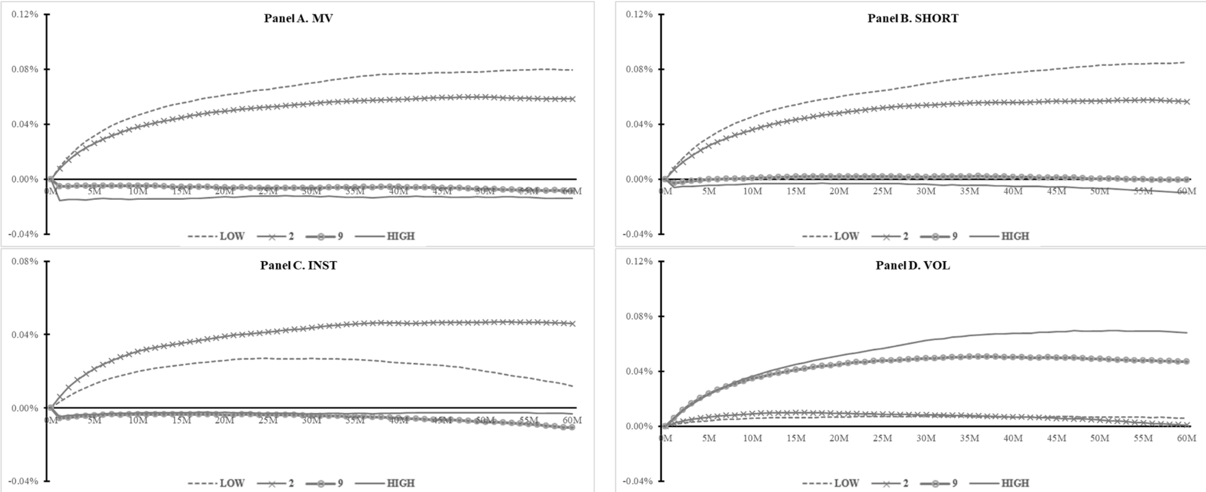

Fig. 3. Continuous Differences in Returns According to Sentiment and Firm Characteristics. This figure shows the difference in the returns of high and low sentiment firms grouped by firm characteristics, that is, firm size (*MV*), the short sales ratio (*SHORT*), the institutional trade ratio (*INST*), and volatility (*VOL*). In each graph, the solid line denotes the highest decile group for the given firm characteristic, the solid line with circles denotes the second highest decile group, the dotted line denotes the smallest decile group, and the solid line with crosses denotes the second smallest decile group. In each figure, the *x*-axis shows the minutes after group construction, and the *y*-axis shows the difference in returns.

We also track the continuous return difference across high and low sentiment firms over 60 min according to firm characteristics. The results are shown in Fig. 3. For readability, we present only the results for the two smallest and two largest decile groups. Fig. 3 clearly shows that the effect of intraday sentiment on subsequent stock returns depends on firm characteristics. The two largest decile groups of *MV*, *SHORT*, and *INST* and the two smallest decile groups of *VOL* are barely affected by sentiment. In these decile groups, the differences in the returns of high and low sentiment firms are nearly zero over 60 min. However, for small firms, firms with low short sales and institutional trade ratios, and high volatility firms, the differences in returns increase over 30 min.

Finally, we define firms in the top 30% for each characteristic as *HIGH* and firms in the bottom 30% for each characteristic as *LOW*, and we run the Fama-MacBeth regression given by Eq. (10) for each group. Through this regression analysis, we investigate differences in the beta of sentiment according to these firm characteristics and the significance of these differences. The results are presented in Table 8.

The betas of sentiment for one-minute returns (i.e., the rows labeled "1M") are significantly positive for the *LOW* groups of *MV*, *SHORT*, and *INST* and the *HIGH* group of *VOL*. Thus, intraday sentiment positively affects returns over the following minute for small firms, firms with low short sales and institutional trade ratios, and firms with high volatility. Interestingly, the betas of sentiment for the *HIGH* groups of *MV*, *SHORT*, and *INST* and the *LOW* group of *VOL* are significantly negative, in contrast to the previous results. Thus, the mispricing caused by intraday sentiment is immediately corrected for large firms, firms with high short sales and institutional trade ratios, and firms with low volatility, that is, easy-to-arbitrage firms. The difference in the betas for large and small firms is significantly negative, suggesting that the mispricing caused by sentiment lasts for one minute only for small firms. This result holds for the other firm characteristics. All of the differences in the betas after 30 min (i.e., the rows labeled "30 M") have the same signs as those after one minute, regardless of firm characteristics, indicating that the effect of sentiment lasts for at least 30 min.

In sum, the results in Tables 7 and 8 show that intraday sentiment positively affects subsequent stock returns only for hard-to-arbitrage firms. However, hard-to-arbitrage firms, that is, small firms, firms with low short sales and institutional trade ratios, and firms with high volatility, are also less liquid. Thus, it takes longer for the effects of temporary price pressure to dissipate for these firms. The previous results may simply be driven by traders' liquidity needs.[8] Thus, we investigate whether the differences in the effects of intraday investor sentiment according to firm characteristics disappear after we control for firms' liquidities. We estimate a firm's illiquidity using Amihud (2002) methodology. Eq. (11) shows the detailed calculation of this measure.

$$illiquidity_t = Average\left(\frac{|r_k|}{TransactionAmount_k}\right) \tag{11}$$

where r_k is the stock return at minute k of day t. $Transaction\ Amount_k$ denotes the transaction amount at minute k of day t. Then, we divide the full sample of firms into two groups according to this illiquidity measure, that is, high and low liquidity firms. Within each liquidity group, we define firms in the top three deciles of the firm characteristics as *High* and firms in the bottom three deciles as *Low*. We conduct a similar analysis to that reported in Table 7 in each liquidity group. Specifically, we calculated differences in returns for firms with positive and negative sentiment in each *High* and *Low* group after controlling for the firms' liquidity, and then compare these

[8] We thank an anonymous reviewer for raising this issue.

Table 8
Effect of Intraday Sentiment According to Firm Characteristics. This table shows the effect of intraday sentiment on subsequent minute-level returns according to firm characteristics, that is, firm size (*MV*), the short sales ratio (*SHORT*), the institutional trade ratio (*INST*), and volatility (*VOL*). The first three columns show the betas of sentiment obtained from Carhart's four-factor regressions. The columns labeled *High* show the betas of sentiment for firms in the top 30% for the given characteristic, and the columns labeled *Low* show the betas of sentiment for firms in the bottom 30% for the given characteristic. The columns labeled *Diff* show the difference in the betas. We estimate this difference using regressions with a dummy variable for the *High* group. Similarly, the last three columns show the betas of sentiment obtained from univariate regressions for each group and their difference. Newey and West *t*-statistics with three lags are given in brackets. The superscripts ** and *** denote statistical significance at the 5% and 1% levels, respectively.

	Four-Factor			Univariate		
	High	Low	Diff	High	Low	Diff
Panel A. MV						
1 M	−0.0059***	0.0118***	−0.0177***	−0.0059***	0.0117***	−0.0176***
	(−37.03)	(12.89)	(−18.11)	(−37.41)	(14.54)	(−20.16)
30 M	−0.0001	0.0012***	−0.0013***	−0.0001	0.0010***	−0.0011***
	(−1.52)	(3.45)	(−4.11)	(−1.32)	(4.14)	(−5.05)
60 M	−0.0003***	0.0000	−0.0003**	−0.0003***	−0.0002**	−0.0001
	(−8.98)	(0.34)	(−2.44)	(−7.33)	(−2.39)	(−1.13)
Panel B. SHORT						
1 M	−0.0034***	0.0115***	−0.0149***	−0.0034***	0.0114***	−0.0148***
	(−27.44)	(10.72)	(−13.52)	(−27.90)	(11.65)	(−14.63)
30 M	−0.0001	0.0014***	−0.0015***	−0.0001	0.0012***	−0.0013***
	(−1.52)	(3.49)	(−4.23)	(−1.38)	(4.25)	(−5.42)
60 M	−0.0002***	0.0001	−0.0004**	−0.0002***	−0.0001	−0.0002**
	(−7.64)	(0.76)	(−2.55)	(−7.58)	(−0.93)	(−2.29)
Panel C. INST						
1 M	−0.0041***	0.0080***	−0.0121***	−0.0041***	0.0080***	−0.0120***
	(−20.77)	(8.06)	(−10.69)	(−20.76)	(8.74)	(−11.40)
30 M	−0.0001**	0.0009***	−0.0010***	−0.0001**	0.0008***	−0.0009***
	(−2.65)	(3.23)	(−3.91)	(−2.58)	(4.10)	(−5.19)
60 M	−0.0003***	−0.0001	−0.0002**	−0.0003***	−0.0002***	−0.0001
	(−11.24)	(−0.55)	(−2.38)	(−12.63)	(−3.26)	(−0.64)
Panel D. VOL						
1 M	0.0094***	−0.0013***	0.0107***	0.0092***	−0.0013***	0.0105***
	(5.59)	(−4.04)	(5.36)	(6.05)	(−3.94)	(5.70)
30 M	0.0011**	0.0000	0.0011**	0.0009**	0.0000	0.0009***
	(2.34)	(0.43)	(2.42)	(2.73)	(0.55)	(2.88)
60 M	−0.0001	−0.0002***	0.0001	−0.0003**	−0.0002***	−0.0001
	(−0.41)	(−4.00)	(0.68)	(−2.77)	(−2.62)	(−0.64)

differences. Table 9 shows the results.

The results in Table 9 show that the effect of intraday sentiment is more prominent for small firms, firms with low short sales and institutional trade ratios, and firms with high volatility even after we control for liquidity. For example, Panel A shows that the difference in returns after one minute for firms with high and low sentiment is greater for small firms. However, in contrast to the results in Table 7, we find that mispricing is not immediately corrected even for large firms if liquidity is low. Thus, we conclude that the results of this study are not driven by liquidity.

4. Conclusion

This study investigates the effect of intraday sentiment on subsequent stock returns in the KOSPI market. We improve upon firm-specific daily measures of investor sentiment by estimating intraday sentiment using minute-level transaction data. By analyzing this very high-frequency data, we determine the extent to which the mispricing caused by sentiment occurs and persists. The results of this analysis show that mispricing is not corrected immediately; instead, it lasts for at least about 30 min. The raw return and alpha for a long-short portfolio constructed based on sentiment are significantly positive over 30 min. Additionally, the beta of sentiment is positive, regardless of whether other factors are controlled. After 30 min, investor sentiment has a negative effect on subsequent stock returns, suggesting that prices start to adjust, at least partially, back to their fundamental values after 30 min. This study also finds that the effect of intraday sentiment depends on the degree of arbitrage. Intraday sentiment has little effect on easy-to-arbitrage firms, that is, large firms, firms with high short sales and institutional trade ratios, and firms with low volatility. The difference in returns after one minute for high and low sentiment firms is nearly zero in these groups, indicating that the mispricing caused by intraday sentiment is immediately corrected for these firms. Conversely, for hard-to-arbitrage firms, the return difference between high and low sentiment firms lasts for about half an hour. Overall, we find that when intraday investor sentiment is high, the subsequent short-term returns increase over the next 30 min but then decrease back to their fundamental values within an hour. We only observe this effect for hard-to-arbitrage firms. These results provide empirical evidence of the effect of intraday investor sentiment and are consistent with the

Table 9

Differences in Subsequent Returns According to Firm Characteristics and Liquidity. This table shows the differences in returns (%) for firms with positive and negative sentiment grouped by firm characteristics, that is, firm size (*MV*), the short sales ratio (*SHORT*), the institutional trade ratio (*INST*), and volatility (*VOL*), after controlling for the firms' liquidity. The first three columns show the results for firms with low liquidities, and the last three columns show the results for firms with high liquidities. The columns labeled *High* show the subsequent returns differences for firms with high values of the firm characteristics, that is, firms in the top three deciles. Similarly, the columns labeled *Low* denote the subsequent returns differences for firms with low values of the firm characteristics, that is, firms in the bottom three deciles. The columns labeled *Diff* show the differences for *High* and *Low*. The rows labeled 1 M show returns (%) after one minute, and those labeled 30 M and 60 M show returns (%) from 2 to 30 min and from 30 to 60 min, respectively. Satterthwaite *t*-statistics for subsequent return differences are given in brackets in the *High* and *Low* columns, and Wald chi-square statistics are given in brackets in the *Diff* columns. The superscripts *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Low liquidity			High liquidity		
	High	Low	Diff	High	Low	Diff
Panel A. MV						
1 M	0.0050***	0.0085***	−0.0035***	−0.0124***	0.0004**	−0.0128***
	(30.45)	(39.05)	(169.56)	(−43.14)	(2.24)	(2011.7)
30 M	0.0313***	0.0000***	−0.0252***	0.0031***	0.0071***	−0.0038***
	(59.11)	(73.18)	(784.89)	(4.95)	(12.17)	(11.26)
60 M	−0.0008	0.0069***	−0.0078***	−0.0004	−0.0092***	0.0088***
	(−1.59)	(9.28)	(79.76)	(−0.69)	(−16.39)	(98.31)
Panel B. SHORT						
1 M	0.0060***	0.0084***	−0.0024***	−0.0060***	−0.0003*	−0.0057***
	(34.51)	(38.38)	(78.58)	(−28.98)	(−1.89)	(508.43)
30 M	0.0331***	0.0591***	−0.0260***	0.0006	0.0098***	−0.0093***
	(61.03)	(74.89)	(846.73)	(1.07)	(16.49)	(123.33)
60 M	−0.0014***	0.0112***	−0.0126***	−0.0064***	−0.0069***	0.0005
	(−2.58)	(14.60)	(210.34)	(−12.36)	(−11.87)	(0.35)
Panel C. INST						
1 M	0.0058***	0.0065***	−0.0007***	−0.0051***	−0.0005***	−0.0046***
	(36.46)	(30.12)	(7.71)	(−26.56)	(−2.68)	(356.82)
30 M	0.0358***	0.0437***	−0.0079***	0.0013***	0.0036***	−0.0023
	(70.94)	(56.49)	(82.51)	(2.65)	(5.80)	(7.99)
60 M	0.0022***	0.0003	0.0019**	−0.0028***	−0.0108***	0.0080***
	(4.40)	(0.42)	(4.87)	(−5.94)	(−17.81)	(100.57)
Panel D. VOL						
1 M	0.0076***	0.0068***	0.0008***	−0.0063***	0.0011***	−0.0074***
	(29.12)	(44.76)	(7.89)	(−32.17)	(5.75)	(621.64)
30 M	0.0581***	0.0378***	0.0204***	0.0017***	0.0081***	−0.0064***
	(60.68)	(79.49)	(469.19)	(2.67)	(13.70)	(44.52)
60 M	0.0058***	0.0026***	0.0032***	−0.0116***	−0.0008	−0.0108***
	(6.19)	(5.67)	(12.04)	(−18.95)	(−1.52)	(135.48)

results of prior studies of investor sentiment.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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