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## Article

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# Investor Sentiment, Cross-sectional Stock Returns, and Short-Sales: Evidence From Korea

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## ABSTRACT

**Purpose:** This study investigates the return co-movements associated with investor sentiment shifts in the cross-sections under a setting where market-wide sentiment interacts with short-sale impediments.

**Design/methodology/approach:** This study estimates the return sensitivity to market sentiment changes (sentiment beta) for each characteristic's portfolio by regressing the return of each quintile portfolio and various high-minus-low portfolios on the sentiment changes index. It examines whether these cross-sectionally different return co-movement patterns is more prevalent during good- than bad-sentiment periods by performing the same regression separately for the good- and bad-sentiment periods.

**Findings:** The result shows that the returns of speculative stocks tend to co-move more strongly with sentiment changes than those of stable stocks, in the sense that speculative stocks have higher sentiment betas than stable stocks. The cross-sectional pattern in return co-movements becomes more pronounced during the good-sentiment period but disappears during the bad-sentiment periods.

**Research limitations/implications:** This study elucidates the return co-movement behavior associated with investor sentiment changes under a setting where market-wide sentiment interacts with short-sale impediments. However, analyzing the relationship between the investment sentiment index and the short-selling activities is reserved for future research.

**Originality/value:** The results provide important implications for investment strategies using investor sentiment in practice, and several suggestions for establishing investor protection policies in the highly individual-crowded market. This study will contribute to enhancing the stock market efficiency and price discovery.

*Keywords: Investor sentiment, Sentiment beta, Return co-movement, Cross-sectional analysis, Short-sales impediments*

## I. Introduction

Whether investor sentiment affects asset prices is an important issue in finance. Classical finance theory supporting the efficient market hypothesis insists that due to the strong competition among

rational investors, market prices of assets equal the discounted value of expected future cash flows in equilibrium. According to this view, the cross-section of expected returns can be explained using the cross-section of systematic risks. The correlation in the returns of two assets is attributed to the contemporaneous change in their fundamental values, which is irrelevant to the broad waves of investor sentiment. Meanwhile, behavioral finance theory (Shleifer and Summers, 1990; Lee et al., 1991; DeLong et al., 1990), emerging

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as an alternative to the efficient market approach, argues that investor sentiment may cause assets' market prices to deviate from the underlying intrinsic values when the demand shocks occur by the temporal sentiment of irrational investors and when rational arbitrageurs cannot absorb these shocks. As mispricing is the result of an irrational demand shock in the presence of a binding arbitrage constraint, the shifts in investor sentiment have cross-sectionally different effects when irrational demands or a degree of arbitrage limits vary across stocks (Baker and Wurgler, 2006; 2007). Prior studies reported that certain firms and stocks sharing specific characteristics are likely to be more sensitive to temporal demand shocks and more significantly affected by shifts in investor sentiment (Bodurtha et al., 1995; Barberis et al., 2005; Lemmon and Portniaguina, 2006; Franzini and Lamont, 2008; Kumar and Lee, 2006; Lee, 2019, 2020; Kim and Park, 2015; Yang et al., 2017).

If the co-movement in cross-sectional stock returns could result from mispricing driven by investor sentiment, why are these return anomalies not arbitrated away? A feasible explanation is that short-sale constraints might play a role in limiting arbitrage activities. For institutional and cultural reasons, there exists a lack of short selling in the general stock market.<sup>1)</sup> With short-sale impediments, price efficiency could depend on the actions of the existing shareholders for the overpriced stocks. If the existing shareholders are sufficiently sophisticated, they exert selling pressure on the overpriced stocks, but if the existing owners are not sufficiently sophisticated, the stock could stay overpriced, as outside investors cannot sell it because of short-sale constraints. In contrast, if a stock becomes underpriced, outside sophisticated investors can always exert buying pressure and the prices can recover to a fair value. Put differently, short-sales constraints allow only overpricing to persist, but not underpricing (Miller, 1977). Nagel (2005) and Stambaugh et al. (2012) show that the profitability of the long-short strategies exploiting a set of anomalies in cross-sectional returns is mainly driven by low returns

on overvalued stocks, rather than high returns on undervalued stocks.

Combining the market-wide sentiment with the asymmetric mispricing caused by the short-sale constraints, this study examines whether speculative stocks are more sensitive to investor sentiment than stable stocks, in the sense that their returns co-move more with the sentiment changes than those of the stables, and whether the cross-sectional variation observed in the return co-movement is more prevalent during good- than bad-sentiment periods.

What makes certain stocks more speculative than others is the subjectivity of their valuations and the difficulty of arbitrage.<sup>2)</sup> For instance, in the case of companies that are currently young and unprofitable, but have growth potential, investors tend to value them arbitrarily because they lack a history of earnings and face an uncertain future. Thus, in line with contemporaneous sentiment, their valuation ranges spread from very low to very high. Arbitrage trading on these stocks tends to be riskier and costlier because they have a high trading cost and a high degree of idiosyncratic volatilities in the returns. Thus, the market prices of these stocks can remain far above or below their fundamental value in the future. Therefore, they are subject to speculation (Pontiff, 1996). Prior studies suggest that the formal classification for speculative and stable stocks is as follows: speculative stocks are characterized by high volatility, high risk (uncertainty), low liquidity, high growth potential, low profitability, small tangible assets, no dividend, and a no earning history, whereas stable stocks are characterized by low volatility, low risk, high liquidity, low growth potential, consistent profits, steady dividend, and a history of strong financial performance.<sup>3)</sup>

This study hypothesizes that a wave of investor sentiment should have larger effects on speculative stocks than on stable stocks because the former seems to have stronger demand shocks based on prevailing investor sentiment. Baker and Wurgler (2006) report that when beginning-of-period sentiments are low

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1) Nagel (2005), Lamont (2013), Jones and Lamont (2002).

2) Baker and Wurgler (2007)

3) Baker and Wurgler (2006), Kumar and Lee (2006), Lee (2020), Lee and Kim (2022), and Yang et al. (2017).

(high), the subsequent returns are relatively high (low) for speculative stocks, and Baker and Wurgler (2007) find that the high volatility stocks have higher sentiment betas. Lee (2020), Lee and Kim (2022), and Yang et al. (2017), using Korean stock market data, show the different intensities of the sentiment effect across stocks with various firm characteristics. In line with the prior research, this study postulates that stocks with high volatility, small tangible assets, large research and development (R&D) expenses, high growth potential, and individuals' intense trading should be more sensitive to investor sentiment, in the sense that their returns co-move more with sentiment changes.

Next, I hypothesize that the cross-sectionally different co-movement patterns should be more prevalent during good- than bad-sentiment periods. When investor sentiment is good, overpricing occurs market-wide, because the extremely optimistic investors would not be counterbalanced by the less optimistic investors due to short sale restrictions. Especially, sentiment fluctuations affect the overpricing of speculative stocks more than those of stable stocks because optimistic sentiment shifts investment funds from stables to speculative ones. Stambaugh et al. (2012), using the long-short strategies that exploit the anomalies, show that each anomaly is stronger following high levels of sentiment, and that sentiment exhibits a strong relation to returns on the short legs of each strategy, but no relations to those on the long legs. Miller (1977) argues that short sale constraints allow only overpricing to persist, but not underpricing. Nagel (2005) and Wang and Lee (2017) find empirical evidence supporting that overpricing is related to short sale constraints.

Individual investors, known as irrational investor s,<sup>4)</sup> both create and are heavily influenced by market sentiment. As the Korea Securities Dealers Automated Quotation (KSQ) market is an individual-crowded market and the individual investors in the KSQ market

tend to make investment decisions independently, it is a good test bed for studying the issues related to investor sentiment. According to the Korea Stock Exchange, for the KSQ market, the proportions of individual selling and buying value in total trading value are 83.21% and 82.64%, respectively, at the end of 2019.<sup>5)</sup> As Korean individuals tend to make investment decisions using home trading system (HTS) or mobile trading system (MTS) without expert advice, their unique trading behaviors can be clearly observed in the KSQ market. Nevertheless, there has been little prior research that created a market sentiment index for the KSQ market and examined the impact of the sentiment on the KSQ market.

Based on the principal component analysis (PCA)<sup>6)</sup>, a monthly sentiment level index and a monthly sentiment changes index for the KSQ market, using six key sentiment proxies and their changes, were developed.<sup>7)</sup> To increase the reliability of the indices and their comparability with international research, this study develops these indices in a manner similar to Baker and Wurgler (2006, 2007). These indices seem to succeed in capturing the investor sentiment because they align well with the anecdotal accounts of bubbles and crashes in the KSQ during the sample period.

Using these indices and the monthly returns of all common KSQ stocks from 2001 to 2021, this study examines the impact of shifts in investor sentiment on the cross-section of stock returns in terms of

4) Previous studies (Odean, 1999; Barber and Odean, 2000; 2003, Battalio and Mendenhall, 2005) showed that individual investors spend less time on investment analysis, engage in more attention-based trading, and respond to earnings news differently than professional investors do.

5) <http://marketdata.krx.co.kr/mdi#document=121106>. This figure is higher than any other market internationally, including the KOSPI market. For the KOSPI, the proportions of individual selling and buying value in total trading value are 47.64%, and 43.87%, respectively.

6) PCA methodology can identify the most important underlying factors, produce unbiased weights for each variable, and remove the idiosyncratic noise of each variable, making it possible to create a more reliable sentiment index. Due to these advantages, some Korean studies (Kim and Byun, 2010; Lee and Yoon, 2018; Ryu et al., 2018) have established a composite index of sentiment based on common variations among sentiment proxies by the PCA.

7) The six variables are as follows: the KSQ volatility premium, the KSQ share turnover, the individual trading imbalance, the initial public offering (IPO) number, the IPO first-day returns, and the share of a company with seasonal equity offerings in the total company.

sensitivity to sentiment. For this, the entire sample stocks were sorted according to various stock characteristic variables, assigned into a quintile portfolio, and the monthly equal-weighted average returns of quintiles were then computed. The strategy that goes long the stocks in the highest-tercile and goes short those in the lowest-tercile after which the returns of various high-minus-low portfolios are computed was also considered. Then, the returns of each quintile portfolio and high-minus-low portfolio were regressed on the sentiment changes index, the Fama-French (1993) factors, and the Carhart (1997) momentum factor. Consistent with the prediction, the stocks with high market-to-book (MTB) ratio, high volatility, low net plant, property, and equipment to total asset (PPE) ratio, high sales growth, and high individual investors' trading imbalances (BSI) respond more sensitively to the changes in investor sentiment than those with low MTB ratio, low volatility, high PPE ratio, low sales growth, and low BSI. The returns of speculative stocks tend to co-move more strongly with the sentiment changes than those of stable stocks.

Then, whether the cross-sectionally different return co-movement patterns is more prevalent during good-than bad-sentiment periods, was examined. All sample periods were classified into a good- or a bad-sentiment month and then regression was performed separately for the two periods. Expectedly, the cross-sectional variation in the return co-movement becomes pronounced (disappears) during the good-sentiment (bad-sentiment) periods.

This study sheds light on the return co-movement behavior associated with investor sentiment changes under a setting where market-wide sentiment interacts with short-sale impediments. The results provide significant implications for developing investment strategies using investor sentiment in practice,<sup>8)</sup> and for establishing investor protection policies in the highly individual-crowded market. Most importantly, this study can contribute to enhancing the stock market

efficiency and the price discovery function by investigating the effect of investor sentiment on cross-sectional stock returns, separately for the good- and bad-sentiment periods.

The remainder of this paper proceeds as follows. Section II introduces relevant previous studies, and section III explains the investor sentiment indices, sample, and main variables. Section IV presents the main empirical results. Finally, Section V concludes the paper.

## II. Literature Review

Prior studies in behavioral finance find that the impact of investor sentiment varies depending on the stock characteristics. Bodurtha et al. (1995), and Barberis et al. (2005) suggest a clientele-based model in which different investor groups restrict themselves to trading within groups of stocks; thus, the returns of individual stocks reflect not only fundamental risk, but also changes in the systematic time-varying sentiment of important investor groups. Kumar and Lee (2006), Lee (2014), and Kang et al. (2013) find that systematic retail trading explains return co-movement for small-cap, value, lower institutional ownership, and lower priced stock. Baker and Wurgler (2006) analyze the cross-sectional predictability patterns in stock returns conditional on beginning-of-period sentiment and report that stocks that are smaller, newer, more volatile, unprofitable, non-dividend paying, distressed, or with extreme growth potential are likely to be sensitive to shifts in investor sentiment. Furthermore, Baker and Wurgler (2007) find that speculative stocks have positive sentiment betas, however, extremely bond-like stocks have negative sentiment betas. Using Korean data, Yang et al. (2017) and Kim and Lee (2022) create an individual firm-level sentiment index and find that investor sentiment has a greater impact on stock returns vis-à-vis firm characteristics. Lee (2019, 2020) creates a market-wide sentiment index of the KOSPI market, revealing that

8) Zheng et al. (2018) report that in the Taiwan stock market hedge funds with negative sentiment exposure recorded an average annual return of 1.7~2.4% higher than hedge funds with positive sentiment exposure.

market sentiment has a cross-sectionally different effect on stock returns. Kim and Park (2015) show that individual investor sentiment has no explanatory power for cross-sectional stock returns; however, individual trades can move stock prices by their contrarian behaviors. Huerta and Perez-Liston (2011) examine the impact of hurricanes on investor sentiment and stock returns, and Zhou (2009) reveals that trading strategies following signals from market sentiment do not generate excess returns in China.

Miller (1977) argues that short-sales constraints allow only overpricing to persist, but not underpricing. Nagel (2005) shows that several cross-sectional patterns, such as the BTM effect are stronger when short-sale constraints are strong and reports that the patterns are mainly driven by low returns on overvalued stocks, rather than high returns on undervalued stocks. Stambaugh et al. (2012) find that the profitability of the long-short strategies exploiting a set of anomalies in cross-sectional returns is greater following high sentiment and that sentiment exhibit strong relation to returns on the short legs of each strategy but no relations to those on the long legs. Wang and Lee (2017) report that PEAD (post-earning announcement drift) is related to short sale constraints. Enkhzul and Jun (2021) reveal that short-selling makes stock prices more predictable, however, margin trading makes stock prices more random. Larson et al. (2001) elaborate on the asymmetric mispricing in ADRs where short selling is not allowed.

A key difference between this study and previous studies (Baker and Wurgler, 2006; Bodurtha et al., 1995; Barberis et al., 2005; Yang et al., 2017; Kim and Lee, 2022) is that this study creates a market-level sentiment index (not individual stock-level sentiment index) and explores the return co-movement with the contemporaneous changes in market-wide sentiment by estimating a "sentiment beta" at the portfolio level. Previous studies have examined the predictability of the sentiment index or the relationship between the index level and stock returns. Further, unlike previous research, the cross-sectional pattern in return co-movements becoming more distinct during the good-sentiment period has been successfully demonstrated.

### III. Research Methods

#### A. Investor Sentiment Indices

In general, an external shock in investor sentiment might have a series of effects on money flows in the stock market, individuals trading activities, dividend (volatility) premium, corporate financing activities, and so on. It might appear first in surveyed investor beliefs, and this belief translates to observable patterns of investor trading activities. In the presence of limited arbitrage, these demand shocks might cause some mispricing, which might be observed using relative valuation measures. Mispricing might lead to opportunistic actions by insiders, such as corporate executives, to take advantage of this mispricing.

Based on this phenomenon, some studies have attempted to establish a composite index of sentiment based on common variations among sentiment proxies. Baker and Wurgler (2006, 2007) form an annual sentiment index from 1962 to 2001 based on the first principal component of six underlying sentiment proxies: the closed-end fund discount, the NYSE share turnover, the number and average first-day returns on initial public offerings (IPOs), the equity share in new issues, and the dividend premium.<sup>9)</sup> By performing the principal component analysis (PCA), they can filter out idiosyncratic noise in the proxy variables and isolate the common component.

In this study, the monthly sentiment level and change indices are constructed based on the first principal components of six key sentiment proxies and their changes: the volatility premium, the KSQ share turnover, the individual trading imbalance, the number and average first-day returns on IPOs, and the share of the company with seasonal equity offerings in the total company. To increase the reliability of the indices and their comparability with international

9) The Korean previous studies (Kim and Byun, 2010; Lee and Yoon, 2018; Ryu et al., 2018; Lee, 2019) have followed the methodology of Baker and Wurgler (2006, 2007) to create various sentiment indices by analyzing several proxies, such as trading imbalance of individual investors, inflows of equity funds, consumer confidence index, KOSPI share turnover, VKOSPI and ETF disparity.

research, the sentiment indices were developed in as much a similar manner to Baker and Wurgler (2006, 2007) as possible. Specifically, to reduce the arbitrary selection of proxy variables, this study attempts to use the same proxy as Baker and Wurgler (2006, 2007), but use alternative variables only in the absence of the same variables.<sup>10)</sup> The six proxies are described below, and the time-series movements for each proxy are presented in Figure 1.

The volatility premium (VPRM) identifies the relative valuations of stocks with high volatility and stocks with low volatility. This is an alternative variable to the relative valuation of dividend- and non-dividend-paying stocks. The motivation for this variable derives from the theoretical prediction that sentiment has its strongest effects on hard-to-value and hard-to-arbitrage stocks. All else being equal, volatile stocks are attractive to irrational traders who defend extreme values in keeping with their optimism or pessimism. Such stocks are unattractive to arbitrageurs because volatility brings higher trading costs (Glosten and Milgrom, 1985) and fundamental risk (Pontiff, 1996; Wurgler and Zhuravskaya, 2002). In this study, VPRM is defined as the ratio of the equal-weighted average MTB ratio of high-volatile stocks to that of low-volatile stocks.<sup>11)</sup> High (low) volatility denotes one of the top (bottom) three deciles of the standard deviation of the daily residual returns after controlling for any association with market beta among all KSQ stocks (see Panel A).<sup>12)</sup>

The KSQ share turnover (TO) is the monthly ratio of average trading volume to the average number of shares listed in the KSQ. As turnover displays

a negative trend over our sample period, in this study, TO has been defined as the turnover ratio detrended by the six-month moving average. According to Baker and Stein (2004), in a market with short-sales constraints, irrational investors participate and add liquidity only when they are optimistic; hence, turnover can serve as a sentiment proxy (see Panel B).

The individual trading imbalance (buy-sell imbalance, BSI) is constructed by subtracting the selling volume of individual investors from their buying volume and then standardizing by the total trading volume in that month. A monthly BSI indicates whether individual investors are net buyers or net sellers over a given month, at an aggregate level. As there is no long-term data on closed-end funds in the KSQ, this study uses the BSI instead of the closed-end fund discounts used by Baker and Wurgler (2006, 2007). Kumar and Lee (2006) find that individual trading imbalances have a greater explanatory power for return co-movement than the closed-end fund variables and argued that individual trading imbalance is a direct variable to measure the sentiment of retail investors rather than closed-end discounts (see Panel C).

The fourth and fifth proxies are the number and average first-day returns on IPOs (NIPO and RIPO, respectively). The number of IPO tends to increase during the market boom and decrease during the market recession. As the initial returns on IPOs increase in hot markets, high first-day returns on IPOs have been cited as a measure of investor enthusiasm (Ritter, 1991). NIPO is defined as the natural log of the number of IPOs, and RIPO, as the average of IPOs' first-day returns, is calculated by the first-day closing price relative to the initial offering price. The IPO stock data<sup>13)</sup> is collected from KIND (a public disclosure channel of the Korea Stock Exchange) (Panels D~E).

The share of companies with seasonal equity offerings (NSO) is a broader measure of financing activities as this ratio reflects the equity financing

10) The same three proxies are the KSQ share turnover, the number and average first-day returns on IPOs, and three alternative proxies are the volatility premium instead of the dividend premium, the individual trading imbalance instead of the closed-end fund discount, and the share of the company with seasonal equity offerings instead of the equity share in new issuances.

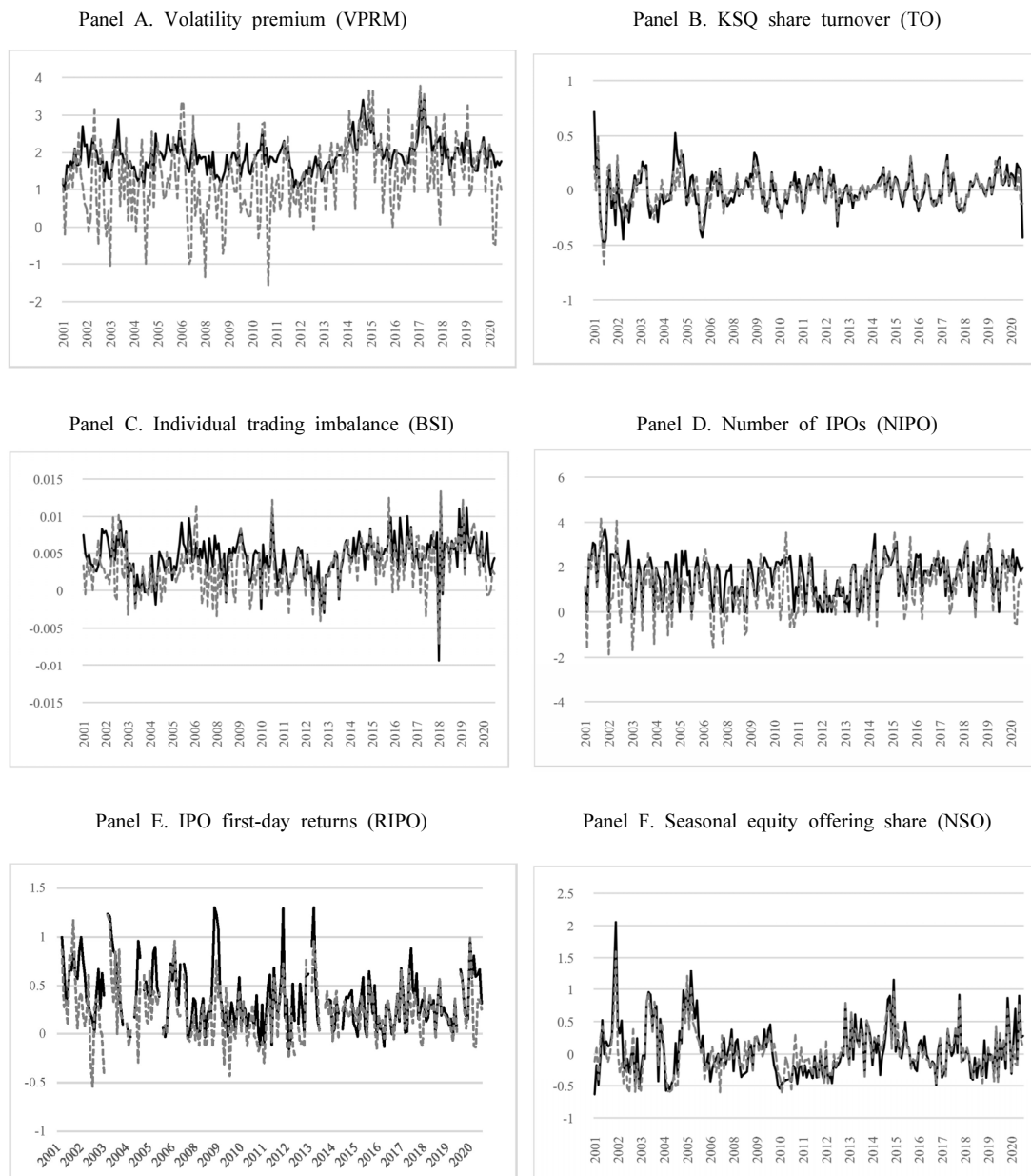
11) To exclude the distorting effects of extreme MTB values, MTBs are winsorized at 99.5% and 0.5%.

12) The volatility premium is computed based on beta-adjusted idiosyncratic volatility; however, for simplicity, I continue to refer to this variable as "the volatility premium." For stocks with less than 10 trading days per month, its idiosyncratic risk is reported as a missing value.

13) As the stock issuance market is an abstract market without specific trading locations, the variables related to the issuance activities (IPO and seasonal equity offering) are calculated by summing the values of KOSPI and KSQ.

activities of all publicly traded firms, not merely IPOs. According to Baker and Wurgler (2004), firms seek to reduce their overall cost of capital by exploiting

sentiment-induced mispricing. Baker and Wurgler (2006, 2007) find that a high share of equity issue in total equity and debt issue predicts low stock market



These panels present the time-series patterns of each sentiment proxy, such as the volatility premium, the KSQ share turnover, the individual trading imbalance, the number and average first-day returns of IPOs, and the share of companies with seasonal equity offerings in total companies over the sample periods. A solid line indicates the raw value of proxies, and a dotted line indicates the orthogonalized value of proxies.

**Figure 1.** Time-series patterns of proxy variables for investor sentiment



returns, and they suggest the equity share in new issues as a sentiment proxy variable. To obtain the monthly NSO, the proportion of stocks with seasonal equity offerings in all listed stocks was calculated, and then adjusted for seasonality. Seasonal equity offerings data is collected from SEIBro, an information portal provided by Korea Securities Depository (Panel F).

As some of the sentiment proxies reflect business cycles and economic fundamentals, each proxy and its change was regressed on a set of macroeconomic indicators-growth in industrial production, changes in the inflation rate, and changes in the unemployment rate, after which the residuals from these regressions were used as the sentiment proxies. To iron out the remaining idiosyncratic noises and isolate the common sentiment component, the PCA was performed using these orthogonalized proxies and changes. A monthly sentiment level index ( $Sent_t$ ) is the first principal component of six orthogonalized sentiment proxies, and a sentiment changes index ( $\Delta Sent_t$ ) is the first component of their orthogonalized changes. A sentiment level index is used to determine the current state of market-wide sentiment, and a sentiment change index is used to test for return co-movement patterns associated with changes in sentiment. When constructing the sentiment level index ( $Sent_t$ ), this study considers

a lead-lag relationship among variables. To reflect these lead-lag relationships, the study estimates the first principal components of the six variables and their lags and obtains a first-stage index with 12 loadings, one for each of the current and lagged variables. Then, the study selects each variable's lead or lag, whichever has a higher correlation with the first-stage index. Thereafter, the sentiment index is constructed as the first principal component of these selected six variables. This procedure leads to a parsimonious index. The results of PCA are as below<sup>14)</sup> (Table 1).

$$Sent_t = 0.52 \times VPRM_{t-1} + 0.12 \times TO_{t-1} \\ + 0.43 \times BSI_t + 0.52 \times NIPO_t \\ + 0.44 \times RIPO_{t-1} + 0.26 \times NSO_t$$

$$\Delta Sent_t = 0.30 \times \Delta VPRM_t + 0.57 \times \Delta TO_t \\ + 0.05 \Delta BSI_t + 0.36 \times \Delta NIPO_t \\ + 0.50 \times \Delta RIPO_t + 0.45 \times \Delta NSO_t$$

Each individual proxies and changes enter with the expected sign, that is, all variables are positively associated with sentiment levels and changes. Almost all variables have the expected timing, that is, the

**Table 1.** Sentiment proxies and sentiment indices

Panel A	$VPRM_{t-1}$	$TO_{t-1}$	$BSI_t$	$NIPO_t$	$RIPO_{t-1}$	$NSO_t$
Mean	1.370	0.001	0.003	1.156	0.245	0.039
STD.	0.998	0.146	0.003	1.106	0.303	0.357
N	223	223	223	223	223	223
$VPRM_{t-1}$	1					
$TO_{t-1}$	0.011	1				
$BSI_t$	0.224	0.098	1			
$NIPO_t$	0.356	-0.049	0.555	1		
$RIPO_{t-1}$	0.486	0.209	0.065	0.189	1	
$NSO_t$	0.172	0.045	0.008	0.153	0.199	1
$Sent_t$	0.520	0.121	0.432	0.521	0.438	0.255

14) The first principal components of the six proxies and their changes explain 45% and 32% of the sample variance, respectively.

Table 1. Continued

Panel B	$\Delta VPRM_t$	$\Delta TO_t$	$\Delta BSI_t$	$\Delta NIPO_t$	$\Delta RIPO_t$	$\Delta NSO_t$
Mean	-0.007	-0.001	0.000	0.107	-0.023	0.015
STD.	0.324	0.120	0.003	0.844	0.252	0.354
N	210	210	210	210	210	210
$\Delta VPRM_t$	1					
$\Delta TO_t$	0.043	1				
$\Delta BSI_t$	0.120	0.006	1			
$\Delta NIPO_t$	-0.047	0.067	-0.079	1		
$\Delta RIPO_t$	-0.026	0.171	0.030	0.010	1	
$\Delta NSO_t$	0.141	0.004	-0.034	0.116	0.027	1
$\Delta Sent_t$	0.297	0.572	0.046	0.362	0.496	0.453

Means, standard deviations, and correlations for six sentiment proxies and their changes: the volatility premium, the KSQ share turnover, the individual trading imbalances, the number and average first-day returns of IPOs, and the share of companies with seasonal equity offerings in the total company

**Panel A** presents the six orthogonalized proxies and the sentiment level index ( $Sent_t$ ), which is the first principal component of the six proxies.

**Panel B** presents the orthogonalized changes in six proxies and the sentiment changes index ( $\Delta Sent_t$ ), which is the first principal component of those changes.

proxies that involve firms' financing activities (NIPO and NSO) lag the proxies that are related to trading volume and price movements (VPRM, TO, and RIPO) (Ibbotson and Jaffe, 1975; Lowry and Schwert, 2002; Benveniste et al., 2003).

Figure 2 graphically shows two sentiment indices. The  $Sent_t$  (Panel A) visibly coincides with the historical movement of the KSQ index. Perhaps the best evidence that the sentiment level index has succeeded in capturing investor sentiment is simply that it aligns well with the anecdotal accounts of bubbles and crashes.

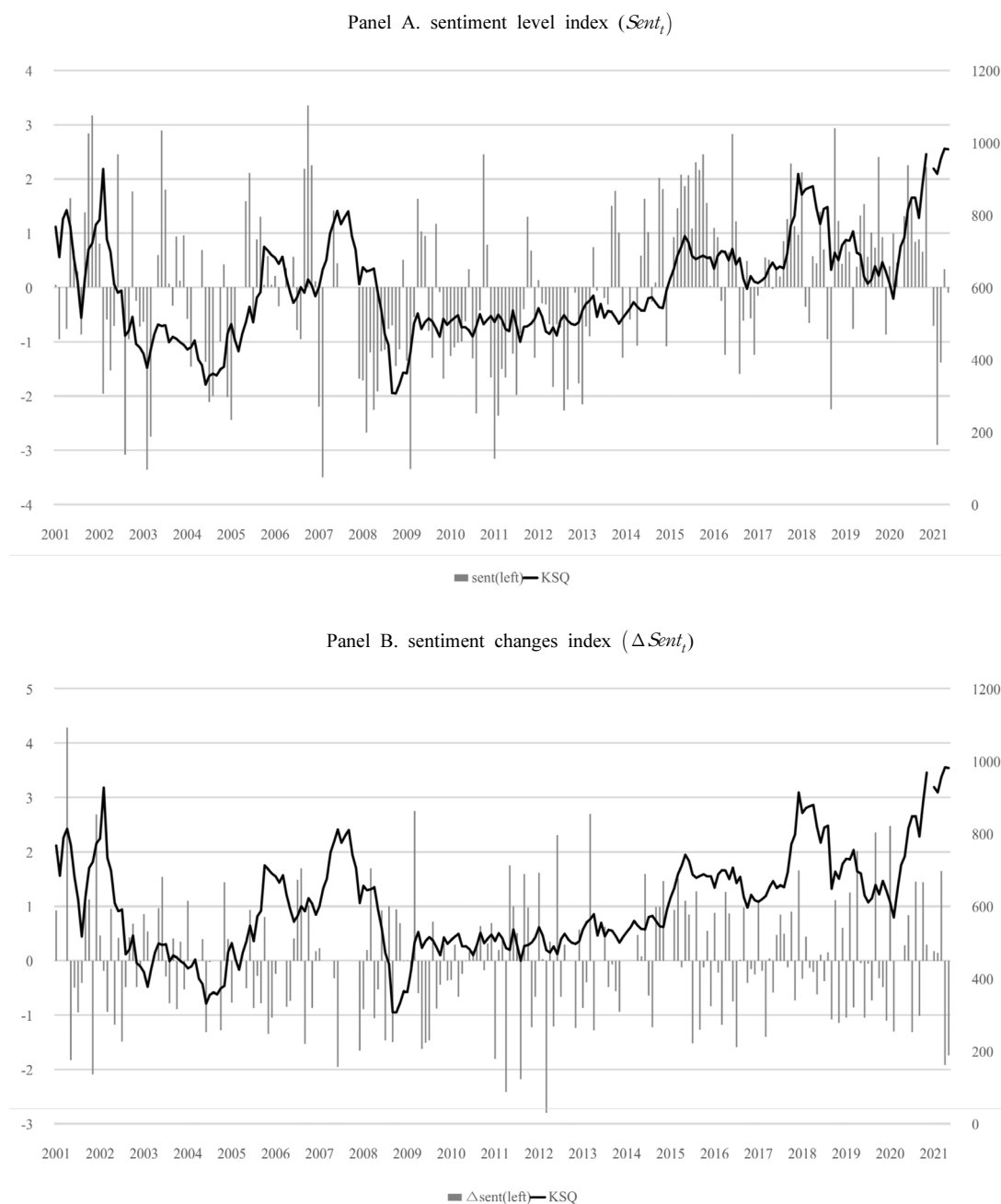
To confirm that the sentiment level and changes indices accurately reflect the fluctuations of investor sentiment, the correlation coefficients between the two indices and several variables known to represent the market atmosphere were examined. According to Table 2, the  $Sent_t$  has a positive relationship with the changes in the amount of stock purchases on credit and the amount of stock loans. This is strong evidence supporting that the index tracks real investor sentiment well because when optimism prevails, investors tend to buy stocks on credit or use stock loans to buy additional shares. The  $\Delta Sent_t$  has a significantly positive relationship with the contemporaneous market

return, but it shows no significant relationship with the returns on SMB (the difference between returns on small and big market equity portfolios), HML (the difference between returns on high and low book equity to market equity portfolios), and MOM (the difference between returns on high-momentum stocks and low-momentum stocks) factor portfolios.

## B. Sample and Variables

This study analyzes all common stocks on the KSQ market from January 2001 to May 2021. The KSQ market data provided by KISVALUE (database maintained by National Information and Credit Evaluation) is matched with the accounting data provided by DATAGUIDE (financial database maintained by FnGuide) using 12-digit stock codes. The stocks without market data or accounting data were excluded from the sample. This procedure results in a sample of 194,124 stock-months.

This study hypothesizes that fluctuations in investor sentiment have a greater effect on speculative stocks than on stable stocks. To test the hypothesis, the formal criteria for distinguishing between speculative



Panels A and B show the sentiment level index and changes index during the sample periods (2001~2021), respectively. Both indices are standardized to have zero mean and unit variance over the sample period. The solid bars are the sentiment indices for each month and the solid line is the ending-of-month KSQ index.

**Figure 2.** Time-series of sentiment level index and sentiment changes index

**Table 2.** Relationships between the sentiment indices and the stock market variables

	$Sent_t$	$\Delta Sent_t$	$\Delta Misu$	$\Delta Cpurchase$	$\Delta Deposit$	$\Delta Sloan$	$r_f$	$r_{m,t-1}$	$r_{m,t}$	$r_{m,t+1}$	SMB	HML	MOM
$Sent_t$	1												
$\Delta Sent_t$	0.033	1											
$\Delta Misu$	0.031	-0.029	1										
$\Delta Cpurchase$	<b>0.096</b>	<b>0.193</b>	-0.036	1									
$\Delta Deposit$	0.014	0.087	0.005	0.058	1								
$\Delta Sloan$	<b>0.271</b>	0.054	<b>-0.202</b>	<b>0.361</b>	0.084	1							
$r_f$	<b>-0.252</b>	-0.021	<b>0.454</b>	<b>-0.145</b>	<b>-0.186</b>	<b>-0.381</b>	1						
$r_{m,t-1}$	<b>0.137</b>	-0.006	0.101	<b>0.128</b>	0.076	<b>0.222</b>	<b>-0.172</b>	1					
$r_{m,t}$	0.100	<b>0.305</b>	0.094	<b>0.332</b>	<b>0.237</b>	<b>0.156</b>	<b>-0.184</b>	0.043	1				
$r_{m,t+1}$	0.004	0.009	-0.053	-0.007	0.083	-0.031	<b>-0.176</b>	0.030	0.043	1			
SMB	0.082	-0.038	-0.002	0.093	-0.051	<b>0.127</b>	<b>-0.126</b>	0.090	<b>-0.265</b>	0.019	1		
HML	-0.057	-0.081	0.015	<b>0.143</b>	<b>-0.197</b>	0.019	0.063	-0.035	<b>-0.177</b>	0.061	<b>0.133</b>	1	
MOM	-0.052	0.002	<b>0.140</b>	0.097	-0.082	-0.009	<b>0.224</b>	0.016	0.096	-0.096	<b>-0.299</b>	-0.014	1

This table presents the correlation coefficients between the sentiment indices and several stock market variables known to represent the market atmosphere. The sentiment indices include  $Sent_t$ , and  $\Delta Sent_t$ . Stock market variables include the monthly changes of money-flow variables, such as the amount of margin trading ( $\Delta Misu$ ), the amount of stock purchases on credit ( $\Delta Cpurchase$ ), the amount of temporary deposits for stock purchases ( $\Delta Deposit$ ), the amount of stock loans ( $\Delta Sloan$ ). The previous, contemporaneous, and future market returns, risk-free rate, returns on SMB, HML, and MOM factors are also included. Numbers in bold indicate statistical significance at the 10% level.

and stable stocks is important. According to previous studies (BW, 2006, 2007; Kumar and Lee, 2006; Lee, 2020; Lee and Kim, 2022; Yang et al., 2017 Stambaugh et al. 2012), this study uses eight characteristic variables such as MTB ratio, idiosyncratic and total volatilities, PPE ratio, profitability, R&D ratio, sales growth, and the individual trading imbalance as a sorting criterion.

The MTB ratio is calculated by dividing the market equity, measured as price times shares outstanding at the end of every month, by the book equity, measured as shareholders' equity at the end of the previous fiscal year. Idiosyncratic volatility is the standard deviation of daily residual returns after controlling for association with market beta, and total volatility is the standard deviation of daily returns. PPE ratio, a measure of asset tangibility, is the amount of plant, property, and equipment scaled by total assets. Profitability is measured by the operating margin, which is the operating income to sales ratio. R&D ratio is the amount of research and development expenses scaled by assets. Sales growth is calculated by the natural log of the ratio of sales this year to sales in the previous year. The BSI is constructed

by subtracting the selling volume of individual investors from their buying volume and then standardizing it by the total trading volume in that month. For stocks with total sales of less than one billion won (approximately 90 million dollars), their sales growth and profitability are changed to missing values. Yearly accounting data from the fiscal year ending in  $t-1$  are matched to monthly market data from January through December of year  $t$ . MTB ratio, idiosyncratic and total volatilities, and BSI are calculated monthly, however, PPE ratio, profitability, R&D ratio, and sales growth are calculated annually.

## IV. Results and Discussion

### A. Cross-sectional Patterns of Return

#### Co-movement with the Sentiment Changes

This study explores whether speculative stocks are more sensitive to market-wide sentiment than stable stocks, in the sense that their returns co-move more with the changes in investor sentiment. To examine the cross-sectional difference in the return

co-movement with the sentiment changes, the entire sample stocks were sorted according to various stock characteristic variables <sup>15)</sup>, then each stock was assigned to a quintile portfolio, after which the monthly equal-weighted average returns of all stocks in the portfolio for each month was computed, and a five-factor time-series regression was performed. The regression model is as follows:

$$r_{p,t} - r_{f,t} = \beta_0 + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \beta_5 \Delta Sent_t + u_{p,t} \quad < \text{Model 1} >$$

$$p \in \{Q1, \dots, Q5\}$$

In this model, the dependent variable is the monthly excess return of each quintile portfolio over the risk-free rate. The RMRF is the excess return of the value-weighted market over the risk-free rate. As explained in Fama-French (1993), SMB is the difference between returns on small and big ME (market equity) portfolios, and HML is the difference between returns on high and low BE/ME (book equity to market equity) portfolios. The MOM (Carhart, 1997) is the difference between return on high-momentum stocks and low-momentum stocks, where momentum is measured over months [-12, -2].  $\beta_5$ s, the coefficients on the sentiment changes index, show the effect of one-standard-deviation changes in the sentiment measure on average excess returns. In finance parlance, this refers to "sentiment beta" (Baker and Wurgler, 2007). For stocks that are heavily sensitive to changes in investor sentiment,  $\beta_5$  would have a large value, however, for less sensitive stocks, the  $\beta_5$  would have a small value. For stocks whose returns move in the opposite direction to the sentiment changes,  $\beta_5$  would report a negative value.

15) MTB ratio, idiosyncratic and total volatilities, individual trading imbalance take the values at the end of the prior month, whereas PPE ratio, profitability, R&D ratio, and sales growth take the values at the end of the previous fiscal year. As the R&D value of 59,040 out of 194,124 total samples is 0, all stocks with no R&D expenses are classified into Q1, and the remaining samples are classified into Q2-Q5.

The "Total" rows in Table 3 and the "Total" columns in Figure 3 summarize the estimation results. Across the quintile portfolios, it is found that the higher the MTB ratio, the greater the total volatility, the smaller the PPE ratio, the faster the sales growth, and the higher the BSI, the greater the coefficient of  $\Delta Sent_t$ .  $\beta_5$  are significantly positive for the Q4 or Q5 based on MTB,  $\sigma_{total}$ , sales growth, and BSI, and for the Q2 based on PPEA. These results support the hypothesis that the returns of speculative stocks tend to co-move more strongly with the sentiment changes than those of stable stocks. There are no significant patterns in quintile portfolios formed by  $\sigma_{residual}$ , Profitability, and R&D.

Another way to look for a cross-sectional effect is to examine whether the shifts in market-wide sentiment are related to the returns of equal-weighted portfolios that are long on the stocks with high values of a characteristic and short on those with low values. A multivariate time-series regression of the monthly return of each long-short strategy on the contemporaneous sentiment change index was performed.

$$\begin{aligned} r_{X_{t-1} = high, t} - r_{X_{t-1} = low, t} \\ = \beta_0 + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t \\ + \beta_4 MOM_t + \beta_5 \Delta Sent_t + u_{i,t} \quad < \text{Model 2} > \end{aligned}$$

The long-short portfolios are formed based on the value of the eight stock characteristic variables at the end of t-1. High, medium, and low portfolios consist of firms in the top (T3), middle (T2), and bottom (T1) terciles, respectively. The returns of various high-minus-low portfolios (T3-T1) on the sentiment changes index, RMRF, SMB, HML, and MOM, were regressed. To examine the non-linear relationship between the portfolio returns and changes in sentiment, a regression using the high-minus-medium portfolio returns (T3-T2) and medium-minus-low portfolio returns (T2-T1) was also conducted.

Although the statistical significance is weak, the sentiment changes index is positively related to the returns of the T3-T1 based on the MTB ratio, total volatility, sales growth, and BSI, but negatively related

**Table 3.** Cross-sectional patterns of return co-movement with the sentiment changes

Variable	Periods	Q1	Q2	Q3	Q4	Q5
MTB	Total	-0.15	-0.04	0.15	0.01	0.21*
	Good	-0.35*	-0.14	0.12	0.13	0.50**
	Bad	0.06	0.09	0.15	-0.11	-0.13
$\sigma_{residual}$	Total	0.01	0.03	0.02	0.10	0.09
	Good	-0.04	-0.07	-0.19	0.19	0.38*
	Bad	0.07	0.17	0.23	-0.03	-0.23
$\sigma_{total}$	Total	-0.11	-0.13	0.14	0.18*	0.08
	Good	-0.09	-0.34**	0.09	0.12	0.48*
	Bad	-0.08	0.12	0.17	0.23	-0.37
PPEA	Total	0.1	0.26***	-0.12	-0.06	-0.11
	Good	0.16	0.38***	-0.09	0.05	-0.14
	Bad	-0.06	0.15	-0.15	-0.10	-0.11
Profitability	Total	-0.11	0.07	0.10	-0.03	0.04
	Good	-0.13	0.01	0.17	0.12	0.17
	Bad	-0.08	0.14	0.03	-0.18	-0.08
R&D	Total	0.05	0.02	-0.05	-0.09	0.11
	Good	-0.07	-0.10	0.12	-0.05	0.49**
	Bad	0.19	0.14	-0.26	-0.07	-0.29
Growth	Total	-0.05	0.02	0.00	-0.02	0.31**
	Good	-0.04	0.05	-0.06	0.17	0.40**
	Bad	-0.01	-0.02	0.07	-0.26	0.26
BSI	Total	-0.02	0.01	-0.10	0.23*	0.18*
	Good	0.02	0.00	-0.14	0.28*	0.29*
	Bad	-0.04	0.05	-0.09	0.16	0.08

The quintile portfolios are formed based on the firm characteristics (MTB,  $\sigma_{residual}$ ,  $\sigma_{total}$ , PPEA, profitability, R&D ratio, sales growth, and BSI) at the end of the previous period (t-1). I run a regression of the monthly equal-weighted returns of each quintile portfolio on the contemporaneous sentiment changes index ( $\Delta Sent_t$ ), the market risk premium (RMRF), the Fama-French (1994)'s factors (SMB and HML), and the Carhart (1997) factor (MOM). To examine whether the return co-movement patterns in the cross-sections depend on the sentiment level, I classify all sample months into either a good- or a bad-sentiment month and perform the same regression for the good- and bad-sentiment periods, separately. The "Total," "Good," and "Bad" rows report the results for regression using the total periods, good- and bad-sentiment periods, respectively. Each cell in this table presents the coefficient and t-statistics of  $\Delta Sent_t$ . \*\*\* indicates significance at the 1% level, \*\* indicates significance at the 5% level, and \* indicates significance at the 10% level.

to the returns of the T3-T1 based on PPEA (Panel A of Table 4). The results signified that highly volatile stocks, stocks with small tangible assets but high growth potential, and stocks with individuals' intense buying are likely to be sensitive to broad waves of investor sentiment. In the case of companies with high return volatility, little tangible assets, but great growth potential, as investors tend to value them subjectively, their valuation ranges can spread from very low to very high in line with contemporaneous sentiment. Arbitrageurs' trading activity may be limited

due to high trading cost and a high idiosyncratic volatility in their returns. Thus, the market prices of these stocks can remain far above or below their fundamental value in the future. The results support the argument that speculative stocks are more influenced by the shift in the prevailing market sentiment than stable stocks.

**Table 4.** Regressions of the long-short portfolio returns on the sentiment changes index

		MTB	$\sigma_{residual}$	$\sigma_{total}$	PPEA	Profit.	R&D	Growth	BSI
Panel A. T total periods									
T3-T1	Coeff.	0.16	0.02	0.23	-0.16	-0.04	0.09	0.13	0.17
	t-value	1.07	0.10	1.07	-1.08	-0.23	0.57	1.07	1.31
T3-T2	Coeff.	0.05	0.04	0.15	-0.07	-0.10	0.07	0.14	0.15
	t-value	0.30	0.19	0.85	-0.66	-0.75	0.49	1.08	0.96
T2-T1	Coeff.	0.11	-0.02	0.08	-0.10	0.06	0.02	-0.01	0.02
	t-value	0.86	-0.14	0.62	-0.70	0.36	0.17	-0.07	0.14
Panel B. Good-sentiment periods ( $Sent_t > 0$ )									
T3-T1	Coeff.	0.58**	0.32	0.46*	-0.37*	0.28*	0.41**	0.26	0.31*
	t-value	2.06	1.14	1.68	-1.85	1.74	2.22	1.54	1.87
T3-T2	Coeff.	0.25	0.48**	0.45*	0.18	0.06	-0.19	-0.26	-0.27
	t-value	1.18	1.99	1.98	1.21	0.38	-1.04	-1.45	-1.30
T2-T1	Coeff.	0.33**	-0.16	0.01	-0.20	0.25	0.22	0.00	0.04
	t-value	2.01	-1.09	0.03	-1.05	1.37	1.44	-0.01	0.20
Panel C. Bad-sentiment periods ( $Sent_t < 0$ )									
T3-T1	Coeff.	-0.30	-0.34	-0.05	0.07	-0.28	-0.24	-0.02	0.02
	t-value	-1.00	-1.14	-0.16	0.29	-0.92	-0.99	-0.07	0.12
T3-T2	Coeff.	-0.18	-0.45	-0.15	0.05	-0.14	-0.02	0.01	0.07
	t-value	-0.71	-1.62	-0.53	0.33	-0.69	-0.09	0.07	0.31
T2-T1	Coeff.	-0.13	0.11	0.10	0.02	-0.13	-0.22	-0.03	-0.04
	t-value	-0.62	0.70	0.56	0.09	-0.52	-1.19	-0.16	-0.19

I regress the long-short portfolio returns on the sentiment changes index ( $\Delta Sent_t$ ), RMRF, SMB, HML, and MOM. The long-short portfolios are formed based on the firm characteristics at the end of the previous period ( $t-1$ ). The high (T3), medium (T2), and low (T1) portfolios consist of firms in the top, middle, and bottom terciles, respectively. I regress the returns of the high-minus-low portfolios (T3-T1), high-minus-medium portfolios (T3-T2) and medium-minus-low portfolio (T2-T1) on the contemporaneous sentiment changes index ( $\Delta Sent_t$ ). Panel A shows the results of regressions using the entire sample periods. Panel B and C show the results of regressions using the good- and bad-sentiment period, respectively. Each cell in this table presents the coefficient and t-statistics of  $\Delta Sent_t$ . \*\*\* indicates significance at the 1% level, \*\* indicates significance at the 5% level, and \* indicates significance at the 10% level.

## B. Cross-sectional Return Co-movement Patterns Depending on Good- versus Bad-sentiment Periods

This section examines whether the different co-movement patterns observed in the cross-section of stock returns, which are the results of sentiment-related mispricing, become more pronounced during good- than bad-sentiment periods. According to Miller (1977), Nagel (2005), and Stambaugh et al. (2012), the cross-sectional patterns should be more prevalent during good-sentiment periods because the primary form of mispricing is overpricing, due to short sale constraints.

This study classifies all sample months into either a good- or a bad-sentiment month. A good (bad) - sentiment month is one in which the sentiment level index ( $Sent_t$ ) above (below) the median value for the entire sample periods.<sup>16)</sup> Then the same multivariate regression as <Model 1> was performed for each sub-period separately. The "Good" and "Bad" columns of Table 3 and Figure 3 summarize the estimation

16) The 210 entire sample months are divided into two sub-periods, each of which consists of 105 months. As the number of samples is reduced, the regression analysis using sub-period produces more conservative results in terms of statistical significance.

results for two sub-period regressions.

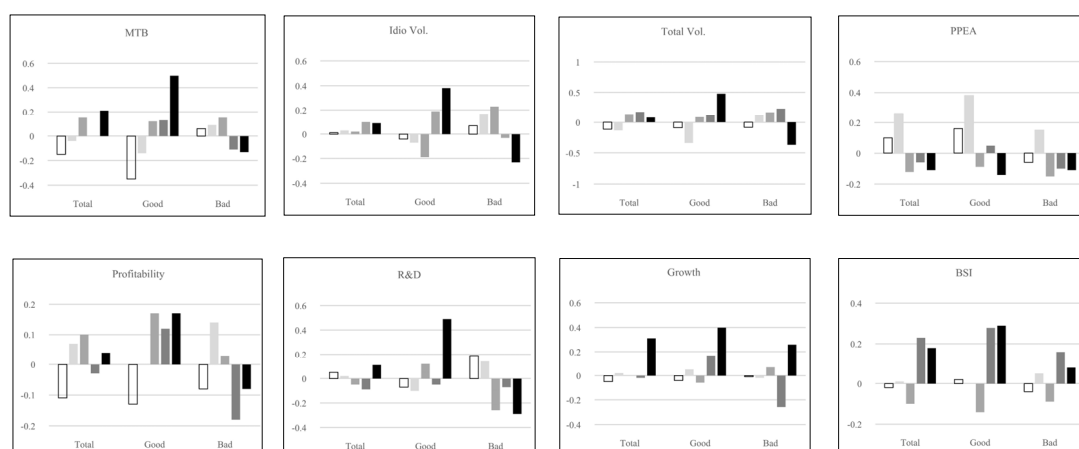
The "sentiment seesaw," a phenomenon in which the coefficient of  $\Delta Sent_t$  ( $\beta_5$ ) increases as one goes from the stable portfolio to the speculative portfolio, is steeper for the good-sentiment periods than for the total periods. Specifically, stocks with high MTB ratio, high volatilities, low PPE ratio, high R&D expenses, high sales growth, and high individual trading imbalance report the larger positive  $\beta_5$ . It means that because the sentiment beta of the speculative stocks increases during the good-sentiment periods, the "sentiment seesaw" becomes steeper, in other words, the cross-sectional difference in the return co-movement becomes pronounced. Interestingly, unlike the regression results using total sample periods,  $\beta_5$  increases from Q1 to Q5 across quintiles based on profitability and R&D ratio during good-sentiment periods. This means that high-tech firms with high profitability and high R&D expenses are sensitive to changes in investor sentiment, only when market sentiment is good.

For the analysis using the bad-sentiment periods, the "sentiment seesaw" across quintiles disappears for almost all stock characteristic portfolios and the  $\beta_5$ s are insignificant for all quintile portfolios. It means

that the cross-sectional co-movement patterns are not observed during the bad-sentiment periods. According to Stambaugh et al. (2012), during the bad-sentiment periods, the most optimistic views tend to be those of rational investors, and they can always exert buying pressure on underpriced stocks. Thus, underpricing induced by the market sentiment is less likely to occur, and the co-movement pattern between the investment sentiment and stock returns might disappear.

For a rigorous test, this study considers the strategy that goes long on the stocks in the high-tercile and short on those in the low-tercile and examines whether the co-movement of the long-short portfolio returns associated with the sentiment changes is more pronounced during the good- than bad-sentiment periods. The regression was performed as <Model 2> for each sub-periods, separately, and whether the explanatory power of the sentiment changes on the returns of the long-short portfolio depends on the state of market-wide sentiment was examined.

Consistent with the above results, when using good-sentiment periods (Panel B of Table 4), the  $\beta_5$ s are significantly positive for the regressions using the return of the long-short portfolio formed by MTB ratio, volatilities, profitability, R&D ratio, sales growth,



The quintile portfolios are formed based on the firm characteristics at the end of the previous period ( $t-1$ ). I run the regression of the monthly equal-weighted returns of each quintile portfolio on the contemporaneous sentiment changes index ( $\Delta Sent_t$ ), RMRF, SMB, HML, and MOM. To examine whether the return co-movement patterns in the cross-sections depend on the sentiment level, the above regression is performed, separately, for the good- and bad-sentiment periods. The "Total," "Good," and "Bad" columns report the results for the regression using total, good-, and bad-sentiment periods, respectively.

**Figure 3.** Cross-sectional patterns of return co-movement with the sentiment changes: good- versus bad-sentiment periods



and BSI, but negative for the regression using the returns of the long-short portfolio formed by PPE ratio. Six coefficients (MTB,  $\sigma_{total}$ , PPEA, Profitability, R&D, BSI) are significant at the 10% level and two coefficients ( $\sigma_{residual}$ , and sales growth) are marginally significant. This means that among all eight return anomalies, there exist strong differences in loadings between long and short legs, during good-sentiment periods.

However, for the analysis using the bad-sentiment periods (Panel C of Table 4), there are no significant differences in loadings between long and short legs in all stock characteristics portfolios, meaning that the  $\Delta Sent_t$  has no incremental explanatory power on the return of the long-short portfolio. This result is consistent with Figure 3 and Table 3, in the sense that during the bad-sentiment periods, the sentiment seesaw across quintiles disappears.

In summary, the cross-sectional co-movement patterns, to the extent they reflect mispricing, are more pronounced during good-sentiment periods than bad-sentiment periods. The result is consistent with the findings of Miller (1997) and Stambaugh et al. (2012).

### C. Robustness Tests

For robustness checks, several alternative variables quantifying the changes in investor sentiment instead of  $\Delta Sent_t$  were considered. At first, changes in the sentiment level index ( $Sent_t - Sent_{t-1}$ ) were used as the alternative to the  $\Delta Sent_t$  and the same regression as <Model 2> was conducted. The result (Table 5) was very similar to that in Table 4. In six out of eight long-short portfolios formed by stock characteristics variables, there existed strong differences in loading between long and short legs during good-sentiment periods, but there was no loading difference between long and short legs during bad-sentiment periods.

There would remain the possibility of the omitted risk factor's premium exhibiting the correlation with the sentiment changes. In this case, the results could be explained by a risk-based explanation, not sentiment-driven overpricing. To check the possibility of a risk-based explanation, an additional set of macroeconomic variable-growth in industrial production, increase in the inflation rate, and changes in unemployment were included, and the same regression as <Model 2> was

**Table 5.** Robustness test: The regressions of the long-short portfolio returns on the changes in the sentiment level index

		MTB	$\sigma_{residual}$	$\sigma_{total}$	PPEA	Profit.	R&D	Growth	BSI
Panel A. Total periods									
T3-T1	Coeff.	0.24	0.09	0.18	0.01	-0.25	0.06	0.12	-0.09
	t-value	1.28	0.5	0.92	0.01	-1.45	0.43	0.91	-0.75
T3-T2	Coeff.	0.07	0.22	0.32*	0.07	-0.14	-0.06	0.01	0.03
	t-value	0.45	1.35	1.95	0.73	-1.19	-0.49	0.06	0.19
T2-T1	Coeff.	0.17	-0.13	-0.14	-0.06	-0.11	0.12	0.12	-0.11
	t-value	1.5	-1.34	-1.25	-0.52	-0.82	1.1	1.08	-0.88
Panel B. Good-sentiment periods ( $Sent_t > 0$ )									
T3-T1	Coeff.	0.67**	0.49*	0.49*	-0.18	0.12	0.34**	0.13	0.05
	t-value	2.53	1.88	1.89	-0.93	0.52	1.98	0.75	0.31
T3-T2	Coeff.	0.36*	0.56**	0.46**	-0.07	0.06	0.11	0.12	0.1
	t-value	1.78	2.39	2.16	-0.52	0.38	0.63	0.74	0.52
T2-T1	Coeff.	0.31**	-0.06	0.03	-0.1	0.06	0.24	0.01	-0.05
	t-value	2	-0.44	0.18	-0.6	0.36	1.66	0.07	-0.32

Table 5. Continued

		MTB	$\sigma_{residual}$	$\sigma_{total}$	PPEA	Profit.	R&D	Growth	BSI
Panel C. Bad-sentiment periods ( $Sent_t < 0$ )									
T3-T1	Coeff.	-0.21	-0.33	-0.11	0.14	-0.66**	-0.27	0.05	-0.19
	t-value	-0.77	-1.29	-0.37	0.68	-2.44	-1.29	0.24	-1.07
T3-T2	Coeff.	-0.25	-0.15	0.15	0.21	-0.41**	-0.21	-0.1	0.08
	t-value	-1.17	-0.6	0.58	1.39	-2.22	-1.16	-0.59	0.41
T2-T1	Coeff.	0.05	-0.18	-0.26*	-0.07	-0.25	-0.07	0.15	-0.27
	t-value	0.25	-1.27	-1.66	-0.38	-1.11	-0.4	0.95	-1.34

For the robustness check, I use the changes in the sentiment level index ( $Sent_t - Sent_{t-1}$ ) instead of the  $\Delta Sent_t$ , and perform the same multivariate regressions as <Model 2>. Panel A shows the results of regressions using the entire sample periods, and Panels B and C show those using the good- and bad-sentiment periods, respectively. Each cell in this table presents the coefficient and t-statistics of  $Sent_t - Sent_{t-1}$ . \*\*\* indicates significance at the 1% level, \*\* indicates significance at the 5% level, and \* indicates significance at the 10% level.

Table 6. Robustness test: The regressions of the long-short portfolio returns on the sentiment changes index controlling for the additional macro variables.

		MTB	$\sigma_{residual}$	$\sigma_{total}$	PPEA	Profit	R&D	Growth	BSI
Panel A. Total periods									
T3-T1	Coeff.	0.16	0.01	0.23	-0.15	-0.06	0.09	0.13	0.17
	t-value	0.76	0.07	1.05	-1.03	-0.29	0.58	0.89	1.31
T3-T2	Coeff.	0.05	0.03	0.15	-0.07	-0.10	0.06	0.14	0.15
	t-value	0.29	0.17	0.83	-0.64	-0.74	0.47	1.09	0.96
T2-T1	Coeff.	0.11	-0.02	0.08	-0.09	0.04	0.02	-0.01	0.02
	t-value	0.85	-0.14	0.61	-0.65	0.28	0.20	-0.06	0.14
Panel B. Good-sentiment periods ( $Sent_t > 0$ )									
T3-T1	Coeff.	0.57**	0.32	0.46	-0.37*	0.18	0.42**	0.28*	0.29*
	t-value	2.00	1.11	1.62	-1.84	0.73	2.21	1.65	1.76
T3-T2	Coeff.	0.25	0.49**	0.45*	-0.18	-0.06	0.19	0.26	0.27
	t-value	1.15	2.00	1.96	-1.19	-0.33	1.04	1.42	1.27
T2-T1	Coeff.	0.33*	-0.18	0.01	-0.19	0.24	0.22	0.02	0.02
	t-value	1.95	-1.15	0.04	-1.04	1.31	1.44	0.13	0.13
Panel C. Bad-sentiment periods ( $Sent_t < 0$ )									
T3-T1	Coeff.	-0.30	-0.33	-0.04	0.07	-0.31	-0.24	-0.02	0.03
	t-value	-0.98	-1.12	-0.13	0.32	-1.04	-0.98	-0.10	0.13
T3-T2	Coeff.	-0.19	-0.45	-0.15	0.05	-0.16	-0.02	0.02	0.07
	t-value	-0.74	-1.62	-0.51	0.34	-0.80	-0.10	0.11	0.30
T2-T1	Coeff.	-0.12	0.12	0.10	0.02	-0.14	-0.22	-0.04	-0.04
	t-value	-0.56	0.71	0.58	0.12	-0.56	-1.17	-0.25	-0.18

I perform the same multivariate regressions as <Model 2> controlling for a set of macro-related variables. The table reports the coefficient and t-statistics of  $\Delta Sent_t$  in the regressions in which long-short portfolio returns are regressed on the contemporaneous sentiment changes index ( $\Delta Sent_t$ ), RMRF, SMB, HML, MOM, and the three macro-related variables. Panel A shows the results of regressions using the entire sample periods, and Panels B and C show those using the good- and bad-sentiment period, respectively. \*\*\* indicates significance at the 1% level, \*\* indicates significance at the 5% level, and \* indicates significance at the 10% level.

performed. According to Table 6, the effects of investor sentiment changes remain largely unchanged by including the additional macro variables.

## V. Conclusion

Similar to Baker and Wurgler (2006, 2007), this study develops a sentiment level index and a sentiment change index that measures the investor sentiment of the KSQ market. Using these indices and the monthly returns of the KSQ common stocks from 2001 to 2021, this study analyzes whether speculative stocks are more sensitive to market-wide sentiment than stable stocks, and whether the different co-movement pattern observed in the cross-sectional stock returns becomes more pronounced during good-sentiment periods than bad-sentiment periods.

To classify the entire samples into speculative and stable stocks, this study uses stock characteristic variables such as MTB ratio, idiosyncratic and total volatilities, PPE ratio, profitability, R&D ratio, sales growth, and the individual trading imbalance (BSI). The equal-weighted quintile portfolios were formed based on these variables and the monthly return time-series of each quintile portfolio and each high-minus-low portfolio was constructed, after which the five-factor regression for the entire sample periods and two subperiods was performed. Consistent with the hypothesis, stocks with high MTB ratio, high volatility, low PPE ratio, high sales growth, and high individual trading imbalance are more sensitive to changes in investor sentiment than stocks with low MTB ratio, low volatility, high PPE ratio, low sales growth, and low individual trading imbalance. In other words, the return on speculative stocks tends to co-move more strongly with sentiment changes than the return on stable stocks. During the good-sentiment periods, the different co-movement pattern observed in the cross-sectional stock returns becomes pronounced, however, during the low-sentiment period, the pattern disappears. The result is consistent with

previous studies (Miller, 1977; Nagel, 2005; Stambaugh et al., 2012), that is, the cross-sectional anomalies should be more prevalent during the high-sentiment period because the primary form of mispricing is overpricing with short-sale impediments.

This study sheds light on the return co-movement behavior in the cross-sections under a setting where market-wide sentiment interacts with short-sale impediments. The results provide some implications for developing investment strategies using investment sentiment and for establishing investor protection policies in the highly individual-crowded market.

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