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An Investigation into Behavioral Biases Among Investors in Korean Distribution Firms*

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Abstract

Purpose: This study examines how psychological heuristics influence stock price dynamics in Korea's distribution industry after significant price shocks. **Research Design, Data, and Methodology:** The study analyzes daily stock price movements exceeding 10% for Korean distribution companies from 1993 to 2022. It establishes anchoring heuristic reference points, including the 52-week high and low, and segments the sample based on company size and volatility. **Results:** We analyzed a sample previously studied by Lee et al. (2023). Our findings indicate that when a stock experiences a positive (negative) price shock near its 52-week high (or lowest price), investors in large (small) companies exhibit an optimism (pessimism) bias. This leads to overreactions and subsequent stock price reversals after the event date. Conversely, when a stock encounters a negative (positive) price shock near its 52-week high (or lowest price), investors tend to underreact due to anchoring heuristics. This results in a drift effect on the stock price after the event day. Notably, investor behavior around 52-week highs or lows directly impacts their heuristic behavior related to those price points. **Conclusions:** This paper uniquely examines behavioral biases among distribution-related stock investors in Korea, shedding light on stock price reversal and drift effects.

Keywords: Anchoring Heuristics, Reversal Effects, Drift Effects, 52-Week High/Low Price, Distribution Industry.

JEL Classification Code: G11, G12, G40, C30.

1. Introduction

This study investigates cognitive biases among investors in Korean distribution firms and their impact on stock prices. We focus on optimism/pessimism bias and anchoring heuristic behavior. These biases influence how investors subjectively weigh stock value information on event dates, leading to overreactions (optimism/pessimism bias) and underreactions (anchoring heuristics) to new stock price information.

Investors often anchor their perceptions to a specific stock price. When faced with a significant price shock, this anchoring bias can lead them to assign excessive weight to the anchored price, even as circumstances change.

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Paradoxically, this fixation on the anchor can result in underestimating the impact of intrinsic value changes following the stock price shock.

Investors in Korea's distribution industry often exhibit anchoring behavior, leading to underreactions following stock price shocks. As a result, price adjustments may not fully reflect new information. Post-event, we observe stock price drifts as prices gradually converge toward adjusted intrinsic values. Notably, Tversky and Kahneman (1974) were pioneers in highlighting cognitive bias among investors through anchoring heuristics.

Focusing on the anchoring heuristic reference points is crucial. The 52-week high and low prices serve as key anchors for investors. When a stock price approaches these levels, investors tend to use them as reference points for their estimates. Empirical studies by Sturm (2008), Baker et al. (2012), and Tsao et al. (2017) have consistently supported this idea. By examining large-scale stock price shocks near the 52-week low and high, this research can shed light on the validity of the anchoring rule-of-thumb hypothesis in the Korean distribution industry.

Cognitive bias resulting from anchoring heuristics varies at the 52-week high and low-price reference points. When stock prices are near the 52-week high, investors tend to anchor to that price, emphasizing it disproportionately. As a result, they assign insufficient weight to the stock's adjusted intrinsic value. This inadequate adjustment leads to a drift effect, causing stock prices to continue falling after the event date. Additionally, optimistic cognitive bias among investors in Korea's distribution industry can amplify this effect, especially for large-cap stocks.

When stock prices are near the 52-week low and subsequently experience a significant rise, investors in the distribution industry tend to anchor to the 52-week low price. As a result, they assign excessive weight to this reference point and insufficient weight to the new intrinsic value that exceeds the low price. This inadequate adjustment leads to a stock price drift effect, resulting in continued price appreciation after the event date. Notably, this drift effect is more pronounced when investors in Korea's distribution industry exhibit a pessimistic cognitive bias toward small-cap stock prices. Empirical analysis confirms that small-cap stocks within Korea's distribution sector exhibit a relatively larger stock price drift effect near the 52-week low compared to large-cap stocks.

Stock price shocks can lead to overreactions by investors with different biases. When stock prices rise significantly from the 52-week high, large-cap investors (optimistic bias) tend to overreact, causing a subsequent price reversal. Conversely, when prices fall significantly from the 52-week low, small-cap investors (pessimistic bias) overreact, resulting in another price reversal. This study extends the analysis by examining stock price drift effect based on anchoring rules for Korean distribution companies. It considers company size and volatility around specific reference points. The findings highlight a systematic relationship between optimism/pessimism bias and anchoring heuristics, explaining both stock price reversal effects and stock price drifts.

This study's multiple regression analysis confirms that even after controlling for stock returns using various financial theory control variables, the reversal and drift effect of stock prices remains significant at the 52-week high and lowest prices following a stock price shock. The paper's structure includes a review of existing research literature on anchoring heuristics in Section 2, the establishment of the research hypothesis in Section 3, presentation of data and research methodology in Section 4, empirical analysis results in Section 5, and a concluding discussion in Section 6.

2. Literature Review

The Academic research on stock price changes following large-scale stock price shocks can be broadly categorized into two main approaches: those based on the efficient market hypothesis (EMH) and those rooted in behavioral finance. The EMH posits that asset prices fully incorporate all available information, and decisions made under uncertainty are rational (e.g., Fama, 1997). Key economic concepts associated with the EMH include random walk theory (e.g., Kendall and Hill, 1953), expected utility theory (Von Neumann and Morgenstern, 1944), and rational expectations (Lucas, 1978).

In the context of the efficient market hypothesis (EMH), traditional decision-making theories under uncertainty calculate outcomes objectively, without being influenced by subjective weightings. Expected profit and risk, determined based on ex post probability distributions and corresponding utilities, significantly impact decisions related to uncertain profit structures. Notably, even after large-scale stock price shocks, prices remain unaffected by investors' subjective weightings, resulting in an absence of specific bias.

Researchers, including Lehmann (1990), Hamelink (1999), and Cox and Peterson (1994), have explored stock price changes following large shocks within the efficient market hypothesis (EMH). Their findings suggest that post-shock stock price reversals, despite bid-ask spreads and transaction costs, do not yield significant profits or violate the EMH. Lasfer et al. (2003) and Masouz et al. (2009) also studied abnormal stock price returns after substantial fluctuations, but these returns were not statistically significant after adjusting for risk.

Behavioral finance combines economics and psychology to analyze decision-making under uncertainty from a cognitive perspective. Unlike the efficient market hypothesis, behavioral finance recognizes cognitive limitations that prevent investors from fully processing all available information (e.g., March, 1978). It acknowledges that subjective assessments of specific prices influence the choice of alternatives and their associated probabilities (e.g., Brady & Premti, 2019). Representative studies in behavioral finance explore concepts like bounded rationality (e.g., Simon, 1972), psychological factors affecting human judgment (e.g., Slovic, 1972), prospect theory (e.g., Kahneman & Tversky, 1979), and market anomalies (e.g., Kahneman, Knetsch, & Thaler, 1991).

Behavioral finance theory suggests that investors predict stock price trends using historical information. However, these predictions are influenced by cognitive biases and speculative elements. Anchoring heuristics, as highlighted by Tversky and Kahneman (1974), lead investors to overvalue stock prices as reference points while undervaluing intrinsic value factors. Consequently, behavioral biases can cause stock price drift. Recent studies, such as Pompian (2012), demonstrate that anchoring to initial stock prices results in adjustments influenced by cognitive biases following specific events. Shin and Park (2018) explore cognitive bias effects on stock prices in developed countries' capital markets.

Empirical studies investigating stock price effects resulting from cognitive biases due to anchoring heuristics include Schnusenberg and Madura's (2001) work. They analyzed the US stock index, revealing a persistent short-term impact on stock prices following significant price shocks. Beyond the US, Lasfer et al. (2003) studied 39 international stock indices, finding that the drift effect remains even after stock price shocks, supporting the behavioral bias hypothesis among investors, especially following negative price shocks.

Investigating individual stocks, Mazouz et al. (2009) rigorously tested stock returns following substantial price shocks. Their findings revealed a significant stock price drift effect. Additionally, Benou (2003), Pritamani and Singal (2001), and Chan (2003) demonstrated that investors react slowly to new information, leading to incomplete price adjustments and significant stock price drift. Empirical evidence supports these observations. Moreover, Brady and Premti (2019) confirmed this effect in a comprehensive study on investors' behavioral biases anchored in heuristics, using CRSP data from the United States.

In our study, we use the 52-week high and low as anchors for estimating investor behavior. These reference points align with prior research by Baker et al. (2012) and Tsao et al. (2017). Additionally, we analyze the cumulative rate of return over the 5 days before the incident date as a proxy variable to assess private information. Specifically, this variable serves as a CONTRADICTION factor in our multiple regression analysis, drawing inspiration from studies by Madura and Premti (2014) and Christophe et al. (2010).

Recent academic efforts have focused on explaining the impact of behavioral bias caused by investors' guesses on stock prices. Specifically, this paper analyzes the impact of investors' guesses on large-scale stock price shocks, with a primary focus on the US market. Representative studies highlight how investors' availability heuristics lead to a stock price reversal effect after significant price shocks (e.g., Kliger and Kudryavtsev, 2010; Kudryavtsev, 2013, 2017, 2018, 2019). Additionally, Brady and Premti (2019) find that investors' anchoring heuristics contribute to a drift effect in stock prices following such shocks. Dasli et al. (2019) also suggest that investor behavior biases, including anchoring and heuristics, play a role in stock price abnormalities.

Lee et al. (2023) conducted a study on the impact of investors' behavioral bias on stock prices in the Korean stock market. They focused on availability heuristic and anchoring heuristic hypotheses, analyzing a large sample of distribution-related stocks. Their findings suggest that the stock price drift effect due to investors' anchoring heuristics is more dominant than the stock price reversal effect resulting from availability heuristics when large-scale stock price shocks occur in Korean distribution-related stocks.

In contrast to Lee et al. (2023)'s interpretation of the stock price reversal phenomenon as a simple mean reversion, our paper suggests that it results from investors' overreaction due to optimism/pessimism bias. Furthermore, we propose a systematic relationship between optimism/ pessimism bias and anchoring heuristics based on shared company characteristics. Using these findings, we explain the stock price reversal and drift effects in Korean distribution-related stocks according to investor behavioral biases.

3. Research Hypothesis

This study examined stock price shocks, specifically daily returns exceeding 10% for individual stocks in the Korean distribution industry. Significant stock price increases had a drift effect, leading to continued growth after the initial incident. Conversely, substantial declines resulted in a stock price reversal effect. Determining whether post-shock movements are influenced by drift (moving in the same direction as the initial shock) or reversal remains challenging.

In our study, we investigate the impact of cognitive bias on stock price movements, specifically focusing on the anchoring heuristic proposed by Tversky and Kahneman (1974). Our empirical analysis centers on Korean distribution industry stocks. To validate the hypothesis, we establish reference points based on the 52-week high and low values. These reference points provide insights into how investors' anchoring heuristics operate. Notably, when stock prices approach the 52-week low, they attract attention and serve as crucial reference points for navigating uncertain market conditions.

When stock prices are near their 52-week low and positive news suddenly emerges, leading to a significant increase in intrinsic value and a substantial stock price shock, investors exhibit behavioral biases. They rely on anchoring and heuristics, assigning disproportionately high subjective probability weights to the 52-week low price. Over time, stock prices gradually adjust to reflect new intrinsic values, initially resulting in a short-term drift effect.

In scenarios where the 52-week high price index exceeds 0.7, investors often anchor their assessments to this conspicuous price level. Now, consider a situation where adverse news suddenly emerges, causing a significant decline in the stock's intrinsic value and resulting in a substantial negative stock price shock. Under such heightened uncertainty, investors exhibit a behavioral bias, relying on heuristic guesswork—specifically, anchoring—to estimate the revised intrinsic value of the stock. During this process, subjective probability weights are assigned. Notably, the existing 52-week high price receives relatively high weight, while the new intrinsic value corresponding to the altered circumstances is assigned a relatively low weight. Consequently, stock prices persistently decline in alignment with the initial stock price drop observed on the incident date.

In this study, we examine the behavioral bias exhibited by investors due to the anchoring heuristic during the estimation of new intrinsic values following events that intensify uncertainty, such as large-scale stock price shocks. Our theoretical proposition posits that this bias significantly impacts stock prices beyond the event date, resulting in a drift effect. To empirically investigate the magnitude of this post-event drift effect across different time windows and stock categories, we formulate the following research hypotheses.

H1: For events with large positive(negative) stock price shocks (10% or more), we see significant positive (negative) cumulative returns within 20 days if the closing price before the event date was near the 52-week low(high), with a 52-week low(high) price index of 0.7 or higher.

In our study, we analyzed investor behavior in response to both positive and negative news when stock prices are near their 52-week highs and lows. When the stock's highest price index exceeds 0.7, optimistic investors tend to overestimate the positive impact, leading to an exaggerated rise in stock prices on the event date. Conversely, when the stock's lowest price index exceeds 0.7, pessimistic investors tend to overestimate the negative impact, resulting in an exaggerated decline in stock prices on the event date. However, in both cases, there is a subsequent price reversal effect, where the stock price rebounds or falls again after the incident date. Our analysis focuses on the size of stocks with high volatility and company-specific factors.

H2: For events with large positive(negative) stock price shocks (10% or more), we see significant negative (positive) cumulative returns within 20 days if the closing price before the event date was near the 52-week high(low), with a 52-week high(low) price index of 0.7 or higher.

4. Data Description and Research Design

In our research, we looked at the daily closing prices of 215 stocks related to distribution industry on the KOSPI market. We've included a variety of sectors under 'distribution-related industries': 61 stocks are from distribution, 24 from transport and storage, 38 from food and beverage, 23 from textiles and apparel, and 73 from transport equipment. We chose these sectors for their close ties to distribution, giving us a comprehensive overview.

The daily returns were calculated using log returns ($\ln(S_t) - \ln(S_{t-1})$). The research data spans from January 1, 2004, to December 31, 2022. All closing price and market capitalization data for individual stocks were sourced from the FnGuide database.

This study used three sampling principles: first, data was collected for 250 trading days before and 20 trading days after the incident date. Second, market capitalization information was available for each stock, allowing us to categorize them as large-cap or small-cap. Third, a condition was imposed to ensure daily stock price changes did not exceed 50%, facilitating the extraction of returns of 10% or more

In our study, we define a significant stock price shock as a scenario where the daily stock price return exceeds 10% in either direction. This definition captures substantial movements that likely reflect intrinsic value changes or broader market psychology. We use the rate of return as the criterion for event determination.

Table 1: Descriptive statistics

Panel A : Descriptive Statistics for the Total Sample									
Proxy/ Threshold	Number of event	Market capitalization, (100 million KRW)		St.Dev.of historical stock returns, %		HI		LO	
		Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev	Mean	St.Dev.
Proxy A : $\lvert \mathbf{SR0}_i \rvert > \mathbf{10}\%$	10,711								
Price increases	7,330	3,900	12,200	3.94	1.26	0.68	0.25	0.61	0.23
Price decreases	3,381	4,300	15,900	4.04	1.30	0.64	0.26	0.64	0.27
Proxy B: $\lvert \mathbf{AR0}_i \rvert > \mathbf{10}\%$	9,062								
Price increases	6,559	3,400	11,000	3.96	1.27	0.69	0.25	0.60	0.23
Price decreases	2,503	3,900	13,500	4.27	1.35	0.69	0.26	0.56	0.26
Panel B : Descriptive Statistics for the Sample Divided by 52_WK_HI and 52_WK_LO									
Proxy	Number of event	Stock returns, %		St.Dev.of historical stock returns, %		52_WK_HI		52_WK_LO	
		Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev	Mean	St.Dev.
Proxy A : $\lvert \mathbf{SR0}_i \rvert > \mathbf{10}\%$									
Price increases	(6,810)								
$52\_WI\_HI \geq 0.7$	3,899	15.00	4.63	3.63	1.41	0.88	0.09	0.52	0.20
$52\_WI\_LO \geq 0.7$	2,911	14.51	4.44	3.43	1.06	0.55	0.23	0.85	0.09
Price decreases	(2,639)								
$52\_WI\_HI \geq 0.7$	1,156	-13.17	2.96	3.88	1.20	0.88	0.09	0.48	0.21
$52\_WI\_LO \geq 0.7$	1,483	-13.35	3.19	3.48	1.11	0.49	0.21	0.90	0.10
Proxy B: $\lvert \mathbf{AR0}_i \rvert > \mathbf{10}\%$									
Price increases	(6,095								
$52\_WI\_HI \geq 0.7$	3,640	15.25	4.68	3.64	1.14	0.88	0.09	0.52	0.20
$52\_WI\_LO \geq 0.7$	2,455	14.78	4.76	3.40	1.08	0.57	0.23	0.84	0.08
Price decreases	(2,193)								
$52\_WI\_HI \geq 0.7$	1,407	-13.10	3.22	4.03	1.23	0.88	0.09	0.45	0.20
$52\_WI\_LO \geq 0.7$	786	-13.88	3.90	3.56	1.15	0.52	0.23	0.88	0.10

Specifically, an event occurs when the absolute value of the simple daily log rate of return exceeds 10% ($\lvert SR0_i \rvert$>0, proxy A). Additionally, we consider instances where the absolute value of excess return, as defined by the Capital Asset Pricing Model (CAPM), surpasses 10% on the event date ($\lvert AR0_i \rvert$>0, proxy B).

The abnormal rate of return, defined in proxy B, represents the excess rate of return estimated by the Capital Asset Pricing Model (CAPM) on the event date. This measure reflects a market risk-adjusted rate of return. Specifically, the abnormal return $AR0_i$ estimated using proxy B corresponds to the regression coefficient in an equation.

This equation regresses the stock price return for the one-year period prior to the occurrence date of the individual company against the market return for the corresponding period. In simpler terms, $AR0_i$ is extracted using the following equation:

$$E(r_i) - r_f = \widehat{\alpha_{im}} + \widehat{\beta_{im}}(E(r_m - r_f)$$
$$AR0_i = SR0_i - E(r_i) \tag{1}$$

In our regression, we used Korea's daily 'Call Rate' as a proxy for the risk-free rate of return, denoted as r_f. Examining Panel A in Table 1, we found 10,711 instances of large-scale price shocks using proxy variable A. Among these, 7,330 cases exhibited upward movement, while 3,381 cases experienced downward movement. Additionally, we identified 9,062 samples of large-scale price shocks using proxy variable B. Among these, 6,559 cases showed an increase, while 2,503 cases demonstrated a decrease.

Subsequently, following the research approach outlined by Brady and Premti (2019), this study operationalized the anchoring heuristic hypothesis. Specifically, we utilized the 52-week high index and 52-week low index to empirically examine the research hypothesis.

$$HI = \frac{The\ Closing\ price\ the\ day\ before\ the\ major\ event}{52-week\ highest\ price} \quad (2)$$

$$LO = \frac{52-week\ lowest\ price}{The\ Closing\ price\ the\ day\ before\ the\ major\ event} \quad (3)$$

The HI index (equation (2)) equals 1 when the closing price one day before a large-scale stock price shock matches the 52-week high. A higher HI index value indicates that the previous day's closing price is closer to the 52-week high.

Similarly, the LO index (equation (3)) equals 1 when the closing price one day before an event coincides with the 52-week low. A LO index value close to 1 suggests that the stock price the day before the event date is close to the 52-week low, while a value close to 0 indicates a relatively high stock price compared to the 52-week lowest price.

In Panel B of Table 1, we observe the following: Among the total samples extracted using proxy variable A, there were 2,911 samples that exhibited a price shock of more than 10% near the 52-week low, and an equal number of samples (2,911) that showed a price shock of more than 10% near the 52-week high. Additionally, there were 1,156 samples that experienced a price shock.

Similarly, among the total samples extracted using proxy variable B, 2,455 samples demonstrated price shocks rising by more than 10% near the 52-week low, while 2,455 samples showed price shocks decreasing by 10% or less near the 52-week high. The total count for this subset was 1,407 samples.

When we restrict the sample by applying the 52-week high and 52-week low as anchoring standards, the number of samples significantly decreases compared to the overall sample in Panel A. However, it is evident that we still have a sufficient number of samples for event research and statistical analysis.

5. Results and Discussion

5.1. Testing Significance of Post-event Cumulative Returns

In the forthcoming analysis, we will scrutinize the impact of cumulative returns post-event date, utilizing the comprehensive dataset. The period for accruing returns subsequent to the event date spans 2, 5, or 20 days. Employing the full dataset under unbounded conditions necessitates an assessment to ascertain the predominance of either the drift effect on stock prices or the reversal effect following a substantial fluctuation in stock prices.

Table 2 delineates the outcomes of a T-test conducted to ascertain if the cumulative returns, across diverse return accumulation intervals, deviate significantly from zero. Within this table, the term '$CSR0_i$ measure' denotes the aggregate of daily simple logarithmic returns, while '$CAR0_i$ measure' refers to the cumulative daily abnormal return as per the CAPM framework. Under the $CSR0_i$ criterion, instances of stock price ascensions exceeding 10% totaled 7,330, alongside 3,381 instances of pronounced declines below 10%. Concurrently, the $CAR0_i$ metric recorded 6,559 instances of stock price surges beyond 10%, and 2,503 instances of stock price reductions to 10% or lower.

Substantial price escalations trigger a discernible drift effect within the 1, 2, and 1-5 day windows, as evidenced by the $CSR0_i$ measure. Conversely, the 1-20 day window exhibits a marked reversal effect. A parallel trend is observable under the $CAR0_i$ measure; however, the drift effect's significance from days 1 to 5 is marginally diminished in comparison to the $CSR0_i$ measure. Overall, a significant stock price drift effect is evident in the immediate aftermath, up to 5 days post-event, when prices surge markedly. On extending the observation period to approximately 20 days post-event, the stock price reversal effect becomes pronounced under both evaluative criteria.

When there is a considerable decline in prices, the ensuing pattern of cumulative returns post-event date diverges between the two metrics. Specifically, under the $CSR0_i$ measure, a significant stock price drift effect is substantiated solely within the 1-day and 2-day windows, while the stock price reversal effect is deemed inconsequential within the 5-day and 20-day windows. In instances of pronounced price reductions, the drift effect is notably prevalent under the $CAR0_i$ measure. Nevertheless, the drift effect's significance is observed to diminish slightly within the 5-day window.

In aggregate, the trajectory of stock prices within the distribution sector post the large-scale shock event indicates a predominant drift effect, albeit with a partial manifestation of the reversal effect. This pattern diverges from the behavior observed in the U.S. stock market. Kudryavtsev (2018), utilizing U.S. stock price data, revealed a prevailing reversal effect during significant price movements, irrespective of the direction. These findings suggest that the U.S. market's investor behavior, characterized by an overreaction to news precipitating substantial price volatility, culminates in a reversal of stock prices.

Nevertheless, the findings depicted in Table 2 stand in contrast to the empirical analyses conducted by Kudryavtsev (2018). Consequently, it becomes imperative to construe the stock price movements within Korea's distribution sector, post a significant price shock, as indicative of an underreaction by investors to such events, rather than an overreaction to the precipitating information. This paper posits that the post-shock price dynamics in the Korean distribution industry are reflective of a behavioral bias stemming from investors' anchoring heuristics, for which we provide empirical substantiation.

Upon reviewing Table 2, it becomes evident that within the comprehensive sample of stocks from Korea's distribution industry, the price drift effect manifests with pronounced significance across various windows subsequent to a large-scale price shock. Predominantly, the price drift effect is extensively significant and prevails over the price reversal effect in numerous windows. The insights from Table 2 necessitate a meticulous examination of the behavioral bias—specifically the drift effect—in stock prices, which may be attributed to the anchoring heuristics of investors.

Table 2: Abnormal cumulative stock returns following large stock price increases and decreases: Total sample case.

Panel A: Large stock price increases		
Days relative to event	**Average AR following initial price changes, % (2-tailed p values)**	
	|CSR0i|>10%	**|CAR0i|>10%**
	(7,330 events)	**(6,559events)**
1	0.89***	0.85***
	(0.0%)	(0.0%)
2	0.91***	0.76***
	(0.0%)	(0.0%)
1 to 5	0.63***	0.39*
	(0.3%)	(9.4%)
1 to 20	-1.36***	-1.86***
	(0.01%)	(0.0%)
Panel B: Large stock price decreases		
Days relative to event	**Average AR following initial price changes, % (2-tailed p values)**	
	|CSR0i|>10%	**|CAR0i|>10%**
	(3,381 events)	**(2,503 events)**
1	-0.77***	-0.73***
	(0.0%)	(0.0%)
2	-0.55***	-0.91***
	(0.51%)	(0.01%)
1 to 5	0.21	-0.53*
	(38.51%)	(8.7%)
1 to 20	0.62	-2.11***
	(15.76%)	(0.02%)

Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

5.2. Assessment of Cumulative Return Significance at the Anchor Drop Reference Point

5.2.1. Analysis of Cumulative Returns Significance Subject to Constraints of 52-Week Pean and Trough Index Levels

In this section, we formulate testable hypotheses regarding the stock price reversal effect and stock price drift effect observed following significant stock price changes in the distribution industry. Our focus is on the behavioral bias exhibited by distribution industry investors. To establish reference points, we define the 52-week low and 52-week high prices based on anchoring. Specifically, if the stock price before the event date exceeds a value of 0.7 when converted to the HI index and LO index values given in equations (2) and (3) above, we consider it to be 'near' the reference point.

For instance, when the LO index value of a stock exceeds 0.7, investors often establish an 'anchor' using the readily observable 52-week low price as the reference point for the stock's intrinsic value. In such cases, if a substantial negative stock price shock occurs, investors with a pessimistic outlook on their investments tend to overreact to new information. As a consequence, we observe a reversal effect where stock prices rise after the event date.

Investors with a pessimistic outlook tend to anchor strongly even as the stock price rises from the 52-week low. They assign an excessively high subjective probability weight to the 52-week low, while placing an overly low weight on the newly adjusted high intrinsic value. Consequently, the stock price does not immediately and smoothly adjust to the new intrinsic value, leading to a drift effect where the stock price continuously converges toward an intrinsic value higher than the current stock price. Notably, when a large positive stock price shock occurs near the 52-week low, significant positive cumulative returns can be expected across various time windows. This phenomenon serves as a driving factor for the positive stock price drift effect observed in the entire sample.

Also, let's say the stock price is close to the 52-week high and the HI index shows a value of 0.7 or higher. In this case, when a large-scale positive stock price shock occurs and the intrinsic value of the stock rises significantly, investors with an optimistic bias toward the stock they have invested in will have an overly optimistic outlook on the increased stock price information. Accordingly, a stock price reversal effect occurs where the stock price falls after the incident date.

Investors with an optimistic outlook often assign an overly high subjective probability weight to the 52-week high price, even when the stock price falls from that level. Consequently, they assign an excessively low weight to the newly adjusted stock price information. As a result, a drift effect occurs in the stock price, where it continues to decline after the incident date. Notably, when a large-scale negative stock price shock occurs near the 52-week high, significant negative cumulative returns can be expected across various time windows. This phenomenon serves as a driving factor for the negative stock price drift effect observed in the entire sample.

If you look at Table 3 below, you can see that the empirical analysis results are consistent with this logical analysis. Under the $CSR0_i$ measure in Panel A of Table 3, the stock price remained near the 52-week low, so the number of events in which the LO index was above 0.7 and a large-scale negative stock price shock occurred was 1,483. In this case, it is confirmed that a significant positive stock price reversal effect is occurring in the 5-day and 20-day windows. Additionally, the number of cases where positive stock price shocks occurred near the 52-week low was 2,911. In this case as well, very highly significant positive cumulative returns appear sequentially for all 1-day, 2-day, 5-day, and 20-day windows, confirming that a systematic stock price drift effect is occurring.

In addition, when the HI index value is above 0.7 and the stock price is near the 52-week high, the number of events in which a large positive stock price shock occurred is 3,899. In this case as well, a significant stock price reversal effect is confirmed in the 20-day window. In addition, the number of events in which large-scale negative stock price shocks occurred near the 52-week high is 1,556, and highly significant negative cumulative returns are shown for all 1-day, 2-day, 5-day, and 20-day windows, indicating a drift effect in stock prices. It can be confirmed that it appears systematically and very strongly.

Meanwhile, under the $CAR0_i$ measure in Panel B of Table 3, it is confirmed that the stock price reversal effect and stock price drift effect are systematically occurring around the 52-week low and high prices. Based on these empirical analysis results, research hypotheses 1 and 2 of this paper could be adopted.

Table 3: Abnormal stock returns following large stock price increases and decreases, by the size of 52_WK_HI/LO

Panel A: $CSR0_i$ Measure			
Days relative to event	Cumulative returns following initial price changes, % (2-tailed p values)		
	$\lvert CSR0_i \rvert \geq 10\%$, Large Stock Price Increases		
	$\mathbf{HI \geq 0.7}$ (3,899 events)	$\mathbf{LO \geq 0.7}$ (2,911 events)	Difference
1	0.82***	0.91***	-0.09
	(0.0%)	(0.0%)	(65.89%)
2	0.66***	1.37***	-0.71**
	(0.67%)	(0.0%)	(3.4%)
1 to 5	0.08	1.64***	-1.56***
	(79.8%)	(0.0%)	(0.02%)
1 to 20	-2.81***	2.41***	-5.22***
	(0.0%)	(0.0%)	(0.0%)
Days relative to event	Cumulative returns following initial price changes, % (2-tailed p values)		
	$\lvert CSR0_i \rvert \geq 10\%$, Large Stock Price decreases		
	$\mathbf{HI \geq 0.7}$ (1,556 events)	$\mathbf{LO \geq 0.7}$ (1,483 events)	Difference
1	-0.75***	-0.77***	0.02
	(0.0%)	(0.0%)	(93.81%)
2	-1.32***	0.03	-1.35***
	(0.0%)	(90.5%)	(0.05%)
1 to 5	-1.65***	2.36***	-4.01***
	(0.0%)	(0.0%)	(0.0%)
1 to 20	-5.35***	8.21***	-13.56***
	(0.0%)	(0.0%)	(0.0%)
Panel B: $CAR0_i$ Measure			
Days relative to event	Cumulative returns following initial price changes, % (2-tailed p values)		
	$\lvert CAR0_i \rvert \geq 10\%$, Large Stock Price Increases		
	$\mathbf{HI \geq 0.7}$ (3,640 events)	$\mathbf{LO \geq 0.7}$ (2,455 events)	Difference
1	0.85***	0.78***	0.08
	(0.0%)	(0.0%)	(72.32%)
2	0.62**	1.07***	-0.45
	(1.58%)	(0.0%)	(21.53%)
1 to 5	0.05	1.13***	-1.09**
	(88.68%)	(0.08%)	(1.88%)
1 to 20	-2.72***	1.38***	-4.1***
	(0.0%)	(0.87%)	(0.0%)
Days relative to event	Cumulative returns following initial price changes, % (2-tailed p values)		
	$\lvert CAR0_i \rvert \geq 10\%$, Large Stock Price decreases		
	$\mathbf{HI \geq 0.7}$ (1,407 events)	$\mathbf{LO \geq 0.7}$ (786 events)	Difference
1	-0.87***	-0.50**	-0.38
	(0.0%)	(4.89%)	(23.03%)
2	-1.81***	0.41	-2.21***
	(0.0%)	(32.04%)	(0.0%)
1 to 5	-2.40***	3.00***	-5.41***
	(0.0%)	(0.0%)	(0.0%)
1 to 20	-6.48***	7.18***	-13.66***
	(0.0%)	(0.0%)	(0.0%)

Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

5.2.2 Cumulative Return Significance Test under Company Size Constraints

In this section, we conduct a detailed examination of the impact of investors' anchoring heuristics on stock prices. Specifically, we focus on the top 30% and bottom 30% of market capitalization within our sample. We select companies where the 52-week high index and 52-week low index on the event date are both 0.7 or higher. Our analysis centers on the cumulative returns difference after the event date.

Referencing Table 4, within the $CSR0_i$ framework, the small-cap segment—identified by a significant stock price increase proximate to the 52-week low—included 873 entities, closely matching the 874 entities in the large-cap segment. The small-cap segment demonstrated cumulative abnormal returns of 1.29%, 2.05%, 2.22%, and 3.93% across the 1-day, 2-day, 5-day, and 20-day intervals, respectively. These returns are not only substantially positive but also exceed those observed in the large-cap segment.

In the scenario where stock prices experienced a substantial decline near the 52-week high, the large-cap segment was represented by 467 entities, which is nearly equivalent to the 466 entities in the small-cap segment. The large-cap group's cumulative abnormal returns were -1.19%, -1.54%, -2.19%, and -6.87% within the 1-day, 2-day, 5-day, and 20-day periods, respectively, all indicating significant negative trends. In contrast, the small-cap group's cumulative abnormal returns were not statistically significant across these time frames. Under the $CAR0_i$ measure, it is observed that the cumulative return patterns of the large-cap and small-cap groups are consistent with those under the $CSR0_i$ measure, yet the magnitude of the variance is more pronounced.

The findings presented in Table 4 suggest that investor valuations exhibit a discernible pessimism bias in the assessment of small-cap stocks. This bias becomes apparent when the stock prices of small-cap entities ascend markedly near their 52-week lows, leading to a drift effect in stock prices attributable to investor underreaction. Conversely, a pronounced decline in stock prices near the 52-week lows indicates an overreaction by investors, compounded by the pessimism bias in valuation, culminating in a notable reversal effect in stock prices.

The analysis presented in Table 4 may be construed as reflecting an optimism bias in the valuation of large-cap stocks by investors. This optimistic valuation tendency is observed to cause a drift effect in stock prices, which is attributed to investor underreaction when large-cap stock prices experience a significant drop near the 52-week high. On the other hand, a substantial rise in stock prices near the 52-week high is met with investor overreaction, influenced by the optimism bias, leading to a notable reversal effect in stock prices. These findings provide critical insights into the valuation behaviors of Korean investors, highlighting the influence of company size on stock price assessments.

In this study, we observe that large-cap investors tend to exhibit a relatively optimistic bias compared to small-cap investors when the stock price is near the 52-week high. Conversely, small-cap investors demonstrate a relatively pessimistic bias compared to large-cap investors around the 52-week low. While this paper provides additional insights, it also highlights the need for future research. Specifically, we emphasize that company-specific factors, such as company size and volatility, significantly influence investors' optimistic or pessimistic bias based on the stock price's proximity to the 52-week high or lowest price. However, this analysis represents only a theoretical step toward a comprehensive examination. Subsequent in-depth research in this area is essential.

Nevertheless, when we examine why investors exhibit an optimistic bias toward large-cap stocks near their 52-week highs, several trust factors come into play. These include excellent credit ratings, financial stability, robust corporate management, and effective strategic diversification. Collectively, these company-specific attributes contribute to enhancing investor trust. Furthermore, the presence of a robust Investor Relations (IR) system, which facilitates efficient communication and dissemination of corporate information, plays a crucial role in bolstering investor confidence.

Table 4: Abnormal stock returns following large stock price increases and decreases for high/low market capitalization

Panel A: $CSR0_i$ Measure			
Days relative to event	**Cumulative returns following initial price changes for high/low market capitalization, %**		
	$\lvert CSR0_i \rvert \geq 10\%$, Large Stock Price Increases		
	$HI \geq 0.7$	**$LO \geq 0.7$**	**Difference**
	(1,170/1,169)	**(874/873)**	
1	-0.0/1.19***	0.83***/1.29***	-0.84***/-0.09
2	-1.0***/1.62***	1.49***/2.05***	-2.49***/-0.43**
1 to 5	-1.6***/1.61***	1.78***/2.22***	-3.39***/-0.61***
1 to 20	-6.31***/1.41***	2.31***/3.93***	-8.62***/-2.53***
Days relative to event	**Cumulative returns following initial price changes for high/low market capitalization, %**		
	$\lvert CSR0_i \rvert \geq 10\%$, Large Stock Price decreases		
	$HI \geq 0.7$	**$LO \geq 0.7$**	**Difference**
	(467/466)	**(445/444)**	
1	-1.19***/-0.36	-1.19***/-0.62	0.0/0.26
2	-1.54***/-0.92	-0.73/0.2	-0.81/-1.13
1 to 5	-2.19***/-0.95	1.4***/2.49***	-3.6***/-3.44***
1 to 20	-6.87***/-1.33	5.48***/9.02***	-12.35***/-10.36***
Panel B: $CAR0_i$ Measure			
Days relative to event	**Cumulative returns following initial price changes for high/low market capitalization, %**		
	$\lvert CAR0_i \rvert \geq 10\%$, Large Stock Price Increases		
	$HI \geq 0.7$	**$LO \geq 0.7$**	**Difference**
	(1,092/1,091)	**(737/736)**	
1	0.06/1.35***	0.78***/1.32***	-0.72**/0.03
2	-1.12***/1.75***	1.35***/1.68***	-2.48***/0.07
1 to 5	-1.9***/1.82***	1.55***/1.77***	-3.45***/0.05
1 to 20	-6.57***/1.76	0.92/3.0***	-7.48***/-1.24
Days relative to event	**Cumulative returns following initial price changes for high/low market capitalization, %**		
	$\lvert CAR0_i \rvert \geq 10\%$, Large Stock Price decreases		
	$HI \geq 0.7$	**$LO \geq 0.7$**	**Difference**
	(423/422)	**(236/235)**	
1	-1.37***/-0.51	-1.66***/-0.16	0.29/-0.36
2	-2.28***/-1.43***	-1.82***/1.2	-0.45/-2.63***
1 to 5	-3.28***/-1.73***	-0.01/4.57***	-3.27***/-6.3***
1 to 20	-8.85***/-1.73***	2.03/10.38***	-10.88***/-12.11***

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

5.2.3 Cumulative Return Significance Test under Volatility Constraints

In this section, we analyze the influence of investors' behavioral bias on stock prices by categorizing individual stocks in the distribution industry listed on the exchange based on the magnitude of stock return volatility. Referencing Table 5, the CSR metric revealed that subsequent to a pronounced positive price adjustment near the 52-week low, the top 30% volatility bracket comprised 865 cases. The cumulative abnormal returns (CAR) for this high-volatility cohort were 1.42%, 2.66%, 3.32%, and 3.07% across the 1-day, 2-day, 5-day, and 20-day intervals, respectively, denoting a significantly positive trajectory.

Upon the occurrence of a significant negative price fluctuation proximal to the 52-week zenith, the high volatility category encompassed 462 instances. The cumulative abnormal returns for this uppermost volatility tier were -1.11%, -2.67%, -4.13%, and -13.23% for the 1-day, 2-day, 5-day, and 20-day durations, respectively, each manifesting substantial negative figures. Notwithstanding variances in magnitude under the $CAR0_i$ metric, a congruent pattern was discernible across all temporal windows, akin to the return rates observed with the $CSR0_i$ metric.

The examination of stocks within Korea's distribution industry has revealed that the drift effect among the high volatility stock group is more systematic compared to that of the low volatility group. Investors in highly volatile stocks tend to exhibit an optimistic bias, leading to overreactions when stock prices rise near their 52-week highs. Consequently, a strong stock price reversal effect occurs, with prices declining again after the event date. Conversely, when stock prices fall near the 52-week high, high-volatility stock investors maintain an optimistic outlook and adhere more strongly to the 52-week high price compared to low-volatility stock investors. This behavior reflects an anchoring rule of thumb. As a result, a drift effect is observed in stock prices, where they continue to decline after the incident date.

Investors with a pessimistic bias toward high-volatility stocks tend to overreact to large-scale stock price shocks that cause prices to fall near the 52-week low. As a result, a stock price reversal effect occurs, with prices rising strongly again after the event date. In contrast, when stock prices rise near the 52-week low, high-volatility stock investors anchor to this level more strongly than their low-volatility counterparts, exhibiting heuristic behavior. This anchoring effect leads to a stock price drift effect, where they continue to rise after the incident date. Interestingly, even low-volatility investors demonstrate significant anchoring behavior near the 52-week low, contributing to the observed drift effect.

To further elucidate, elevated stock price volatility is indicative of increased uncertainty and risk. The findings suggest that heightened levels of uncertainty and risk lead investors to rely more heavily on conjecture for stock valuation. Consequently, investor behavior tends to be more biased under conditions of high uncertainty, exerting a greater impact on stock price movements following significant price shocks.

Table 5: Abnormal stock returns following large stock price increases and decreases for high/low volatility stocks

Panel A: $CSR0_i$ Measure			
Days relative to event	**Cumulative returns following initial price changes for high/low Volatility stocks, %**		
	$\lvert CSR0_i\rvert \geq 10\%$, Large Stock Price Increases		
	$HI \geq 0.7$	**$LO \geq 0.7$**	**Difference**
	(1,170/1,179)	**(865/887)**	
1	1.24***/0.66***	1.42***/0.38	-0.19/0.29
2	0.91*/0.53	2.66***/0.09	-1.75**/0.43
1 to 5	-0.21/0.24	3.32***/-0.12	-3.53***/0.36
1 to 20	-7.12***/-0.83	3.07***/0.51	-10.2***/-1.34
Days relative to event	**Cumulative returns following initial price changes for high/low Volatility stocks, %**		
	$\lvert CSR0_i\rvert \geq 10\%$, Large Stock Price decreases		
	$HI \geq 0.7$	**$LO \geq 0.7$**	**Difference**
	(462/469)	**(444/444)**	
1	-1.11***/-0.25	-0.74**/-0.49*	-0.36/0.24
2	-2.67***/-0.22	0.01/-0.54	-2.68***/0.31
1 to 5	-4.13***/-0.28	2.25***/1.59***	-6.38***/-1.86***
1 to 20	-13.23***/0.12	8.05***/8.39***	-21.28***/-8.27***
Panel B: $CAR0_i$ Measure			
Days relative to event	**Cumulative returns following initial price changes for high/low Volatility stocks, %**		
	$\lvert CAR0_i\rvert \geq 10\%$, Large Stock Price Increases		
	$HI \geq 0.7$	**$LO \geq 0.7$**	**Difference**
	(1,087/1,091)	**(734/743)**	
1	1.15***/0.69***	1.17***/0.37	-0.02/0.32
2	0.75/0.46	2.43***/0.03	-1.69**/0.43
1 to 5	-0.31/0.13	2.88***/-0.4	-3.2***/0.52
1 to 20	-7.39***/-0.6	2.07*/-0.16	-9.45***/-0.44
Days relative to event	**Cumulative returns following initial price changes for high/low Volatility stocks, %**		
	$\lvert CAR0_i\rvert \geq 10\%$, Large Stock Price decreases		
	$HI \geq 0.7$	**$LO \geq 0.7$**	**Difference**
	(419/423)	**(236/237)**	
1	-1.56***/-0.28	-0.32/-0.59	-1.25**/0.31
2	-3.33***/-0.83**	0.6/-0.38	-3.93***/-0.45
1 to 5	-5.18***/-1.04**	4.67***/0.74	-9.85***/-1.78**
1 to 20	-14.7***/0.21	9.51***/5.74***	-24.21***/-5.54***

Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

5.3. Results of the Multiple Regression Analysis

In the current analysis, we investigate the determinants influencing stock return volatility subsequent to the event date. The post-event stock price return is designated as the dependent variable, while the HI index, LO index, and an index indicative of private information accrued by investors are employed as independent variables. A multifactor regression analysis is conducted, incorporating a contradiction factor (CF) alongside various control variables. This multifactor regression analysis is executed in alignment with the methodology established by Brady and Premti (2019). The regression model formulated to quantify the drift effect on stock prices is articulated as follows.

$$CAR_{it} = \beta_0 + \beta_1 HI_{it} + \beta_2 LO_{it} + \beta_3 CF_{it} + Controls + \epsilon_{it} \quad (4)$$

In the aforementioned Equation (4), the cumulative return rate over the 3-day, 5-day, and 20-day intervals subsequent to the event date is posited as the dependent variable. Within this framework, the HI index quantifies the proximity of the stock price to its annual zenith, while the LO index gauges its closeness to the annual nadir. Furthermore, the CF variable is introduced as a binary indicator, assuming a value of 1 in instances where the aggregate return rate for the 5-day period antecedent to a significant positive stock price perturbation is negative, and 0 when it is positive. Conversely, this indicator adopts a value of 1 when the cumulative return preceding a major negative stock price disturbance is positive, and 0 if otherwise.

Should the CF variable be assigned a value of 1, it implies a heightened emphasis on proprietary information by investors, relative to extensive stock price fluctuations, culminating in a subdued response to the event date. A positive coefficient for the CF variable indicates that the investors' private insights are contrarian to the stock price movement on the event date. Consequently, this enhances the model's ability to account for the post-event stock price drift, attributable to an underreaction to the event date information. Conversely, a negative coefficient suggests that the investors' private information aligns with the direction of the stock price movement on the event date, thereby augmenting the model's explanatory capacity for the post-event stock price reversal, stemming from an overreaction to the event date information.

In Equation (4), we delineate several control variables that are posited to influence stock returns. These include $RET0$, which represents the stock return on the event date, serving as an event-centric determinant. The variable LN_MKTVAL denotes the natural logarithm of the firm's market capitalization, acting as a firm-specific moderator that accounts for the effects of company size on stock returns. $MOMENTUM$ is introduced as a variable to adjust for the impact of prior returns on current stock performance. Lastly, $VKOSPI$ is the volatility index of the stock market, incorporated as a measure to calibrate the impact of market volatility on stock returns.

The variable $TOBINQ$ is utilized to adjust for the influence of a firm's investment opportunities on stock returns. LN_VOL, representing the natural logarithm of trading volume, serves to moderate the impact of market liquidity on stock returns. The $BETA$ is employed as a measure of market risk's effect on stock returns. $JANUARY$ is a binary variable that accounts for the January effect, assuming a value of 1 in January and 0 in all other months. $MONDAY$ is a variable introduced to control for the Monday effect. Given that the 5-day and 20-day cumulative returns invariably encompass Monday, it is applied exclusively as a binary variable for the 3-day cumulative return.

Upon examination of the analytical outcomes delineated in Table 6, it is observed that among the control variables, $RET0$ serves as an event-centric determinant. LN_MKTVAL is indicative of a firm-specific characteristic, while $VKOSPI$ quantifies market volatility. $TOBINQ$ is reflective of investment opportunities, and LN_VOL assesses the liquidity effect. Additionally, variables such as $BETA$, which measures market risk, and $JANUARY$, accounting for the January effect, have been identified as significant contributors to the variance in stock price returns for firms within the Korean distribution sector subsequent to major stock price shock events.

Table 6 delineates the analytical results pertaining to the CSR0 metric, constrained by spatial limitations, with analogous outcomes observed for the remaining metrics. The aggregate sample size mirrors that of Panel A in Table 1, totaling 10,711 instances, comprising 7,330 increments and 3,381 decrements.

In Table 6, we analyze cases where large-scale positive stock price shocks occurred in Panel A. The coefficient estimates for LO, the 52-week lowest price index, shows insignificant values in the 3-day and 5-day windows after the event date. However, it exhibits a significant positive value in the 20-day window, indicating that the stock price drift effect dominates during this period. Additionally, the coefficient estimates for the HI index demonstrate significant negative values in the 3-day and 5-day windows, suggesting that the stock price reversal effect prevails in this scenario.

The coefficient estimate for CF shows low significance across all windows. This implies that when a large-scale positive stock price shock occurs, the underreaction resulting from investors' anchoring and the overreaction due to investors' optimism/pessimism bias offset each other. Consequently, investors' expectations are not concentrated in a single direction.

Turning our attention to Panel B of Table 6, we observe that when a large-scale negative stock price shock occurs, the coefficient estimate for LO (the 52-week lowest price index) exhibits a significant positive value in both the 5-day and 20-day windows following the event date. This suggests that the stock price reversal effect dominates due to investors overreacting to information, particularly when the stock price experiences a significant shock near its 52-week low. In contrast, the coefficient estimates for the HI index remain insignificant across all windows. This implies that the drift effect of stock prices resulting from investors' heuristic anchoring around the 52-week high is counterbalanced by the stock price reversal effect driven by pessimism bias, resulting in no overall significant effect. Furthermore, the coefficient estimate for CF shows a significant negative value across all windows, indicating strong pessimism bias among investors, leading to overreactions to declining stock prices and reinforcing the dominance of the stock price reversal effect.

In the case of LN_MKTVAL, which refers to company size, the price increase shock in Panel A exhibits a significant negative coefficient estimate across all windows. Interpreting this within the analytical framework of this paper, we can infer that the effect of optimism bias among large-cap stocks near the 52-week high is stronger than the effect of anchoring bias among small-cap stocks near the 52-week low on stock prices. Additionally, the price drop shock in Panel B appears highly significant for the 5-day and 20-day windows. This suggests that the anchoring bias of small-cap stocks near the 52-week high influences the stock price of large-cap stocks near the 52-week low. Notably, the optimism bias has a more pronounced effect than the impact on stock prices.

Furthermore, the coefficient estimates for the $VKOSPI$ variable, utilized as a proxy for availability estimation, exhibits significant negative values across all windows in Panel A (where a positive stock price shock occurred). Conversely, in Panel B (where a negative stock price shock occurred), the 5-day and 20-day windows show a significant positive value. This observation confirms that the $VKOSPI$ variable contributes explanatory power to the stock price reversal effect associated with the availability heuristic.

Furthermore, in the case of $TOBINQ$, which is related to corporate investment, it holds significance within the analytical framework of this paper, particularly concerning stocks located near the 52-week high price. In Panel A, these stocks exhibit a significant price reversal effect due to optimism bias in response to stock price rise shocks. Conversely, Panel B confirms that when a stock price shock occurs for these stocks, the anchoring effect of investors on the 52-week high price predominantly prevails, resulting in a stock price drift effect.

Similar to $TOBINQ$, the variable LN_VOL, which indicates liquidity, holds significance near the 52-week high price. When stock prices rise, abundant liquidity induces investors' optimism bias, resulting in a stock price reversal effect following positive stock price shocks. This inference is supported by the significant negative coefficient estimates of LN_VOL in Panel A. However, in contrast, Panel B—where a negative price shock occurred—reveals that the anchoring effect of investors on the 52-week high price predominantly influences stock prices, leading to a stock price drift effect. These findings align with the fundamental analysis explored in this paper.

Table 6: Multifactor Regression Analysis of CSR0 Following Large Stock Price Movements: Abnormal Returns for Various Time Windows

Panel A:Large stock price increases			
Explanatory variables	**Coefficient estimates, %(2-tailed p-values)**		
	|SR0i|>10% (7,330 events)		
	CAR3	**CAR5**	**CAR20**
constant	11.12***(0.0%)	14.96***(0.0%)	16.91***(0.0%)
52_WK_HI	-2.53***(0.13%)	-3.2***(0.12%)	-1.83(24.75%)
52_WK_LO	-0.62(46.26%)	-0.83(43.29%)	13.77*** (0.0%)
CF	-0.43(21.83%)	-0.56(20.68%)	-1.36*(5.51%)
RET0	0.16***(0.01%)	0.13***(0.76%)	0.07(37.72%)
LN_MKTVAL	-0.55***(0.01%)	-0.64***(0.02%)	-1.52***(0.0%)
MOMENTUM	-0.0(16.32%)	0.01(13.85%)	0.01(14.9%)
VKOSPI	-0.07***(0.99%)	-0.09***(0.58%)	-0.16***(0.2%)
TOBINQ	-0.01*(8.58%)	-0.17**(2.62%)	-0.33*** (0.63%)
LN_VOL	-0.37***(0.0%)	-0.61***(0.0%)	-0.92***(0.0%)
BETA	-1.03(94.59%)	-0.38(54.87%)	2.83*** (0.39%)
JANUARY	0.74(24.53%)	2.18*** (0.81%)	10.59*** (0.0%)
MONDAY	0.85**(1.21%)		
Panel B:Large stock price decreases			
Explanatory variables	**Coefficient estimates, %(2-tailed p-values)**		
	|SR0i|>10% (7,247 events)		
	CAR1	**CAR5**	**CAR20**
constant	3.13(15.18%)	1.1(68.31%)	-1.97(67.1%)
52_WK_HI	0.73(44.22%)	-0.7(54.89%)	-3.08(12.6%)
52_WK_LO	0.85(38.12%)	4.72*** (0.01%)	25.29*** (0.0%)
CF	-1.28***(0.18%)	-2.45***(0.0%)	-1.55*(7.35%)
RET0	0.25***(0.01%)	0.06(48.08%)	-0.18(18.71%)
LN_MKTVAL	-0.24*(9.59%)	-0.36**(4.31%)	-1.59*** (0.0%)
MOMENTUM	0.0(26.32%)	0.01**(2.89%)	0.04*** (0.0%)
VKOSPI	0.12***(0.0%)	0.09***(0.01%)	0.01(87.68%)
TOBINQ	-0.35***(0.01%)	-0.58***(0.0%)	-0.55***(0.3%)
LN_VOL	0.11(24.42%)	-0.0(97.13%)	-0.21(29.99%)
BETA	0.83(12.98%)	1.45**(3.17%)	3.25*** (0.52%)
JANUARY	-0.61(45.44%)	0.58(57.62%)	2.16(22.39%)
MONDAY	-1.72***(0.0%)		

Robust standard errors in parentheses ***p<0.01, **p<0.05, * p<0.1

6. Conclusions

This study conducted an event analysis similar to Lee et al.'s (2023) examination of large-scale stock price shocks. The sample was divided into cases occurring at the 52-week high and 52-week low. The study utilized the HI and LO indices as primary explanatory variables in multifactor regression analysis, following the approach of Brady and Premti (2019). Notably, our empirical analysis differs from Brady and Premti (2019) by employing a filtering method that focuses on cases where these index values exceeded 0.7.

This study extends Lee et al.'s (2023) work by analyzing large-scale stock price shocks based on company size and volatility groups. We uncover insights related to investor behavioral biases in the Korean distribution industry. Specifically, when stock prices exceed the 52-week reference point (based on average price), investors tend to overreact, leading to a subsequent price reversal effect. Conversely, when price shocks move toward convergence with the average price, investors exhibit underreaction due to anchoring heuristics, contributing to the stock price drift effect—where prices continue to converge toward the central value post-event.

In our study, we found that investor biases—whether optimistic or pessimistic—are influenced by company size and the location of stock price volatility shocks. These biases play a crucial role in stock price reversal effects and are connected to the anchoring heuristic. By systematically analyzing these insights, our research provides a comprehensive framework for understanding stock price behavior following significant market shocks in the Korean distribution industry. This represents a significant advancement beyond Lee et al.'s (2023) work. Further examination based on the location of price shocks allows us to organize these findings effectively.

In the context of stock market dynamics, when a stock price experiences a shock that surpasses the 52-week high, investors—particularly those in large-cap stocks—tend to react excessively optimistically to news of rising stock prices. However, this initial optimism is often followed by a sharp decline in stock prices after the incident. Notably, this stock price reversal effect is more pronounced for large-cap stocks compared to small-cap stocks. Interestingly, when a positive stock price shock occurs near the 52-week high, small-cap stocks do not exhibit the same reversal effect. Consequently, this study concludes that large-cap investors exhibit a relatively more optimistic bias around the 52-week high price.

Large-cap investors exhibit a pronounced optimism bias around the 52-week high, which in turn influences their anchoring heuristic behavior. When stock prices decline significantly near the 52-week high, these investors tend to react more passively to the information compared to small-cap investors due to their inherent optimism. Consequently, the drift effect on large-cap stock prices after such incidents is significantly greater than that observed for small-cap stocks. The drift effect near the 52-week high for small-cap stocks is comparatively smaller and lacks statistical significance.

In contrast, when a stock price shock occurs in the form of a downward deviation around the 52-week low, small-cap investors exhibit an excessive sensitivity to information on stock price declines compared to large-cap investors. Consequently, small-cap stock prices decline after such incidents. Interestingly, the reversal effect—where stock prices rise at a greater rate than those of large stocks—was observed in the small-cap group. Based on this phenomenon, this paper concludes that small-cap investors tend to harbor a relatively more pessimistic bias than their large-cap counterparts near the 52-week low.

Furthermore, the relatively stronger pessimism bias among small-cap investors near the 52-week low influences their anchoring heuristic behavior differently compared to that of large-cap stocks. When stock prices rise rapidly near the 52-week low, small-cap investors tend to react more passively to information about stock price increases than large-cap investors due to their entrenched pessimistic bias. Consequently, the drift effect on small-cap stock prices after the incident date appears relatively larger than that observed for large-cap stocks. Notably, even in the case of large-cap stocks near the 52-week low, a significant stock price drift effect exists, albeit with a smaller magnitude than that of small-cap stocks.

This study also investigated whether the magnitude of the drift effect varied based on the volatility group. Notably, high-volatility stock investors exhibit an optimistic bias around the 52-week high price. Consequently, when a robust positive stock price shock occurs in this vicinity, a pronounced stock price reversal effect is observed after the event date. Furthermore, the optimism bias among high-volatility stock investors regarding the 52-week high price influences the anchoring behavior associated with this reference point. As a result, a substantial drift effect on stock prices persists after the event date, particularly when a strong negative stock price shock occurs around this reference point.

Furthermore, high-volatility stock investors exhibit a pessimistic bias near the 52-week low. Consequently, when a strong negative stock price shock occurs in this range, a robust positive stock price reversal effect is observed after the event date. Additionally, the pessimistic bias of high-volatility stock investors around the 52-week low influences their anchoring behavior related to this reference point. If a strong positive stock price shock occurs around this point, a substantial drift effect on the stock price persists after the event date. This phenomenon has been empirically confirmed. Essentially, investors in high-volatility stocks, which carry inherent risk, exhibit stronger optimism/pessimism biases and related behavioral tendencies, such as anchoring heuristics. These behavioral biases can significantly impact stock prices.

Finally, this study conducted a multiple regression analysis, as previously done by Brady and Premti (2019), to examine whether the factors associated with optimism/pessimism bias and anchoring heuristics—discussed in this paper—systematically influenced the stock price reversal effect after the event date across the entire sample. The analysis aimed to verify whether these factors had a significant impact on the drift effect. The summarized test results focus on factors that exhibit relatively high significance in the coefficient estimates.

In our multiple regression analysis, we examined factors influencing stock price reversal and drift effects. Notably, during large-scale stock price rises, the HI index, LN_MKTVAL, $VKOSPI$, and $TOBINQ$ variables explain the reversal effect. Conversely, only $VKOSPI$ contributes to the reversal effect when stock prices fall. For drift effects during stock price increases, the LO index, RET0, and BETA variables play significant roles. Additionally, LN_MKTVAL and $TOBINQ$ are influential during large stock price declines. However, consistent explanatory power across the entire sample remains elusive due to mixed effects. This underscores the importance of systematically observing investors' behavioral biases by segmenting the sample around the 52-week high and low points.

This study examines how the behavioral bias of distribution-related stock investors in Korea systematically impacts stock prices. Specifically, large-cap investors exhibit an optimistic bias around the 52-week high price, leading to a stock price reversal effect after positive shocks and a stock price drift effect after negative shocks. Conversely, small-cap investors display a pessimistic bias around the 52-week low price, resulting in a strong stock price reversal effect after negative shocks and a significant stock price drift effect following positive shocks. These findings provide valuable insights for investment practitioners, including fund managers, navigating the market.

While the method of subdividing the entire sample based on the 52-week high and low may seem straightforward, this paper reveals that investors' behavioral bias—specifically, optimism/pessimism bias—operates consistently around these reference points. This leads to a robust, systematic stock price reversal effect after positive shocks and a significant drift effect following negative shocks. The logical consistency of these biases and their impact on anchoring heuristics provides a foundation for stable profitability in the financial investment industry.

In this study, large-cap investors exhibit a relatively optimistic bias around the 52-week high, while small-cap investors display a relatively pessimistic bias near the 52-week low. However, this distinction represents just one example of company-specific factors influencing investors' optimism/pessimism bias. Future research should explore additional company-specific variables, such as credit rating, financial soundness, management stability, and strategic diversification, to better understand these biases. A detailed investigation into these factors remains a valuable avenue for future research.

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