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An Empirical Inquiry into Psychological Heuristics in the Context of the Korean Distribution Industry within the Stock Market*

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Abstract

Purpose: This paper aims to assess psychological heuristics' effectiveness on cumulative returns after significant stock price changes. Specifically, it compares availability and anchoring heuristics' empirical validity due to conflicting stock return predictions. **Research Design, Data, and Methodology:** This paper analyzes stock price changes of Korean distribution industry stocks in the KOSPI market from January 2004 to July 2022, where daily fluctuations exceed 10%. It evaluates availability heuristics using daily KOSPI index changes and tests anchoring heuristics using 52-week high and low stock prices as reference points. **Results:** As a result of the empirical analysis, stock price reversals did not consistently appear alongside changes in the daily KOSPI index. By contrast, stock price drifts consistently appeared around the 52-week highest stock price and 52-week lowest stock price. The result of the multiple regression analysis which controlled for both company-specific and event-specific variables supported the anchoring heuristics. **Conclusions:** For stocks related to the Korean distribution industry in the KOSPI market, the anchoring heuristics theory provides a consistent explanation for stock returns after large-scale stock price fluctuations that initially appear to be random movements.

Keywords: Availability Heuristics, Anchoring Heuristics, Drifts, Large-Price Change, Korean Distribution Industry.

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

1. Introduction

In recent years, there have been multiple academic studies investigating stock returns after large-scale stock price fluctuation events (e.g., Amini et al., 2013; Savor, 2012; Baker et al., 2012; Tsao et al., 2017). These studies are also directly related to broader discussions on stock price predictability and market efficiency. In academia, the overreaction hypothesis and the underreaction hypothesis approach to stock returns after a stock price shock are in conflict with each other (e.g., Pritamani & Singal, 2001). Empirical studies analyzing short-term returns after a price shock have not reached a consensus on a broad framework and have obtained conflicting results (e.g., Amini et al., 2013).

A representative example of a behavioral economics theory that supports the hypothesis about investor

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overreaction is the availability heuristics theory (e.g., Kudryavtsev, 2018). According to the overreaction hypothesis, an overreaction occurs during a price shock, and since the stock price has deviated greatly from the intrinsic value, a stock price reversal phenomenon wherein the price returns to the intrinsic value will occur after the event date. Meanwhile, a representative example of a behavioral economics theory that theoretically supports the hypothesis about investor underreaction is the anchoring heuristics theory (e.g., Brady & Premti, 2019). According to the underreaction hypothesis, underreaction occurs during a price shock and stock prices fall short of intrinsic value, so a residual effect in the stock prices that continues to approach the intrinsic value can be seen after the event date. These two theories provide conflicting predictions about stock returns following large-scale stock fluctuations.

The present work examines these two theories in empirically verifiable forms. It also aims to determine what theory provides a more consistent and effective explanation for the stock return of stocks related to the distribution industry in Korea. The primary motivation for this study is to examine which theory, among the two representative approaches in behavioral economics that are currently at odds in academia, provides a more consistent explanation for the reality of stock prices in Korea's distribution industry. The secondary aim of this study is to help inform an investment strategy that provides stable excess returns that can beat the market based on empirical research results.

To test the availability heuristics theory, this paper refers to Kudryavtsev (2018). By studying events in which daily stock price changes of 10% or more occurred for individual stocks included in the US S&P500 index, the author of that study found that investors overreacted in a systematic and consistent manner to both rising and falling prices in the US market. Accordingly, he reported that a stock price reversal had occurred. He specifically used changes in the daily stock index representing investor moods to test the availability heuristics theory. When individual stock movements and stock index movements occur in the same direction, investor moods induce an overreaction to individual stock movements, thus amplifying individual stock movements. As a result, he showed that the yield reversal phenomenon was more pronounced in stock returns after the event date. In this work, while referring to the empirical study on the availability heuristics of Kudryavtsev (2018), an event study was conducted on large-scale price changes of 10% or more per day for individual stocks related to the distribution industry traded in the KOSPI market. By examining the stock price change after the event, it could be seen that when the stock price rose significantly, a stock price drift phenomenon was found; however, when the stock price fell sharply, a stock price reversal phenomenon occurred in which the stock price rose again. As a result, consistency was not maintained in the stock price reversal after the event date.

Meanwhile, to empirically test the anchoring heuristics theory, the present work referred to Brady and Premti (2019). They conducted an event study examining daily stock price changes of more than 10% using US CSP data. They specifically looked at whether investors were anchoring at the 52-week highest price and 52-week lowest price. When the stock price increased, it was found that investors performed anchoring heuristics around the 52-week lowest price; this led to the appearance of significant drifts phenomena in the stock price after the event date. When the stock price fell, it was found that investors performed anchoring heuristics around the 52-week highest price, which led to the appearance of significant drifts phenomena in the stock price after the event date. These drifts phenomena are attributed to underreactions by investors on the event dates.

This study conducted an event study examining large-scale price changes of 10% or more per day for individual stocks related to the distribution industry traded in the domestic KOSPI market while referencing to the empirical study on anchoring heuristics conducted by Brady and Premti (2019). Examining the change in stock return after the event date confirmed that when the price rose, the stock price drift phenomenon by anchoring heuristics appeared significantly around the 52-week lowest price. Further, when the price fell, it was confirmed that the stock price drift phenomenon by anchoring heuristics was significant near the 52-week highest price.

The structure of the rest of this paper is as follows. Section 2 reviews the existing research literature on availability heuristics and anchoring heuristics. Section 3 defines the research hypothesis of this study. Section 4 presents the data and research methodology. Section 5 presents the results of the empirical analysis. Finally, Section 6 summarizes the results and presents a brief discussion.

2. Literature Review

The phenomenon wherein predictable factors can be seen in stock prices after a large-scale stock price change event leads to questioning of the efficient market hypothesis, and it is also generating a lively debate within financial theory to explain it. Excluding studies that still support the efficient market hypothesis, behavioral economics is the mainstream theory to explain anomalies that appear after large-scale stock price changes. These behavioral economics theories can largely be divided into the overreaction hypothesis and the underreaction hypothesis. However, the roots of these hypotheses of overreaction and underreaction can be found in the classic behavioral economics discussion of Tversky and Kahneman (1973, 1974). Their discussions can be summarized based on the difference in the way investors determine subjective weights for estimating future state probabilities by the principle of behavioral heuristics in decision-making under uncertainty.

First, let us consider the position in which the overreaction of investors on the day of the event has a reversal effect on the stock price after the event date. This position comes from the availability heuristics hypothesis of Tversky and Kahneman (1973). According to their hypothesis, availability heuristics are subjective tendencies that determine the probability that an event will occur in the future. The subjective probability is determined according to the following principles: In determining the probability that an event will occur, people determine the likelihood or probability of an event occurring in the future according to the ease with which they can recall a similar situation in their minds. This is called availability heuristics. DeBondt and Thaler (1985) is a classic case that supports the stock price reversal effect based on this hypothesis. There are many other studies, such as Bremer et al. (1991) and Zarowin (1989), in which the stock price reversal effect appears after the event date as a result of investor overreaction due to availability heuristics. Further, in Angelovska (2016), it was shown that irrational overreaction among uninformed investors is the driving force behind large stock returns.

In another study, Lee et al. (2007) pointed out that, when predicting long-term earning growth, analysts tend to be relatively optimistic when the economy is booming whereas they tend to be relatively pessimistic when the economy is in recession. This can also be seen as a kind of overreaction. Moreover, Wright and Bower (1992) found that mood affects people's judgments related to uncertainty about future events. When the investment mood and the direction of price change coincide, it can be seen that an overreaction appears on the event date. In this paper, we refer to their discussion and borrow from Kudryavtsev's (2018) research to test the hypothesis that daily stock index changes affect investor decision-making. In this paper, the availability heuristics theory is constructed in a form in which it can be empirically analyzed using daily stock index changes.

Next, the position at which price drift effects appear after the event date according to the underreaction of the event date starts from the anchoring heuristics hypothesis of Tversky and Kahneman (1974). Anchoring heuristics refers to the propensity of people to give excessive weight to information or objects that decision-makers have paid prior attention to when making decisions under uncertainty. Investors who have performed anchoring heuristics give too low a weight to the intrinsic or true value of stock prices, and they therefore passively accept the possibility of changes in intrinsic value brought about by price shocks. This under-response hypothesis implies that people underreact to stock price shocks, and stock price adjustments with intrinsic value are not sufficiently adjusted on the event date, so stock price adjustments continue toward an intrinsic value even after the event date. A representative example of an empirical study on stock price drift effects is Masouz et al. (2009). They applied various parametric models to test the significance of abnormal returns after large-scale price changes and presented empirical evidence that price drift effects exist. In another study, Ball and Brown (1968) provided empirical evidence showing that investors tend to passively underreact to the shock of earnings announcements so that excess returns continuously occur in the same direction as stock returns on the event date for a certain period of time thereafter. Further, in a study mainly using stock index returns, Lasfer et al. (2003) showed that the residual effect of stock prices continued to appear.

In this paper, we use the 52-week lowest stock price and the 52-week highest stock price as reference points for anchoring and verify the effect of anchoring heuristics on stock returns after a large-scale stock price change event. Examples of such studies include Baker et al. (2012) and Sturm (2008). They report that anchoring the 52-week highest and 52-week lowest stock price is a subject of psychological consideration in the investment decision-making process. Moreover, Larson and Madura (2003) used CAR(-5, -1) as a proxy variable for private information. In the present work, we use CAR(-5,-1) as a proxy variable for investors' private information in multiple regression analysis. As described above, this study references Brady and Premti (2019) to test the anchoring heuristics theory.

3. Research Hypothesis

Availability heuristics theory and anchoring heuristics theory both predict the stock price trend after the event date based on the subjective probability of the future stock price that investors think of on the event date. The availability heuristics theory judges that investors place excessive weight on the direction in which the stock price moves when the movement of the investor's mood coincides with the movement of the stock price on the day of the event. Excessive weighting among investors of stock price changes causes stock price changes to appear as excessively amplified than appropriate levels. As a result, the availability heuristics theory predicts that a price reversal effect will be observed after the event date.

In this paper, to construct an empirical case for this availability heuristics theory, daily stock index fluctuations are set as a proxy variable for investor mood. When the stock index rises, the investor mood is positive, thus amplifying the rise in the stock price, and when the stock index falls, the investor mood is negative, thus amplifying the fall in the stock price. If the change in the stock index which determines the investor's mood on the event day and the change in individual stock prices move in the same direction, investors overreact to the direction of the stock price change. As a result, the availability heuristics theory predicts that, after the event date, the stock price reversal effect will be observed, in which the stock price moves in an opposite direction to the change in the stock price on the event day. To test whether this stock price reversal effect appears in a significant form in the Korean distribution industry-related stock market, the first research hypothesis is established as follows:

H1: If the large-scale price change on the event date is in the same direction as the change in the stock price index, investors will overreact, and as a result, the stock price reversal phenomenon will occur after the event date.

On the other hand, the anchoring heuristics theory holds that investors underweight the direction in which stock prices move on the event date. On the event day, investors have no choice but to assign relatively less weight to the direction in which the stock prices move on the event day, given that they have already assigned relatively large weight to the exogenously determined 52-week highest price and 52-week lowest price. In this way, investors' underweighting of stock price changes causes stock price changes to appear as they are reduced below an appropriate level. As a result, the anchoring heuristics theory predicts that residual effects will be observed on stock prices after the event date.

To empirically test the anchoring heuristics theory, this paper assumes that investors anchor at the 52-week highest price and 52-week lowest price prior to the event date. Investors are anchored at the 52-week lowest price when a large rally occurs near the 52-week lowest price. Therefore, investors place a low weight on the fact that the stock price will rise after breaking away from the 52-week lowest price, and they react passively to the rise in the stock price. Moreover, when a large stock price decline occurs near the 52-week highest price, investors are anchored at the 52-week high. Therefore, investors view the possibility of a stock price decline as low and accordingly react passively to a stock price decline. In this paper, we focus on the underreaction of investors on the event day due to these anchoring heuristics. We also examine whether the stock price drift effect, which moves in the same direction as the stock price on the event date, appears in a significant form after the event date in the stock market related to the distribution industry in Korea. The research hypothesis for this review is set as follows.

H2: If the stock price immediately before the event date of a large-scale price increase (decrease) occurred was near the 52-week lowest (highest) price, investors would underreact, thus resulting in a stock price drift effect after the event date.

4. Data Description and Research Design

For the sample of this paper, a total of 215 stocks traded in the KOSPI market were selected from stocks related to the distribution industry. The sample period is from January 2004 to July 2022. The sources of individual stock prices and market capitalization of individual stocks related to Korea's distribution industry were obtained from FnGuide. Log return was used to measure daily stock return in this paper, stock index returns were also measured in the same way. Using these data, empirical cases of the availability heuristics theory and the anchoring heuristics theory were constructed, and empirical tests were conducted.

This paper defines a large-scale stock price change event as an event in which the daily simple log stock return exceeds 10%. The threshold of 10% was judged to be large enough to reflect substantial changes in the fundamental value of stock prices or substantial changes in general investor sentiment. Above all, it was judged that a threshold of about 10% was necessary to secure a sufficient sample.

In this paper, for empirical testing of these theoretical models, daily stock price fluctuations were applied with an abnormal return in addition to a simple log return. In this paper, abnormal return is the market risk-adjusted abnormal return. To derive the abnormal rate of return, estimated regression coefficients $\hat{\alpha}$ and $\hat{\beta}$ were obtained from a regression equation in which the stock return for 250 trading days corresponding to one year prior to the event date was regressed to the market return for the same period. Specifically, the abnormal rate of return on the event date is estimated as expressed in Equation (1) below.

$$AR0_i = SR0_i - [\widehat{\alpha} + \hat{\beta} MR0_i] \tag{1}$$

In this way, the cumulative rate of return after the event date is estimated by applying the method of estimating the abnormal rate of return on the date of the event. The cumulative rate of return after the event date defined in this way is calculated by accumulating the daily abnormal rate of return according to the size of the window, which is the period to be considered, such as 5 days or 20 days.

As the first principle of sampling large-scale stock price changes in this paper, it is necessary to have data for 250 trading days prior to the event date to calculate the abnormal rate of return. The second principle of sampling is that a window of 20 days after the event date must be secured to test the predictability of returns.

Table 1: Descriptive Statistics for Stock returns on the Event Date

Proxy/Threshold	Number of large price moves	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 : $\mid \boldsymbol{SR0_i} \mid > \mathbf{10}\%$	10,600								
Price increases	7,247	3,800	11,600	3.81	1.29	**0.72**	**0.23**	0.62	0.22
Price decreases	3,353	4,300	15,900	3.94	1.33	**0.66**	**0.24**	0.64	0.26
Proxy B: $\mid \boldsymbol{AR0_i} \mid > \mathbf{10}\%$	8,952								
Price increases	6,496	3,200	10,100	3.83	1.31	**0.72**	**0.22**	0.60	0.22
Price decreases	2,456	3,700	12,100	4.16	1.37	**0.71**	**0.23**	0.56	0.26

The third principle of sampling was to select stocks whose daily price change did not exceed 50% of the highest and lowest prices. This was done to exclude stocks with excessive volatility. The number of samples for each proxy variable constructed according to these sampling principles and the basic statistics for each proxy variable are presented in Table 1 below.

Further, following the method of Brady and Premti (2019), the 52-week highest price and 52-week lowest price were defined as follows to test the anchoring heuristics hypothesis of this paper.

$$HI = \frac{Closing\ price\ the\ day\ before\ the\ event\ date}{52{-}week\ highest\ price} \tag{2}$$

$$LO = \frac{52{-}week\ lowest\ price}{Closing\ price\ the\ day\ before\ the\ event\ date} \tag{3}$$

For reference, the maximum value of the scale in equation (2) representing the HI variable representing the 52-week high is 1. If this variable is 1, the closing price of the trading day before the event date is the 52-week highest price. An HI variable close to 1 indicates that the stock price is close to its 52-week high. Conversely, when this variable is close to 0, it indicates that the stock price is close to 0.

Moreover, the maximum value of the scale of Equation (3) representing the LOvariable is 1. Similarly, when this variable is 1, it indicates that the closing price of the trading day before the event date is the 52-week lowest price. When the LOvariable is close to 1, it indicates that the stock price is close to its 52-week lowest price, and when this variable is close to 0, it indicates that the stock price is in a very high state.

This paper also considers the Contradiction variable in multiple regression analysis according to the method of Brady and Premti (2019). This variable represents a dummy variable of cumulative returns for the 5 days prior to the event date. In other words, when the price rises (falls), CAR(-5, -1) becomes 1 if it is negative (positive), otherwise it becomes 0. This variable represents the personal information of the investor. For example, if the stock price continuously approaches the 52-week highest price before suddenly turnings to a downtrend, the Contradiction variable will have a value of 1. If the Contradiction variable has a value of 1, investors can understand that an underreaction will appear because they will place a low weight on the situational change due to the rapid stock price change on the event date and plate a high weight on the personal information they have. As a result, the Contradiction variable will also make a certain contribution to the stock price drift effect that occurs after the event date.

5. Results and Discussion

5.1. Ex Post Stock Returns: Total Sample

First, it is necessary to analyze whether the stock price reversal effect or the stock price drift effect prevails after a significant price change event. This requires examining the cumulative rate of return for the entire sample after the event date. Table 2 below presents the cumulative rate of return for the entire sample after the event date of the large-scale price change. In the table, the variable $SR0_i$ represents a simple log return measure, while the variable $AR0_i$ represents an abnormal return measure. Based on the simple rate of return, there were 7,247 cases where the stock price increased by 10% or more, and 3,353 cases where it decreased by 10% or more. In addition, based on the abnormal return measure, there were 6,496 cases where the stock price increased by 10% or more, and 2,456 cases where it decreased by 10% or more.

Furthermore, Table 2 delineates four distinct observation windows for analyzing cumulative returns subsequent to the event date: a 1-day window, a 2-day window, a 1 to 5-day window, and a 1 to 20-day window. The cumulative rate of return within these specified intervals was assessed using the abnormal return metric. Notably, across the entire sample, a notable increase in stock price results in a corresponding rise in the cumulative rate of return for both the simple return measure and the abnormal return measure for up to 5 days after the event date. However, upon considering the 20-day interval following the event date, an intriguing observation emerges, as the cumulative rate of return exhibits a negative value. Although preliminary, this peculiar trend may be construed as indicative of a reversal effect.

Moreover, when confronted with a substantial decline in stock price, a discernible pattern emerges. Employing the simple return measure, it becomes apparent that the stock price experiences a drop on the initial day following the event; however, a subsequent recovery takes place from the second day onwards. Conversely, under the abnormal return measure, a negative cumulative rate of return persists until the 20th day following the event. This intriguing observation presents an opportunity for interpretation, suggesting the presence of a stock price drift effect.

Consequently, the stock price reversal effect does not exist a uniform pattern across the complete spectrum of stocks affiliated with the distribution industry in Korea. This finding stands in contrast to the research by Kudryavtsev (2018) which explores US market data and demonstrates that investors tend to overreact based on availability heuristics when market index fluctuations align with those of the stock price. However, in the context of Korea, the stock price reversal phenomenon lacks consistency across the entire sample of stocks. It is evident that certain stock prices also exhibit a drift phenomenon, leading to an absence of uniformity. This discrepancy in the empirical analysis underscores the necessity for not only the empirical examination of the availability heuristics theory but also the empirical exploration of the anchoring heuristics theory. By delving into both heuristic frameworks, a more comprehensive understanding of the observed differences can be attained.

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

Panel A: Large stock price increases		
Days relative to event	Average AR following initial price changes, % (2-tailed p values)	
	|SR0i|>10%	|AR0i|>10%
	(7,247 events)	(6,496 events)
1	0.91***	0.88***
	(0.0001)	(0.0001)
2	0.03	-0.04
	(0.7355)	(0.6722)
1 to 5	0.64***	0.36
	(0.0028)	(0.1181)
1 to 20	-1.35***	-1.84***
	(0.0001)	(0.0001)

Panel B: Large stock price decreases		
Days relative to event	Average AR following initial price changes, % (2-tailed p values)	
	|SR0i|>10%	|AR0i|>10%
	(3,353 events)	(2,456 events)
1	-0.72***	-0.72***
	(0.0001)	(0.0001)
2	0.07	-0.07
	(0.4954)	(0.5632)
1 to 5	0.39	-0.4
	(0.1173)	(0.2004)
1 to 20	1.00**	-1.79***
	(0.0240)	(0.0019)

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

5.2. Validation of the Availability Heuristics Theory: Using Changes in Market Indices

This paper adopts the approach proposed by Kudryavtsev (2018) wherein the change in the KOSPI200 index serves as the reference point for estimating availability, which, in turn, reflects the investment sentiment of investors. Specifically, if the stock index return on the event date exhibits a positive value, the investor mood on that particular day is considered positive. Conversely, if the stock index return on the event date shows a negative value, the investor mood is regarded as negative. This methodology enables the determination of investor sentiment based on the market’s performance during the event date.

Table 3 below illustrates the variations in the cumulative rate of return following the event date in relation to changes in investor mood. We begin by examining Panel A, which focuses on instances where the stock price experienced a significant increase. Within this category, there were 4,376 cases where both the stock price and the market index return rose concurrently. Additionally, there were 2,871 cases in which the market index yield decreased despite a considerable rise in the stock price.

When the stock price rises in conjunction with a corresponding increase in the market index yield, it is hypothesized that investors may exhibit overreactive behavior, leading to further escalation in the stock price fueled by their positive mood. The underlying rationale stems from the fact that investors when in a positive mood, tend to envisage favorable outcomes in the future. Consequently, they assign higher probability weights to potential stock price increases and engage in active trading, contributing to the upward surge in stock prices. In such instances, a significant portion of the stock price rise is attributed to the positive mood of investors, leading to an elevation of the stock price beyond its intrinsic value.

The anticipated outcome in this study was the manifestation of a reversal effect, represented by the disparity between the intrinsic value and the stock price on the event date. However, the empirical analysis yielded results that deviated from these expectations. As depicted in Table 3, when the stock price exhibits a considerable rise, the cumulative rate of return for the 5-day window following the event date was 1.24%, signifying a statistically significant positive value. And the cumulative rate of return for the 20-day window after the event date displayed a non-significant negative value of -0.51%. As a consequence of this empirical finding, the research hypothesis 1 formulated in this paper encounters challenges in its acceptance.

Conversely, in instances of a substantial decline in the stock price accompanied by a decrease in the market index, the total count of events amounts to 2,388. Within this context, investors encounter a negative investor mood prompted by the market index downturn. As a result, they attribute greater subjective probabilities or weights to potentially unfavorable outcomes in the future, leading to a heightened likelihood of stock prices falling below their intrinsic value.

In this scenario, a portion of the stock price decline can be attributed to the negative mood prevailing among investors. Consequently, one might expect the manifestation of a reversal effect, reflected in the difference between the intrinsic value of the stock and the stock price on the event date. The empirical analysis results are outlined in Table 3. As anticipated, the cumulative returns for both the 5-day window and the 20-day window following the event date amount to 0.91% and 2.23%, respectively, indicating statistically significant positive values.

In instances where the stock price experiences a sharp decline, the stock price reversal effect becomes evident. However, when the stock price rises, the magnitude of the reversal effect diminishes, leading to challenges in adopting research hypothesis 1 posited in this paper.

Table 3: Abnormal stock returns following large stock price Increases and decreases, by the sign of MR0: Proxy A for defining large price moves.

Panel A: Large stock price increases			
Days relative to event	Average AR following initial price changes, % (2-tailed p values)		
	|SR0|>10%		
	MR>0	MR<0	Difference
	(4,376 events)	(2,871 events)	
1	1.05***	0.7***	0.34*
	(0.0001)	(0.0001)	(0.0892)
2	0.03	0.02	0.01
	(0.7544)	(0.8758)	(0.9519)
1 to 5	1.24***	-0.29	1.53***
	(0.0001)	(0.4199)	(0.0006)
1 to 20	-0.51	-2.62***	2.11***
	(0.2276)	(0.0001)	(0.0031)

Panel B: Large stock price decreases			
Days relative to event	Average AR following initial price changes, % (2-tailed p values)		
	|SR0|>10%		
	MR>0	MR<0	Difference
	(965 events)	(2,388 events)	
1	-0.85***	-0.67***	-0.18
	(0.0004)	(0.0001)	(0.5210)
2	-0.31	0.23*	-0.53**
	(0.1273)	(0.0734)	(0.0248)
1 to 5	-0.9*	0.91***	-1.81***
	(0.0780)	(0.0011)	(0.0019)
1 to 20	-2.04**	2.23***	-4.27***
	(0.0440)	(0.0001)	(0.0001)

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

5.3. Validation of the Availability Heuristics Theory: Multiple Regression Analysis Results

This section entails a multi-factor regression analysis aimed at validating the stock price reversal effect after the event date, as postulated by the availability heuristics theory, within a broader framework application to Korea's distribution industry-related stocks. The examination encompasses both company-specific factors and the event-specific factors. Specifically, we investigate whether a substantial increase in the index return elicits a stock price reversal effect subsequent to the event day, in the event of a significant rise in the stock price. Additionally, we explore whether a sharp decline in the stock price corresponds to a reversal effect caused by a decline in the index after the event date. The regression analysis equation utilized to test the stock price reversal effect of market index changes is as follows:

$$CAR = \beta_0 + \beta_1 MR0_i + \beta_2 MCap_i + \beta_3 Mbeta_i \\ + \beta_4 SRVolat_i + \beta_5 |SR0|_i + \beta_6 ABVOL0_i + \epsilon_i \quad (4)$$

In Equation (4), the variable CAR denotes the cumulative rate of return, which is derived by aggregating the daily abnormal rate of return over the 1st, 5th, and 20th days following the event date. $MR0$ is a dummy variable representing the market index return on the event date, taking a positive value of 1 and a negative value of 0. furthermore, $MCap_i$ represents the natural logarithm of the market capitalization pertaining to the stock company associated with the i-th event.

Additionally, $Mbeta_i$ denotes the CAPM beta value of the stock corresponding to the i-th event. This value is obtained by cross-sectionally normalizing the beta value calculated over a one-year period preceding the event date, specifically, over 250 trading days. Similarly, $SRVolat_i$ represents the cross-sectionally normalized standard deviation of the stock price return of the i-th event, covering the 250 trading days preceding the event date. These variables, namely, $MCap_i$, $Mbeta_i$, and $SRVolat_i$ are considered company-specific factors.

Finally, the variable $|SR0|_i$ represents the absolute value of the stock price return associated with the i-th event, while $ABVOL0_i$ represents difference between the stock volume on the event day and the average volume over the previous 250 days, normalized by the standard deviation of the stock volume. These two variables are viewed as event-specific factors. By incorporating these diverse variables into the regression analysis, we aim to examine the validity of the stock price reversal effect concerning changes in the market index within the context of Korea's distribution industry-related stocks.

Table 4 below presents the findings of the multiple regression analysis, assessing the explanatory capacity of the market index dummy variable on the cumulative return subsequent to the event date while accounting for both company-specific and event-specific factors. In the case of a substantial rise in the stock price, we expect the estimated coefficient of $MR0$ to exhibit a negative value for both the 5-day and 20-day windows following the event date, in accordance with the predictions of the availability heuristics theory. However, contrary to these expectations, the corresponding results in the table indicate significant positive values rather than negative values. Consequently, these outcomes lead to the rejection of hypothesis 1 proposed in this paper, which pertains to the availability heuristics theory's theoretical prediction and empirical construction of the stock price reversal effect.

Moreover, in the event of a notable decline in the stock price, we anticipate the estimated coefficient of $MR0$ to demonstrate a significant positive value for both the 5-day and 20-day windows following the event date, aligning with the expectations set forth by the availability heuristics theory. However, the results present a contrasting picture, as the estimated coefficient displays a significant negative value for both scenarios. This observation leads to the rejection of hypothesis 1 in this paper, further challenging the validity of the availability heuristics theory's proposition regarding the stock price reversal effect.

Table 4: Multifactor regression analysis of ARs following large stock price increases and decreases: Dependent variable of stock AR for day 1, 1 to 5, 1 to 20 following the event.

Panel A: Large stock price increases			
Explanatory variables	Coefficient estimates, %(2-tailed p-values)		
	|SR0i|>10% (7,247 events)		
	CAR1	CAR5	CAR20
Constant	-0.79*	1.44	7.62***
	(0.0989)	(0.1720)	(0.0001)
MR0_dum	0.7***	2.19***	2.18***
	(0.0005)	(0.0001)	(0.0023)
MCap	-1.05*	-4.58***	-14.28***
	(0.0818)	(0.0006)	(0.0001)
Mbeta	-1.48***	-1.72*	3.83**
	(0.0015)	(0.0970)	(0.0218)
SRVolat	0.96**	-0.3	-10.92***
	(0.0381)	(0.7699)	(0.0001)
|SR0|	0.13***	0.03	-0.13
	(0.0001)	(0.5741)	(0.1053)
ABVOL0	-0.01	-0.03**	-0.07***
	(12.52)	(0.0473)	(0.0069)
Panel B: Large stock price decreases			
Explanatory variables	**Coefficient estimates, %(2-tailed p-values)**		
	|SR0i|>10% (3,353 events)		
	CAR1	**CAR5**	**CAR20**
Constant	2.92***	3.0**	7.48***
	(0.0001)	(0.0282)	(0.0019)
MR0_dum	-0.58**	-1.68***	-3.28***
	(0.0377)	(0.0030)	(0.0010)
MCap	-1.31*	-4.05***	-15.83***
	(0.0597)	(0.0041)	(0.0001)
Mbeta	0.29	4.16***	11.12***
	(0.6255)	(0.0005)	(0.0001)
SRVolat	-0.73	-6.33***	-21.31***
	(0.1964)	(0.0001)	(0.0001)
|SR0|	-0.21***	0.03	0.39***
	(0.0001)	(0.7194)	(0.0070)
ABVOL0	0.0	-0.0	-0.05
	(0.9748)	(0.9778)	(0.3151)

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

5.4. Validation of the Anchoring Heuristics Theory: Using 52-week Highest and Lowest Price

In this section, we undertake the empirical exploration of the anchoring heuristics theory. Specifically, we investigate the potential emergence of the stock price drift effect by analyzing instances where the HI variable defined in Equation (2) and the LO variable defined in Equation (3) attain values greater than 0.7.

According to the anchoring heuristics theory, when the stock price approaches the 52-week lowest price on the day preceding a substantial rise, there is a heightened likelihood of the stock price drift effect occurring after the event date. Conversely, if the stock price nears the 52-week highest price on the day immediately preceding a significant decline, there is a higher probability of the stock price drift effect taking place after the event date. Investors tend to assign significant importance to these anchored prices when formulating their future expectations. Consequently, when real-world outcomes contradict their initial judgments, investors exhibit a tendency to downplay the significance of these outcomes by assigning them a lower weight.

Upon Closer examination, when the stock price experiences a substantial increase while being in proximity to the 52-week lowest price, investors tend to accord significant weight to the notion that the stock price will eventually reach the 52-week lowest level. Consequently, they view the sharp rise in the stock price as a transient occurrence and consequently, respond passively to this increase by attributing it a lower weight. As a consequence, an underreaction occurs on the event date, and a drift effect materializes in the stock price, leading to continued upward movement beyond the event date.

On the contrary, in the event of a significant decline in the stock price, while it is in close proximity to the 52-week high, investors tend to assign considerable weight to the belief that the stock price will eventually revert to the 52-week highest level. This passive response stems from their tendency to underestimate the impact of a sharp drop in stock prices, considering it as a transitory event. Consequently, a drift effect ensues, wherein the stock price continues to decline even beyond the event date.

To substantiate this theoretical rationale, we restricted the HI and LO variables to instances where their values exceeded 0.7, effectively ensuring that the stock price was closely situated near the 52-week high or 52-week low. By adopting this approach, Table 5 provides compelling evidence that the stock price drift effect consistently exhibits a significant value, aligning precisely with the expectations laid out by the anchoring heuristics theory within this context.

Initially, when examining substantial increases in stock prices, we identified 2,383 instances where the stock price on the day preceding the event was in close proximity to the 52-week low, represented by $LO \geq 0.7$. Notably, within this subset, the cumulative returns displayed noteworthy values, with 1.87% and 3.04% recorded for the 5-day and 20-day windows following the event date, respectively. These figures underscore the significance of positive cumulative returns within the specified time frames.

Moreover, upon analyzing instances of significant declines in the stock price, it was observed that there were 1,593 cases where the stock price on the day before the event closely approached the 52-week high, indicated by $HI \geq 0.7$. Subsequently, the cumulative returns for these cases were found to be -1.62% and -5.51% in the 5th and 20th windows after the event date, respectively. These empirical findings lend support to research hypothesis 2 outlined in this paper. Therefore, based on the consistent results obtained from the empirical construction of anchoring heuristics, research hypothesis 2 is tentatively embraced in this section.

Conversely, in cases where the stock price experiences a substantial increase and the price on the day before the event date closely aligns with the 52-week high, the subsequent cumulative return after the event date demonstrates a negative value. Similarly, if the stock price undergoes a significant decline and the price on the day before the event date is near the 52-week low, the cumulative return after the event date shows a positive value. However, these scenarios can be interpreted as indicative of a simple mean reversion tendency in stock prices, rather than being attributed to stock price reversal effects resulting from behavioral economic overreactions following the adjustment of probability weights for future stock price directions. It is reasonable to assume that the intrinsic value of a stock price lies within the range defined by its 52-week high and 52-week low. Consequently, stocks that fall beyond this boundary exhibit excessive deviation from the mean, and it is reasonably predictable that they will revert to the mean. The empirical findings in Table 5 corroborate this understanding.

Table 5: Abnormal stock returns following large stock price increases and decreases, by the size of HI/LO: Proxy A for defining large price moves.

Panel A:Large stock price increases			
Days relative to event	Average AR following initial price changes, % (2-tailed p values)		
	|SR0|>10%		
	HI>0.7	LO<0.7	Difference
	(3,976 events)	(2,838 events)	
1	0.85***	0.97***	-0.12
	(0.0001)	(0.0001)	(0.5412)
2	-0.01	0.29**	-0.31*
	(0.9132)	(0.0119)	(0.0655)
1 to 5	0.07	1.87***	-1.8***
	(0.8070)	(0.0001)	(0.0001)
1 to 20	-3.09***	3.04***	-6.13***
	(0.0001)	(0.0001)	(0.0001)
Panel B:Large stock price decreases			
Days relative to event	Average AR following initial price changes, % (2-tailed p values)		
	|SR0|>10%		
	HI>0.7	LO<0.7	Difference
	(1,593 events)	(1,463 events)	
1	-0.74***	-0.75***	0.01
	(0.0001)	(0.0001)	(0.9666)
2	-0.23	0.23	-0.46**
	(0.1182)	(0.1335)	(0.0304)
1 to 5	-1.62***	2.72***	-4.34***
	(0.0001)	(0.0001)	(0.0001)
1 to 20	-5.51***	9.2***	-14.71***
	(0.0001)	(0.0001)	(0.0001)

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

5.5. Validation of the Anchoring Heuristics Theory: Multiple Regression Analysis Results

This section presents a comprehensive multi-factor regression analysis to assess the validity of the predictions made by the anchoring heuristics theory within Korea's distribution industry-related stocks, taking into account a broader framework. The primary objective of conducting this analysis is to examine whether the drift effect on stock prices, as predicted by anchoring heuristics, remains significant even after considering company-specific and event-specific factors.

When confronted with heightened uncertainty, such as a significant stock price shock, investors tend to engage in anchoring guesswork, wherein they assign greater weight to information derived from the 52-week highest and lowest prices. Consequently, this leads to an underreaction to sudden stock price shocks. The regression analysis equation used to evaluate investors' underreaction and stock price drifts, as predicted by anchoring heuristics, is as follows:

$$CAR = \beta_0 + \beta_1 HI_i + \beta_2 LO_i + \beta_3 CONTRADICTION_i + \beta_4 MCap_i + \beta_5 Mbeta_i + \beta_6 SRVolat_i + \beta_7 |SR0|_i + \beta_8 ABVOL0_i + \epsilon_i \quad (5)$$

In Equation (5), the cumulative abnormal return was set as the explanatory variable for the windows of 1, 5, and 20 days after the event date. In this equation, the variable HI was defined in Equation (2) above, and the variable LO was defined in Equation (3) above. The contradiction variable represents a dummy variable, that is when the price rises(falls), CAR(-5,-1) becomes 1 if it is negative(positive), otherwise it becomes 0 as explained above. The remaining variables are defined in the same way as in Equation (4).

Table 6 below presents the test results of the multiple regression analysis of equation (5). First, looking at Panel A, which is a collection of events in which large-scale stock price rises occurred, the estimated coefficients of LO show significant positive values of 2.86 and 14.34, respectively, in the 5-day and 20-day windows after the event date. This result means that even when both company-specific and event-specific factors are considered, the closer the stock price immediately before the event date is to the 52-week low, the higher the cumulative value of the abnormal return in the 5-day and 20-day windows after the event. This result supports the residual effect by the anchoring heuristics theory.

When the stock price rose significantly, the coefficient estimates of HI showed significant negative values after the event date. If the stock price on the day before the event date is near the 52-week high, it indicates that after the event day when the stock price rose significantly, downward pressure acts on the cumulative return on the 5^{th} and 20^{th} days. This phenomenon is judged as a mean reversion effect. When a stock price falls outside the 52-week low and 52-week high, it tends to revert to the mean.

Next, let's look at Panel B, which shows the cases of large-scale stock price declines. The estimated coefficients of HI were -6.23 and -17.56, respectively, in the 5-day and 20-day windows after the event, all showing significant negative values. This result means that, even when company-specific and event-specific factors are considered, the cumulative value of the abnormal returns in the 5-day and 20-day windows is negative as the stock price immediately before the event date is close to the 52-week high. As in the case of large stock price rises, this result strongly supports the stock price drift effect.

In the case of a significant drop in the stock price, the estimated coefficients of LO show significant positive values after the event date. As mentioned above, this phenomenon is judged as a mean reversion effect. In addition, the coefficient estimate of the Contradiction variable was found to be distorted and less significant in the 5-day and 20-day windows, respectively. The Contradiction variable is a variable representing the personal information of an investor. This result indicates that the effectiveness of investors' personal information is low in the case of stocks related to the Korean distribution industry.

In summary, it can be seen that the results of this multiple regression analysis support the second research hypothesis of this paper, which was set up for the empirical construction and testing of anchoring heuristics as a whole.

Table 6: Multifactor regression analysis of ARs following large stock price increases and decreases: Dependent variable of stock AR for day 1, 1 to 5, 1 to 20 following the event. and anchoring includes 52 week high and low

Panel A: Large stock price increases			
Explanatory variables	Coefficient estimates, %(2-tailed p-values)		
	|SR0i|>10% (7,247 events)		
	CAR1	CAR5	CAR20
constant	2.96***	4.71*	6.67*
	(0.0076)	(0.0545)	(0.0875)
52_WK_HI	-2.5***	-4.9***	-10.57***
	(0.0001)	(0.0005)	(0.0001)
52_WK_LO	-1.15*	2.86**	14.34***
	(0.0725)	(0.0427)	(0.0001)
CONTRADICTION	-0.69***	-0.49	-1.54**
	(0.0008)	(0.2774)	(0.0315)
MCap	-0.9	-3.27**	-10.42***
	(0.1415)	(0.0148)	(0.0001)
Mbeta	-1.46***	-2.33**	0.43
	(0.0002)	(0.0251)	(0.7948)
SR_volat	-0.37	-1.13	-9.13***
	(0.5631)	(0.4193)	(0.0001)
|SR0|	0.13***	0.04	-0.07
	(0.0001)	(0.3732)	(0.3961)
ABVOL0	-0.01	-0.03*	-0.06**

	(0.1127)	(0.0548)	(0.0142)
Panel B: Large stock price decreases			
Explanatory variables	**Coefficient estimates, %(2-tailed p-values)**		
	|SR0i|>10% (3,353 events)		
	CAR1	**CAR5**	**CAR20**
constant	3.25**	4.0	5.18
	(0.0213)	(0.1547)	(0.2748)
52_WK_HI	-0.35	-6.23***	-17.56***
	(0.6686)	(0.0001)	(0.0001)
52_WK_LO	-0.49	4.23***	21.56***
	(0.5165)	(0.0052)	(0.0001)
CONTRADICTION	0.54	2.24***	0.47
	(0.0352)	(0.0001)	(0.5845)
MCap	-1.34	-3.1**	-11.83***
	(0.0547)	(0.0255)	(0.0001)
Mbeta	0.46	1.87	2.5
	(0.4408)	(0.1146)	(0.2113)
SR_volat	-1.16	-5.84	-15.06
	(0.1249)	(0.0001)	(0.0001)
|SR0|	-0.22	-0.02	0.27
	(0.0001)	(0.7882)	(0.0490)
ABVOL0	-0.0	0.02	0.02
	(0.9589)	(0.4840)	(0.7204)

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

6. Conclusions

In the context of distribution industry-related stocks, a significant stock price shock represents an event that amplifies the exposure of investors to market uncertainty and associated risks. Within this heightened state of uncertainty, investor behavior can significantly influence stock prices following the occurrence of such events. This study aims to investigate whether the behaviors exhibited by investors, which impact stock prices after the event date, align more closely with the availability heuristics theory or the anchoring heuristics theory. By exploring and analyzing these two theories, we seek to gain deeper insights into the underlying mechanisms driving post-event stock price movements in this particular market context.

It is noteworthy that the two theories, when applied to stocks within the distribution industry, yield divergent predictions regarding stock price movements following a significant stock price change. The availability heuristics theory suggests a stock price reversal effect, where the stock price is expected to move in the opposite direction to that observed on the event day after the event date. On the contrary, the anchoring heuristics theory predicts a stock price drift effect, wherein the stock price is anticipated to move in the same direction as observed on the event day after the event date.

The fundamental objective of this paper is to empirically examine and compare the performance of these two prominent behavioral finance theories that offer contrasting forecasts for the same event. By Transforming these theories into a format amenable to empirical analysis, we aim to rigorously evaluate their validity and applicability within the context of the distribution industry's stock market dynamics. This comparative analysis seeks to shed light on the underlying mechanisms driving post-event stock price behaviors and contribute to a deeper understanding of the behavioral factors influencing stock price movements

This paper selectively gathers cases wherein daily returns of prominent stocks traded in the KOSPI market display fluctuations exceeding 10%, focusing on stocks related to the distribution industry. Moreover, an extensive examination of the stock price changes following the event date within the entire sample reveals a combination of both the stock price reversal effect and the stock price residual effect. However, in the absence of a suitable structure allowing empirical analysis, it becomes challenging to substantiate the assertions and hypotheses of the availability heuristics and anchoring heuristics theories.

Given these circumstances, this study adopts a pragmatic approach for the empirical construction of the availability heuristics theory, wherein investors' decision-making processes are assumed to be influenced by changes in the stock index. On the other hand, to formulate the anchoring heuristics theory in an empirical manner, it is posited that investors establish reference points at the 52-week low and the 52-week high and utilize this information when making decisions under conditions of heightened uncertainty. By adopting these assumptions, this paper aims to provide a practical framework to analyze and compare the behavioral aspects of investors in light of the availability heuristics theories and anchoring heuristics theories.

The test results are as follows: Firstly, concerning the validity of the availability heuristics theory, we examined whether a reversal effect manifested by segregating the cases based on whether the stock index rose or decreased on the event date. However, no reverse effect was observed. Furthermore, a comprehensive multiple regression analysis was conducted, taking into account company-specific factors, event-specific factors, and stock index dummy variables across the entire sample. The analysis revealed that the reversal effect id not demonstrate consistency beyond the event date. Consequently, the first research hypothesis, which sought to empirically test the validity of the availability heuristics theory, was refuted.

Moving on to assess the validity of the anchoring heuristics theory, we conducted a stringent control by setting the threshold for the 52-week low and 52-week high index at a level greater than 0.7. Subsequently, we examined the drift effect on stock prices after the event date. Remarkably, we observed a consistent and significant manifestation of the stock price drift effect following the event date.

Furthermore, through a comprehensive multiple regression analysis, taking into account company-specific factors and event-specific factors, we verified that the influence of the 52-week lowest and highest price index persisted in significantly impacting the drift effect of the stock price after the event date, maintaining consistency throughout our analysis.

These findings collectively support the anchoring heuristics theory and indicate a robust connection between investors' reliance on 52-week low and high price anchors and the subsequent behavior of stock prices following significant events.

This study has successfully established the presence of a robust and significant drift effect within the stocks associated with the distribution industry in Korea. The observed drift effect is attributed to investors' anchoring behavior and reliance on heuristics. As a result, these findings hold practical implications for the field of investment practice, suggesting the potential establishment of an investment strategy to leverage the identified drift effects in the distribution industry.

Looking ahead, further research is warranted to investigate the presence of drift effects in a broader context, encompassing not only the KOSPI market but also the KOSDAQ market. This expanded analysis will offer a more comprehensive understanding of drift phenomena within the distribution industry. Additionally, future studies should endeavor to explore the validity of the abnormal return generated by this investment strategy, while also considering the impact of transaction costs. Addressing these aspects will enhance the applicability and reliability of the proposed investment approach.

In conclusion, this paper has contributed valuable insights into the behavior of stock prices in the distribution industry and has laid the groundwork for potential investment strategies. By exploring the implications of anchoring heuristics and drift effects, investors and practitioners in the financial sector can make more informed decisions, and further research can build upon these findings for deeper analysis and refinement.

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