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The role of arbitrage risk in the MAX effect: evidence from the Korean stock market

Jihoon Goh
Pusan National University, Busan, South Korea, and
Donghoon Kim
College of Business, Korea Advanced Institute of Science and Technology, Seoul, South Korea

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Abstract

In this study, we investigate what drives the MAX effect in the South Korean stock market. We find that the MAX effect is significant only for overpriced stocks categorized by the composite mispricing index. Our results suggest that investors' demand for the lottery and the arbitrage risk effect of MAX may overlap and negate each other. Furthermore, MAX itself has independent information apart from idiosyncratic volatility (IVOL), which assures that the high positive correlation between IVOL and MAX does not directly cause our empirical findings. Finally, by analyzing the direct trading behavior of investors, our results suggest that investors' buying pressure for lottery-like stocks is concentrated among overpriced stocks.

Keywords Arbitrage risk, Lottery preference, MAX effect, Individual investor, Abnormal trading volume, South Korea

Paper type Research paper

1. Introduction

Classical asset pricing models presuppose that investors exhibit rational behavior and endeavor to construct portfolios that are both efficient and well-diversified. However, a body of research indicates a departure from rationality, highlighting the influence of investors' predilection for lottery-type securities. This departure from rationality is notably substantiated by theoretical underpinnings grounded in cumulative prospect theory, as expounded by Tversky and Kahneman (1992). The inclination toward lottery-type securities manifests as an overweighting of low-probability extreme events. Consequently, these securities tend to be overpriced, resulting in returns that deviate from the normal distribution and yield negative excess returns.

Studies on the stock market highlight investors' preference for lottery-type stocks, with an emphasis on the role of individual investors. Kumar (2009) and Boyer *et al.* (2010) assert that individual investors favor assets with a low likelihood but high potential for positive returns. Bali *et al.* (2011) measure a stock's extreme return as the maximum daily return (MAX) and identify the MAX effect, showing that stocks with higher MAX in the preceding month tend to yield lower returns, thereby influencing individual investors. Recent research further

JEL Classification — G11, G12

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emphasizes individual investors gravitating toward lottery-like stocks and diverging from institutional preferences (e.g. Lee *et al.*, 2010; Fong and Toh, 2014).

This study aims to explore additional evidence of the MAX effect within the South Korean stock market, a market distinguished by a substantial presence of retail investors, particularly those inclined toward lottery-like stocks. Retail investors play a significant role in the South Korean stock market, accounting for approximately 70–87% of the total trading volume, as emphasized by Chae and Yang (2008) and Kang *et al.* (2013). The prevalence of retail investors in the South Korean stock market renders it an opportune setting for investigating MAX as a proxy for attributes associated with lottery-like stocks, as highlighted in previous studies (e.g. Nartea *et al.*, 2014; Kang *et al.*, 2014; Kang and Sim, 2014; Cheon and Lee, 2018a, b; Byun *et al.*, 2023). Moreover, the distinctive South Korean financial database provides daily trading volumes for each market participant, categorized as individual, institutional, and foreign investors. This dataset provides a unique advantage in that it enables a more precise proxy for the direct trading behavior of market participants concerning lottery characteristics, thereby minimizing measurement errors in our analysis.

In our empirical investigation, we scrutinize the significance of the MAX effect in the South Korean stock market from 2000 to 2020. Furthermore, we explore the variability of the MAX effect across different levels of mispricing. Employing Stambaugh *et al.*'s (2015) methodology, we conduct a bivariate sort analysis, juxtaposing MAX and MIS (mispricing) through the utilization of a composite mispricing index derived from seven market anomalies. Unlike the findings of Zhong and Gray (2016) or Van Hai *et al.* (2020) [1], our results reveal negative returns and the Fama and French (1993) three-factor alphas for high–low MAX portfolios across all MIS quintiles, with statistical significance observed exclusively among overpriced stocks. The outcomes of our Fama and MacBeth (1973) cross-sectional regression analysis align with and complement the insights gleaned from the bivariate sort analysis.

We explain our results as proposing that influences of arbitrage risk and the MAX effect linked to lottery preference emerge as independent factors. This suggests that the presence of the arbitrage risk effect amplifies the adverse MAX effect for overpriced stocks. The effects of arbitrage risk and the MAX effect stemming from lottery preference should be considered as separate and discernible, allowing for potential alignment or counteraction. Specifically, for overpriced stocks, the arbitrage risk effect exacerbates the negative MAX effect arising from lottery preference. Conversely, for underpriced stocks, the arbitrage risk effect associated with lottery preference mitigates the negative MAX effect.

The additional analysis delves into investor trading behavior to elucidate a potential mechanism behind the significant MAX effect among overpriced stock groups. Drawing on the work of Kumar (2009), Cheon and Lee (2018a, b), and Byun *et al.* (2023), we examine the role of increased attention and individual investor actions and find the following:

First, by utilizing trading volume as a metric for attention – in line with the approach of Hong and Stein (2007) and Barber and Odean (2008) – we note a significant surge in trading activity associated with stocks exhibiting exceptionally positive returns, particularly those classified as overpriced. Notably, overpriced stocks in the highest MAX quintile display a substantial 273% increase in trading volume compared to the average of the preceding month. In comparison, the rise for underpriced stocks is 172%, and the disparity between overpriced and underpriced stocks is statistically significant. This supports our hypothesis that stocks with remarkably positive returns become more conspicuous, drawing increased attention from investors.

We further observe a corresponding uptick in buying activity by individual investors in stocks characterized by a high MAX, a trend particularly evident among overpriced stocks. The analysis of individual investor trading data reveals a prevalence of buy trades over sell trades for stocks in the top MAX decile among overpriced stocks, while no discernible relationship is observed among underpriced stocks.

Finally, for stocks exhibiting both overpricing and exceptionally positive returns, those with elevated abnormal trading volume experience negative abnormal returns in the subsequent months compared to their counterparts with lower abnormal trading volume. Notably, the distinction in the MAX spread between overpriced and underpriced stocks is not apparent when considering stocks with low abnormal trading volume. Conversely, a robust MAX effect emerges among overpriced stock groups in comparison to underpriced stocks when focusing on stocks with a substantial increase in trading volume, revealing a return difference of −1.39%. This underscores the pivotal role of attention, as measured by abnormal trading volume, in influencing the overpricing dynamics of stocks with exceptionally positive returns.

Our study contributes to the literature in various ways. First, we add additional evidence to the lottery preference literature. Studies show that investors tend to favor assets with lottery characteristics, particularly those exhibiting low probability but high potential payoff, because psychological values influence probability weighting, leading to the overvaluation of these stocks (e.g. Markowitz, 1952; Tversky and Kahneman, 1992; Mitton and Vorkink, 2007; Barberis and Huang, 2008; Barber *et al.*, 2009; Kumar, 2009; Bali *et al.*, 2011; Dorn *et al.*, 2015; Gao and Lin, 2015; Barberis *et al.*, 2016). We delve into lottery preferences, especially the MAX effect, in South Korea, which provides excellent circumstances for out-of-sample analyses. We provide the possible additional explanation, as arbitrage risk, in explaining the MAX effect.

Second, we contribute to the literature on idiosyncratic volatility (IVOL). Some researchers view IVOL as a gauge of arbitrage risk (e.g. Ang *et al.*, 2006, 2009; Guo and Savickas, 2006; Herskovic *et al.*, 2016; Huang *et al.*, 2010; Hou and Loh, 2016), with Stambaugh *et al.* (2015) arguing that the IVOL puzzle emerges from asymmetric trading in mispriced stocks, primarily due to short-selling constraints on overvalued stocks. Arbitrage risk and asymmetry are identified as key factors in the IVOL puzzle, where noise trading increases IVOL, heightening arbitrage risk. The costs of short-selling further amplify the negative IVOL effect, particularly for overpriced stocks, emphasizing the impact of asymmetrical trading in mispriced stocks.

However, Kumar (2009) characterizes lottery-type stocks as those demonstrating elevated idiosyncratic volatility, high idiosyncratic skewness, and low prices. Idiosyncratic volatility, in this context, can function as an indicator of the degree of lottery preference. In this paper, we establish a connection between the MAX effect and the IVOL puzzle, acknowledging a notable correlation between MAX and IVOL. Despite this correlation, our bivariate sort analysis reveals the sustained presence of the MAX effect even after adjusting for IVOL, indicating independent informational value within the South Korean stock market. Therefore, our findings emphasizing the MAX effect exclusively among overpriced stocks cannot be solely ascribed to the mispricing and IVOL outcomes outlined by Stambaugh *et al.* (2015), as IVOL and MAX encapsulate distinct information.

Third, our study contributes to the literature on individual investors' trading. Existing research suggests that retail investors, often considered unskilled noise traders, exhibit a notable inclination towards behavioral biases, leading to the phenomenon of overpricing (e.g. Barber and Odean, 2000; Kumar and Lee, 2006; Hvidkjaer, 2008; Barber *et al.*, 2009; Kumar, 2009; Han and Kumar, 2013). Notably, Han and Kumar (2013) find that stocks with a high proportion of retail trading tend to be overpriced, aligning with prior US stock market studies indicating that individual investors predominantly trade in small-cap, low-priced, and high-volatility stocks. Our results support individual investors' behavior, especially their preference towards high MAX and overpriced stocks.

Finally, we contribute to the extant literature on the South Korean stock market, establishing the presence of the lottery preference and MAX effect (e.g. Kang *et al.*, 2014; Nartea *et al.*, 2014; Cheon and Lee, 2018a, b; Byun *et al.*, 2023). Our study differs from theirs by providing a new perspective of arbitrage risk in explaining the MAX effect in the South Korean stock market.

The remainder of this paper is structured as follows: Section 2 offers a literature review and explains the development of the hypotheses. Section 3 provides data sources and explains the variable construction. Section 4 explores the MAX effect in the South Korean stock market, considering mispricing levels. Section 5 provides evidence regarding investors' attention and individual investors' trading behavior. Section 6 provides additional robustness checks, and Section 7 concludes the paper.

2. Literature review and hypotheses development

2.1 Lottery preference and mispricing in South Korea

Several studies in the extant literature explore the impact of non-systematic factors on stock price movements in the South Korean stock market; these studies investigate the influence of investor preferences or aversions on stock returns, extreme fluctuations and anomalies in returns, as well as psychological responses and decision-making based on the distribution of past returns.

Some studies collectively establish the presence of the lottery preference and MAX effect in the South Korean stock market. Kang *et al.* (2014) observe a substantial proportion of individual investors in the South Korean stock market exhibiting a preference for lottery-type stocks; this aligns with the characteristics of emerging stock markets where small- and medium-sized investors play a crucial role. Nartea *et al.* (2014) and Kang and Sim (2014) adopt Bali *et al.*'s (2011) methodology and confirm a significant negative relationship between MAX and domestic stock prices, thereby supporting previous research. Additionally, Sim (2016) notes a negative relationship between high estimated skewness and future returns, irrespective of the volatility estimation period. Kho and Kim (2017) and Ohk and Kim (2020) further identify a short-term return reversal for portfolios with the highest maximum return overvaluation. Ahn and Lee (2020) link a more pronounced lottery preference – as indicated by skewness, idiosyncratic risk, and stock prices – with elevated investor overconfidence. This association is particularly notable in the context of increased trading volume by individual investors. Cheon and Lee (2018b) contribute to the discussion by highlighting that the MAX effect is more pronounced during periods of high volatility [2]. Byun *et al.* (2023) present evidence of the MAX effect during low sentiment states, supplementing their findings by incorporating trading volume and net-buying imbalance as measures of investor attention.

Concerning the IVOL of stocks, Kim and Byun (2011) find that portfolios with higher idiosyncratic volatility in the South Korean stock market exhibit significantly lower downside volatility. Kang *et al.* (2013, 2014) state that investors consider stocks with lower prices and higher IVOL to be lottery-like stocks. Kim and Chae (2015) show that portfolios with high absolute idiosyncratic returns tend to have relatively lower future returns. Jang (2016) reveals that stocks with higher intrinsic volatility are overvalued, and those with higher skewness are undervalued. Following the methodology of Stambaugh *et al.* (2015), Chang *et al.* (2016) and Eom (2018) propose that the IVOL puzzle in the South Korean stock market can be elucidated through arbitrage asymmetry measured by mispricing.

In summary, research using data from the South Korean stock market aligns with studies focused on other countries, indicating that investors' lottery preferences and behavioral biases play crucial roles in shaping stock returns and market dynamics.

2.2 Hypothesis development

We hypothesize that the MAX effect, observed through the relationship between maximum daily returns and future stock returns, varies across different levels of mispricing (MIS) in the South Korean stock market. Specifically, we argue that the effects of arbitrage risk and the MAX effect attributed to lottery preference are independent factors. We expect the negative MAX effect among overpriced stocks to be magnified by the presence of the arbitrage risk effect, emphasizing the separate and distinct nature of these influences. Conversely, we anticipate that the arbitrage risk effect from lottery preference will counterbalance the negative MAX effect among underpriced stocks. Our first and second hypotheses are as follows:

H1. There are negative returns and alphas for high–low MAX portfolios across all MIS quintiles, with significance predominantly among overpriced stocks.

H2. The MAX effect in the South Korean stock market retains independent information value even after accounting for the correlation with the IVOL puzzle.

We also seek to understand the mechanism behind the significant MAX effect among overpriced stocks. Our third hypothesis is as follows:

H3. Increased attention and individual investor actions – as measured by trading volume and buying pressure – play a crucial role in driving the overpricing of high MAX stocks, particularly among overpriced stocks.

3. Data and variables

3.1 Data

We use stock data from the South Korean market, delisted and listed on the Korea Composite Stock Price Index (KOSPI) and Korean Securities Dealers Automated Quotations (KOSDAQ) markets, from January 2000 to December 2020. We obtain the daily and monthly firm-level stock returns, outstanding shares, trading volume, and share price for stock-related data, and fiscal variables such as book equity, revenue, and total assets of financial statement data from the South Korean database DataGuide, which is provided by FnGuide. We also obtain various market participants' daily trading data, such as individual investors' trading volume and trading price volume, to use as a proxy for investors' attention. We use the properly converted one-year monetary stabilization bond rate for the daily and monthly risk-free rates.

After constructing the variables, observations with a stock price of less than 1,000 South Korean won (equivalent to 1 US dollar) are excluded to alleviate the concern that our results are driven by micro-cap stocks or the impact of certain stocks with poor data accuracy due to market microstructural reasons. We also exclude stocks that have monthly returns greater than 50,000% [3], which are outliers or experience firm-unexpected events.

3.2 Variables construction

Following Bali *et al.* (2011), we define MAX as the maximum daily return over the previous month. We use the seven firm characteristics for the control variables: market beta (BETA), market capitalization (ME), book-to-market equity ratio (BM), momentum (MOM), short-term reversal (REV), stock price (PRC), and idiosyncratic volatility (IVOL). The firm-characteristic variables are described in Appendix A1. Table 1 presents the summary statistics of these variables. We report their average values for each MAX decile portfolio in Panel A. Consistent with previous studies, stocks in the South Korean stock market with higher MAX tend to have higher market beta, lower market capitalization, a lower book-to-market ratio, higher momentum, higher short-term reversal, lower stock prices, and higher IVOL. We show the correlation coefficients among firm characteristics in Panel B. Notably, in the South Korean stock market, there is a high positive correlation (0.86) between MAX and IVOL. This is higher than that found by Bali *et al.* (2011) in the US stock market (0.75).

Next, following Stambaugh *et al.* (2015), we formulate a composite mispricing measure using seven well-known anomalies. Due to the lack of available data on the South Korean stock market, we adapt only seven anomalies following Chang *et al.* (2016). The seven anomaly variables used are: *Z*-score from Altman (1968), net operating assets (*NOA*), Panel A: Average firm-characteristics

	MAX decile									
	1 (Low)	2	3	4	5	6	7	8	9	10 (High)
MAX (%)	2.12	3.21	3.99	4.76	5.60	6.56	7.77	9.50	12.08	16.41
BETA	0.39	0.56	0.66	0.74	0.80	0.86	0.90	0.92	0.92	0.82
ME (10^9)	75.97	87.45	107.75	100.46	86.89	77.94	47.98	35.72	22.63	14.65
BM	1.70	1.57	1.45	1.39	1.31	1.26	1.20	1.16	1.19	1.57
MOM (%)	2.87	5.02	7.48	10.67	14.51	19.52	24.91	24.91	27.59	31.05
REV (%)	−4.56	−3.76	−3.02	−2.10	−0.93	0.01	2.04	4.07	8.39	18.61
PRC (10^3)	28.99	29.06	28.85	27.87	25.68	24.80	20.69	17.52	13.49	10.52
IVOL	1.28	1.65	1.91	2.14	2.38	2.69	3.05	3.58	4.40	5.86

Panel B: Correlations

	MAX	BETA	ME	BM	MOM	REV	PRC	IVOL
MAX	1							
BETA	0.115	1						
ME	−0.045	0.026	1					
BM	−0.022	−0.082	−0.039	1				
MOM	0.104	0.043	0.007	0.045	1			
REV	0.370	−0.100	0.001	0.035	−0.026	1		
PRC	−0.079	−0.007	0.366	−0.043	0.038	0.010	1	
IVOL	0.859	0.067	−0.060	−0.019	0.161	0.302	−0.093	1

Note(s): This table reports the summary statistics. In Panel A, we sort stocks into deciles based on the maximum daily return in the previous month (MAX). We report the average stock characteristics, including monthly maximum daily return (MAX [%]), market beta (BETA), log of market capitalization (ME), log of book-to-market ratio (BM), intermediate-term momentum (MOM), short-term reversal (REV), stock price (PRC), and idiosyncratic volatility (IVOL), for each MAX decile. Panel B reports the time-series average of the cross-sectional correlations between the firm characteristic variables. The specific definitions of the firm characteristic variables are detailed in Appendix A1. The sample period covers from July 2000 to December 2020
Source(s): Created by the authors

Table 1.
Summary statistics

momentum (*MOM*), gross profitability premium (*GPP*), asset growth (*AG*), gross accruals (*ACC*), and return on assets (*ROA*). Appendix A2 provides detailed definitions of each anomaly variable. Similar to Stambaugh *et al.* (2015), we first divide each stock into percentiles for every month. For each stock i at month t, we define the composite measure MIS as an average of its ranking percentile for each of the seven anomalies considered in this study. The larger the value of MIS, the lower the expected return. As shown in Appendix Table A1, the expected returns gradually decrease from underpriced to overpriced stocks; thus, MIS sufficiently represents the anomalous nature of the stocks.

Finally, we construct a monthly net-buying imbalance of individual investors to investigate the trading behavior toward MAX and MIS. As DataGuide provides daily trading volume and won trading volume for each market participant, we first aggregate the daily buy or sell trading volume or South Korean won volume and obtain a monthly buy volume ($\#Buy_{i,t}^{ind}$) and sell volume ($\#Sell_{i,t}^{ind}$), with buy-won volume ($\$Buy_{i,t}^{ind}$) and sell-won volume ($\$Sell_{i,t}^{ind}$) for each stock, traded by individual investors. We define $\#Trd_{i,t}^{ind}$ as the order imbalance of individual investors (buy volume − sell volume) in month t, scaled by the total number of shares outstanding. $\$Trd_{i,t}^{ind}$ is defined as the monthly individual investors' won volume order imbalance (buy-won volume – sell-won volume) scaled by market capitalization.

$$\#Trd_{i,t}^{ind} = \frac{\#Buy_{i,t}^{ind} - \#Sell_{i,t}^{ind}}{\#\ of\ Shares\ Outstanding_{i,t}}, \$Trd_{i,t}^{ind} = \frac{\$Buy_{i,t}^{ind} - \$Sell_{i,t}^{ind}}{Market\ Capitalization_{i,t}} \quad (1)$$

4. Mispricing, lottery preference, and the MAX effect

4.1 The MAX effect revisited

We first conduct an empirical analysis to determine whether the MAX effect occurs in our sample of the South Korean stock market. Panel A (B) of Table 2 shows the average monthly equal- (value-) weighted excess returns and the Fama and French (1993) three-factor alphas for decile portfolios based on MAX. In the last row of the table, we report the difference in returns and the alphas between the highest and lowest MAX portfolios (high–low MAX portfolio). Newey and West (1987) *t*-statistics are reported in parentheses.

In the equal-weighted portfolio, the average monthly returns and alphas of the high–low MAX portfolio are −2.08% (*t*-stat = −5.01) and −2.00% (*t*-stat = −4.61), which are highly significant. Comparable trends are identified in value-weighted portfolios, affirming the presence of the MAX effect in our dataset. This finding aligns with the observations of Nartea *et al.* (2014), who also document the MAX effect in the South Korean stock market. Notably, our study reveals a divergence from Nartea *et al.* (2014) as the MAX effect manifests more prominently in the equal-weighted portfolio than the value-weighted portfolio within our sample. Moreover, the MAX effect remains robust after accounting for other firm-characteristic variables, as evidenced by the results in Appendix Table A2.

4.2 Bivariate sort analysis

In this section, we investigate how the relationship between MAX and future returns in the South Korean stock market varies among different levels of mispricing using bivariate sort

	MAX decile										
	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	10–1
Panel A: equal-weighted portfolios											
Excess	1.60	1.60	1.48	1.36	1.38	1.21	1.04	0.86	0.42	−0.48	−2.08
return	(3.69)	(3.63)	(3.29)	(3.03)	(3.17)	(2.37)	(2.09)	(1.60)	(0.72)	(−0.76)	(−5.01)
3-factor	1.57	1.63	1.58	1.41	1.48	1.22	1.13	1.00	0.44	−0.43	−2.00
alpha	(3.54)	(3.44)	(3.26)	(2.98)	(2.97)	(2.22)	(2.06)	(1.69)	(0.75)	(−0.64)	(−4.61)
Panel B: value-weighted portfolios											
Excess	0.34	0.67	0.71	0.73	0.92	0.98	0.15	0.70	−0.24	−1.47	−1.80
return	(0.95)	(1.88)	(1.73)	(1.65)	(1.67)	(1.80)	(0.29)	(1.33)	(−0.42)	(−2.42)	(−3.28)
3-factor	0.48	0.72	0.92	0.75	0.94	0.90	0.19	0.87	−0.23	−1.20	−1.68
alpha	(1.28)	(1.88)	(2.16)	(1.68)	(1.72)	(1.71)	(0.35)	(1.54)	(−0.41)	(−1.82)	(−2.88)

Note(s): This table presents the average monthly excess returns and three-factor alphas of the Fama and French (1993) model for each decile sorted by MAX. At the end of each month, stocks are sorted into deciles based on their maximum daily returns (MAX). We report the equal-weighted (value-weighted) average returns and Fama and French (1993) three-factor alphas of these portfolios for the subsequent month in Panel A (B). The column labeled "10–1" indicates the difference in average returns and alphas between the top and bottom MAX decile portfolios. The *t*-statistics corrected by Newey and West (1987) with 12 lags are shown in parentheses. The sample period is from July 2000 to December 2020
Source(s): Created by the authors

Table 2.
MAX portfolio returns

		MAX quintile						
		1 (Low)	2	3	4	5 (High)	5–1	5–1 alpha
Panel A: equal-weighted portfolios								
MIS quintile	1 (Underpriced)	1.62	1.78	1.26	1.40	1.01	−0.61 (−1.88)	−0.60 (−1.83)
	2	1.53	1.52	1.39	1.16	0.37	−1.16 (−3.01)	−0.99 (−2.53)
	3	1.56	1.60	1.42	0.95	0.39	−1.18 (−3.01)	−1.02 (−2.80)
	4	1.89	1.41	1.10	0.89	−0.10	−1.99 (−3.76)	−1.96 (−3.58)
	5 (Overpriced)	1.28	0.97	0.67	0.29	−1.30	−2.58 (−6.58)	−2.78 (−5.79)
	Average						−1.50 (−4.90)	−1.47 (−4.73)
	5–1						−1.96 (−4.74)	−2.17 (−4.72)
Panel B: value-weighted portfolios								
MIS quintile	1 (Underpriced)	1.00	1.13	0.90	0.95	0.45	−0.55 (−1.26)	−0.65 (−1.19)
	2	0.25	0.96	0.64	0.70	0.34	0.09 (0.19)	0.12 (0.23)
	3	0.53	0.45	0.80	0.22	0.15	−0.38 (−0.64)	−0.25 (−0.39)
	4	0.56	0.46	0.53	0.14	−1.15	−1.71 (−2.86)	−1.79 (−2.81)
	5 (Overpriced)	0.46	0.57	0.61	−0.92	−1.84	−2.31 (−3.18)	−2.45 (−3.23)
	Average						−0.97 (−2.56)	−1.01 (−2.48)
	5–1						−1.75 (−2.54)	−1.80 (−2.60)

Note(s): This table presents the average monthly excess returns and alphas of the portfolios generated by a dependent bivariate sort analysis based on the maximum daily return in the previous month (MAX) and the constructed mispricing index (MIS) by following the methodology of Stambaugh *et al.* (2015). MIS is created by aggregating the seven percentile rankings assigned by seven anomalies (*z*-score, net operating assets, momentum, gross profitability premium, asset growth, accrual, and return on assets). We first sort stocks into quintiles based on the MIS, and then, within each MIS quintile, we further sort stocks into quintiles based on MAX. We then report the average monthly excess returns of the constructed 25 portfolios. The column labeled "5–1" and "5–1 alpha" depicts the difference in average returns and the Fama and French (1993) three-factor alphas between the top and bottom MAX quintiles within each MIS quintile. The row labeled "Average" reports the average of the high-low MAX spread across the mispricing quintiles. The row labeled "5–1" reports the difference in the high-low MAX spread between overpriced and underpriced stock groups. The *t*-statistics corrected by Newey and West (1987) with 12 lags are shown in parentheses. The sample period is from July 2000 to December 2020
Source(s): Created by the authors

Table 3.
Bivariate sort analysis

analysis. First, we sort stocks into quintile portfolios based on MIS and MAX. Table 3 reports the average monthly excess returns and the Fama and French (1993) three-factor alphas for each of the 25 portfolios in the equal- and value-weighted scheme. In the last column of the table, we report the average returns and alphas of the high–low MAX portfolio among each MIS quintile.

According to Panel A, using the equal-weighted scheme, the alphas of the high–low MAX portfolio vary from −0.60% (t-stat = −1.83) in the low-MIS group to −2.78% (t-stat = −5.79) in the high MIS stock group. Only the high–low MAX portfolio within the high MIS quintile earns a significantly negative return and alpha. A similar pattern occurs when we use the value-weighted scheme, as shown in Panel B. In addition, we report the difference in returns and alphas of the high–low MAX portfolio between the highest and lowest MIS quintiles in the last row of each panel. The return difference of the high-low MAX portfolio between the highest and lowest MIS from quintiles has a significantly negative value of −1.96% (−1.75%) with a t-statistic of −4.74 (−2.54) for the equal-weighted (value-weighted) scheme. The alpha differences are also negatively significant. These results indicate two things: (1) The MAX effect is significant for overpriced stocks. The MAX effect disappears for underpriced stock groups but is not reversed in sign. (2) The significant MAX effect among the highest MIS is significantly more substantial than the MAX effect among the lowest MIS.

The results suggest that the MAX effect is prominent in the overpriced group in the South Korean stock market, regardless of the weighting schemes. Our results differ substantially from those of Zhong and Gray (2016) in the Australian stock market and Van Hai *et al.* (2020) in the Chinese stock market. Van Hai *et al.* (2020) argue that the MAX effect in the Australian or Chinese stock market is explained by the asymmetric arbitrage role of MAX because MAX shares similar aspects with IVOL. According to Zhong and Gray (2016), the most overvalued stocks have a pronounced MAX effect, whereas, the sign of the MAX anomaly reverses for the most underpriced stocks. Since there is a high correlation between MAX and IVOL, Zhong and Gray (2016) explain their results by following the concept of arbitrage asymmetry introduced by Stambaugh *et al.* (2015). This concept shows that, in contrast to underpriced stocks, overpriced stocks are less likely to be the subject of arbitrageur transactions due to the short-sale restriction. This results in an overall negative relationship between MAX and expected return, known as the MAX effect, where the magnitude of the negative MAX spread among overpriced stocks exceeds the positive MAX spread among underpriced stocks.

In contrast, according to our results, the high–low MAX spread among underpriced stocks does not reverse in sign. Therefore, we interpret our results in several ways, using the concepts of arbitrage risk and the strong lottery preference of individual investors in the South Korean stock market. Because MAX has an effect similar to IVOL, high-MAX stocks typically have high arbitrage risk, as IVOL represents the arbitrage risk, according to Stambaugh *et al.* (2015). The higher the MAX of an overpriced stock, the greater its overvaluation; therefore, they have lower expected returns. In contrast, the higher the MAX of an underpriced stock, the more significant its undervaluation; thus, underpriced stocks tend to attain higher expected returns. However, from a different perspective, the arbitrage risk effect and the MAX effect induced by lottery preference should be considered independent. Thus, these two effects can overlap and negate each other. For overpriced stocks, the arbitrage risk effect of lottery preference amplifies the negative MAX effect. Meanwhile, the arbitrage risk effect from lottery preference offsets the negative MAX effect for underpriced stocks.

Our results are also consistent with the findings of Cao and Han (2016). They assert that arbitrageurs are reluctant to have a position in stocks with high arbitrage risk, resulting in less correction for the mispricing of these stocks. Since high-MAX stocks tend to have high arbitrage costs, their mispricing is more significant than low-MAX stocks. Thus, high-MAX stocks with high MIS are more overpriced, and high-MAX stocks with low MIS are more underpriced. In sum, the magnitude of the MAX effect on overpriced stocks is amplified by the arbitrage risk effect, whereas the MAX effect is diminished on underpriced stocks.

4.3 Fama and MacBeth (1973) cross-sectional regression

To validate the relationship between MIS and MAX at the individual stock level, we perform a traditional Fama and MacBeth (1973) cross-sectional regression. This analysis enables for controlling of various firm-characteristic variables simultaneously. For each month, we run the following regression (2):

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}MAX_{i,t} + \lambda_{2,t}MIS_{i,t} \times MAX_{i,t} + \lambda_{3,t}MIS_{i,t} + \lambda_{4,t}BETA_{i,t} + \lambda_{5,t}ME_{i,t} + \lambda_{6,t}BM_{i,t} + \lambda_{7,t}MOM_{i,t} + \lambda_{8,t}REV_{i,t} + \epsilon_{i,t+1} \quad (2)$$

where $R_{i,t+1}$ is the return on stock i in month $t+1$, $MAX_{i,t}$ is the highest daily return, and $MIS_{i,t}$ is the mispricing index of stock i in month t. The control variables include the market beta (BETA), log of market capitalization (ME), log of book-to-market ratio (BM), intermediate-term momentum (MOM), and short-term reversal (REV). All dependent variables in the regression are standardized and winsorized at the 1% level.

Table 4 reports the monthly averages of the estimated coefficients and the corresponding t-statistic in parentheses. According to models 1, 2, and 3, the coefficient estimates of MAX are significantly negative; after accounting for different firm characteristics, the MAX effect remains considerable. As discussed in Section 4.2., we are interested in the coefficient of the interaction term between MAX and MIS, which is denoted as $\lambda_{2,t}$. Models 4, 5, and 6 show that the coefficients of the interaction terms are all significantly negative. The coefficients of the interaction terms indicate that the overpricing among high-MAX stocks increases as MIS gets higher. For example, according to the results from model 4, the coefficient of MAX would be −0.321 with a two-standard deviation decrease in MIS. However, the coefficient of MAX would be −1.081 with a two-standard deviation increase in MIS, which is strongly negative. In addition, according to models 5 and 6, we find that comparable results of a cross-sectional regression from the portfolio analysis by MAX and MIS are robust after controlling for other variables (i.e. size, book-to-market ratios, market beta, short-term past returns, and stock price).

Consequently, the regression results at the stock-level show that the MAX effect is more pronounced when stocks are overpriced, which is consistent with our results from the bivariate portfolio approach in Section 4.2.

4.4 The MAX effect and the IVOL puzzle

The results in Table 1 show a positive correlation (0.86) between MAX and IVOL. The different MAX effects among each level of mispricing may be due to the positive relationship between MAX and IVOL, combined with the explanation of Stambaugh *et al.* (2015). To ensure that the MAX effect on overpriced stocks is not directly caused by the high positive

Variable	MAX	MIS × MAX	MIS	BETA	ME	BM	MOM	REV
Model 1	−0.787							
	(−6.88)							
Model 2	−0.948			0.477	−0.564	0.482	0.147	
	(−8.46)			(4.33)	(−3.30)	(3.48)	(2.02)	
Model 3	−0.840			0.385	−0.510	0.535	0.103	−0.307
	(−9.72)			(3.85)	(−3.16)	(3.76)	(1.28)	(−2.45)
Model 4	−0.701	−0.190	−0.303					
	(−6.65)	(−4.84)	(−3.44)					
Model 5	−0.858	−0.112	−0.379	0.485	−0.592	0.494	0.006	
	(−8.26)	(−3.50)	(−4.70)	(4.40)	(−3.55)	(3.52)	(0.08)	
Model 6	−0.734	−0.104	−0.395	0.389	−0.532	0.55	−0.044	−0.346
	(−9.81)	(−3.17)	(−4.92)	(3.92)	(−3.37)	(3.80)	(−0.55)	(−2.71)

Note(s): This table presents the results of the time-series average of the coefficients from Fama and Macbeth (1973) cross-sectional regression analysis. For each month, we run the following cross-sectional regression model:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}MAX_{i,t} + \lambda_{2,t}MIS_{i,t} \times MAX_{i,t} + \lambda_{3,t}MIS_{i,t} + \lambda_{4,t}BETA_{i,t} + \lambda_{5,t}ME_{i,t} + \lambda_{6,t}BM_{i,t} + \lambda_{7,t}MOM_{i,t} + \lambda_{8,t}REV_{i,t} + \epsilon_{i,t+1}$$

where $R_{i,t+1}$ is the return on stock i in month t+1, $MAX_{i,t}$ is the maximum daily return in the previous month and $MIS_{i,t}$ is the constructed mispricing index of stock i in month t. The control variables include the market beta (BETA), log of market capitalization (ME), log of book-to-market ratio (BM), intermediate-term momentum (MOM), and short-term reversal (REV). All dependent variables in the regression are standardized and winsorized at the 1% level. The t-statistics corrected by Newey and West (1987) with 12 lags are shown in parentheses. The sample period is from July 2000 to December 2020

Source(s): Created by the authors

Table 4.
Fama and MacBeth (1973) cross-sectional regression

correlation between IVOL and MAX, we examine whether IVOL can fully explain the MAX effect in the South Korean stock market.

First, we examine whether the IVOL puzzle from Ang *et al.* (2006) also exists in our sample. The results from Appendix Table A3 show that the IVOL puzzle is also prevalent in our sample, which is consistent with Kim and Byun (2011) and Chang *et al.* (2016). Furthermore, we investigate whether the MAX effect (IVOL puzzle) has a specific unique information value apart from IVOL (MAX) in the South Korean stock market. We conduct a dependent bivariate portfolio analysis to ensure that MAX has explanatory power on expected returns after IVOL is controlled. We also analyze the reverse direction to determine whether IVOL has predictability power when MAX is controlled. Each month, stocks are sorted into quintiles based on the controlling variable. Within each quintile, stocks are sorted again into quintiles based on the primary or variable of interest. Table 5 shows the results for the IVOL-controlled MAX portfolio and MAX-controlled IVOL portfolio in Panels A and B, respectively. From these results, we will investigate whether each MAX or IVOL has independent predictive power over the other.

Table 5 presents the average of equal-and value-weighted monthly returns and the Fama and French (1993) three-factor alphas of high–low MAX (IVOL) portfolios after controlling for IVOL (MAX) in Panel A (B). According to Panel A, when IVOL is controlled, the MAX effect remains significant. Specifically, after controlling for IVOL, the high–low MAX portfolio earns returns of −0.68% (*t*-stat = −2.28) and alphas of −0.64% (*t*-stat = −2.25) using the value-weighted scheme. Moreover, Panel B shows that the IVOL puzzle remains significant after controlling for MAX.

From the above results, we find that the MAX effect and IVOL puzzle are present in the South Korean stock market, which is consistent with related studies. Moreover, the MAX effect remains significant after controlling for IVOL. Although IVOL and MAX are highly correlated, MAX has an independent information value that IVOL cannot explain. This is important because IVOL and MAX contain distinct information. The MAX effect on overpriced stocks cannot be explained simply by the results of MIS and IVOL from Stambaugh *et al.* (2015).

Table 5. The MAX effect and IVOL puzzle

	1 (Low)	2	3	4	5 (High)	5–1	5–1 alpha
Panel A: MAX portfolio returns controlling for IVOL							
			MAX quintile				
Equal-weighted	1.00	0.89	0.68	0.84	0.60	−0.41 (−2.54)	−0.36 (−2.07)
Value-weighted	0.65	0.41	0.06	0.28	−0.03	−0.68 (−2.28)	−0.64 (−2.25)
Panel B: IVOL portfolio returns controlling for MAX							
			IVOL quintile				
Equal-weighted	1.28	1.21	0.89	0.64	−0.01	−1.29 (−4.83)	−1.26 (−3.83)
Value-weighted	0.55	0.54	0.25	0.18	−0.43	−0.99 (−3.53)	−1.01 (−3.04)

Note(s): This table presents the results for the dependent bivariate sort analysis. Panel A (B) presents the results of the bivariate sort analysis to examine the impact of MAX (IVOL), the variable of interest, on returns after controlling for IVOL (MAX) as the control variable. First, we sort stocks into quintiles based on the control variable; then, within each quintile, we further sort stocks into quintiles based on the variable of interest. We report the average monthly return across quintiles sorted by control variable, for each quintile sorted by the variable of interest, in both equal- and value-weighted schemes. The column labeled "5–1" and "5–1 alpha" reports the difference in average returns and Fama and French (1993) three-factor alphas between the top and bottom quintiles sorted by the variable of interest. The *t*-statistics corrected by Newey and West (1987) with 12 lags are shown in parentheses. The sample period is from July 2000 to December 2020
Source(s): Created by the authors

5. Individual investors, abnormal trading volume, mispricing, and the MAX effect

We next investigate why overvalued stocks with prior maximum positive returns typically have low future returns. Kumar (2009) emphasizes individual investors' heightened attraction toward lottery-like investments. Therefore, we evaluate investor levels of attention and trading directions of individual investors for equities with maximum positive returns at the level of mispricing. Following Barber and Odean (2008) and Kumar and Lee (2006), we employ abnormal trading volume as a proxy for investor interest. In this section, we investigate whether investors' attention (measured by total volume) and individual investors' net-buying imbalance (measured by the number of buy trades and sell trades) are concentrated on overpriced stocks with maximum positive returns.

Table 6 reports the average change in trading volume (ΔVol) as a percentage of each MAX quintile for each mispriced level of a stock. ΔVol is defined as the difference in the number of traded shares relative to the number of shares traded in the prior month (previous 12 months) in Panel A (B) [4]. Panel A shows that in the top MAX quintile of overpriced stocks, there is a 273% rise in ΔVol from the prior month and a 172% rise for underpriced stocks. The difference in ΔVol between the high and low MAX among the overpriced stocks (278%) is approximately 1.62 times the difference in ΔVol between the high and low MAX among the underpriced stocks (172%). The last row of Table 6 shows that the difference in ΔVol between the high and low MAX between overpriced and underpriced stocks is 105.49%, with a significant *t*-statistic of 7.37. These results indicate that investors' attention toward high-MAX stocks to low-MAX stocks is more intense for overpriced stocks compared with underpriced stocks, which is consistent with hypothesis H3.

Table 6. MAX, MIS and abnormal trading volume

		MAX quintile					
		1 (Low)	2	3	4	5 (High)	5–1
Panel A: ΔVol, relative to past 1 month							
MIS quintile	1 (Underpriced)	−0.29	2.54	9.49	29.95	171.96	172.25 (15.39)
	2	0.16	2.88	15.00	33.89	207.96	207.80 (12.73)
	3	−1.17	2.95	15.34	43.34	230.49	231.67 (15.60)
	4	−3.55	2.64	17.17	54.82	246.06	249.61 (15.49)
	5 (Overpriced)	−4.94	2.69	22.21	74.35	272.80	277.74 (13.80)
	5–1						105.49 (7.37)
Panel B: ΔVol, relative to past 12 months average							
MIS quintile	1 (Underpriced)	114.91	193.44	271.07	346.98	559.24	444.33 (11.62)
	2	155.39	283.18	343.05	438.22	624.73	469.35 (9.61)
	3	148.81	306.03	399.99	460.73	709.27	560.46 (13.55)
	4	187.21	286.16	395.44	488.98	737.63	550.43 (12.24)
	5 (Overpriced)	218.41	368.04	451.91	569.00	801.49	583.09 (12.11)
	5–1						138.76 (3.44)

Note(s): This table presents the pattern of trading volume for portfolios created through a dependent bivariate sort analysis based on the maximum daily return in the previous month (MAX) and the constructed mispricing index (MIS). At the end of each month, stocks are sorted into quintiles based on MIS and further sorted into quintiles MAX. In Panel A (B), the average change in volume, ΔVol, which is the ratio of shares traded in month *t* to those traded in the previous month (previous 12 months), is reported in the constructed 25 portfolios. The column labeled "5–1" shows the difference in average ΔVol between the top and bottom quintiles sorted by MAX. The row labeled "5–1" reports the difference in ΔVol of high-low MAX between overpriced and underpriced stocks. The *t*-statistics corrected by Newey and West (1987) with 12 lags are shown in parentheses. The sample period is from July 2000 to December 2020

Source(s): Created by the authors

In line with Kumar (2009), we further concentrate on individual investors and investigate their trading behavior for stocks in different levels of the MAX quintile for various levels of the MIS quintile. Every trade in the South Korean stock market is categorized as being made by an individual investor, a subdivided institutional investor, or a foreign investor. DataGuide provides the daily record of buy and sell trading volumes for each type of investor in both shares and South Korean won. This database allows us to estimate the trading imbalance of individual investors at a daily frequency precisely and without error. As detailed in Section 3.2., we construct $\#Trd_{i,t}^{ind}$ based on shares and $\$Trd_{i,t}^{ind}$ based on South Korean won volume, as the proxies of individual investors' trading behavior and net-buying imbalance.

Table 7 shows the average of individual investors' net-buying imbalance for each MAX quintile further sorted by the MIS quintiles. In Panel A of Table 7, we report the average $\#Trd_{i,t}^{ind}$ (scaled by 10^{-4}) for each of the 25 constructed portfolios based on MAX and MIS. For underpriced stocks, individual investors' excess demand (measured by $\#Trd_{i,t}^{ind}$) for high-MAX stocks is insignificant relative to low-MAX stocks. In contrast, for overpriced stocks, individual investors' net-buying behavior for high-MAX stocks is significantly higher than for low-MAX stocks. The $\#Trd_{i,t}^{ind}$ spread between the highest MAX (3.30) and the lowest MAX (1.19) for the overpriced stock group is 2.10, with a significant t-statistic of 5.00. In the difference-in-differences perspective, the individual investors' preference toward high to low MAX stocks is greater for overpriced stocks than underpriced stocks. The last row of Panel A shows that the $\#Trd_{i,t}^{ind}$ spread between underpriced and overpriced stock groups across the

		MAX quintile					
		1 (Low)	2	3	4	5 (High)	5–1
Panel A: $\#Trd_{i,t}^{ind}$, scaled by 10^{-4}							
MIS quintile	1 (Underpriced)	0.21	−0.29	−0.73	−0.95	0.43	0.22 (1.04)
	2	0.43	0.06	−0.25	−0.51	1.13	0.69 (3.21)
	3	0.55	0.24	0.03	0.18	1.62	1.08 (5.06)
	4	0.61	0.39	0.39	0.57	2.80	2.19 (3.99)
	5 (Overpriced)	1.19	0.88	1.08	1.45	3.30	2.10 (5.00)
	5–1						1.88 (4.36)
Panel B: $\$Trd_{i,t}^{ind}$, scaled by 10^{-4}							
MIS quintile	1 (Underpriced)	0.22	−0.27	−0.69	−0.87	0.59	0.37 (1.75)
	2	0.44	0.09	−0.21	−0.44	1.26	0.81 (3.73)
	3	0.56	0.27	0.08	0.26	1.75	1.18 (5.33)
	4	0.63	0.42	0.44	0.64	3.03	2.40 (3.81)
	5 (Overpriced)	1.22	0.91	1.15	1.54	3.44	2.22 (5.12)
	5–1						1.84 (4.24)

Note(s): This table reports the average net-buying imbalance of individual investors for portfolios sorted by MAX and MIS. At the end of each month t, we sort stocks into quintiles based on MIS and within each quintile, we sort them again into quintiles based on MAX. We report the average net-buying imbalance as the monthly sum of individual investors' daily (Korean Won) order imbalance, buy (Won) volume minus sell (Won) volume, divided by share outstanding (market capitalization), denoted as $\#Trd_{i,t}^{ind}$ ($\$Trd_{i,t}^{ind}$) in Panel A (B). Both $\#Trd_{i,t}^{ind}$ and $\$Trd_{i,t}^{ind}$ are scaled by 10^{-4} for the neatness of the table. The column labeled "5–1" shows the difference in average $\#Trd_{i,t}^{ind}$ or $\$Trd_{i,t}^{ind}$ between the top and bottom quintiles sorted by MAX. The row labeled "5–1" reports the difference in $\#Trd_{i,t}^{ind}$ or $\$Trd_{i,t}^{ind}$ of high-low MAX, between overpriced and underpriced stocks. The t-statistics corrected by Newey and West (1987) with 12 lags are shown in parentheses. The sample period is from July 2000 to December 2020

Source(s): Created by the authors

Table 7. MAX, MIS and trading direction of individual investors

high–low MAX quintile is 1.88, with a significant t-statistic of 4.36. Panel B shows similar results when we use $\$Trd_{i,t}^{ind}$ (scaled by 10^{-4}) as a proxy for individual investors' net-buying imbalance. According to the last row in Panel B, the $\$Trd_{i,t}^{ind}$ spread between the underpriced and overpriced stock groups across the high–low MAX quintile is 1.84, with a significant t-statistic of 4.24. In sum, the results in Panels A and B suggest that individual investors' demand for lottery-like stocks is concentrated among overpriced stocks.

Finally, we employ a triple-sort analysis to examine the pricing implications of heightened investor attention toward overpriced stocks with a high MAX. We aim to investigate the potential economic mechanism behind the observed MAX effect within overpriced stocks. Table 8 presents the average monthly returns and the Fama and French (1993) three-factor alphas for each stock group bivariate sorted by MAX and MIS, at high and low ΔVol levels. At the end of month t, we classify stocks into high and low ΔVol categories. We then further categorize them into quintiles based on the mispricing index and independently into quintiles based on MAX. Afterward, we report the average returns and alphas of the MIS-MAX-ΔVol groups in month $t + 1$.

Table 8 reveals an intriguing pattern: the MAX effect among overpriced stocks is primarily driven by stocks experiencing a substantial increase in trading volume. Among low ΔVol stocks, there is no discernible distinction in the alpha spread between the high–low MAX for overpriced and underpriced stocks. This implies that heightened attention triggers stock overpricing within the top MIS and MAX quintiles. In contrast, for high ΔVol stocks, we observe an amplified economic magnitude of our primary result. In the "difference-in-differences" perspective, the high–low MAX spread between the top MIS and MAX quintiles is -1.60% (t-statistic: -2.38) when the stocks increase in trading volume.

In summary, when stocks are overpriced and earn maximum positive returns, both investors' attention and individual investors' trading behavior are concentrated on these stocks. This phenomenon is pronounced among overpriced stocks. We conclude that our results from the bivariate sort analysis and cross-sectional regression in the previous sections are due to the investors' attention and individual investors' trading behavior being concentrated in the stocks that are both overpriced and have a history of maximum high returns; this leads to the stocks having relatively low expected returns.

Table 8.
Triple sort analysis on MAX-MIS-ΔVol

		MIS quintile						
		1 (Low)	2	3	4	5 (High)	5–1	5–1 alpha
Equal-weighted	High ΔVol	−1.06	−1.33	−2.51	−2.22	−2.45	−1.39	−1.60
		(−2.86)	(−3.01)	(−3.52)	(−4.07)	(−4.23)	(−2.35)	(−2.38)
	Low ΔVol	−0.53	−0.22	−0.38	−0.11	−0.85	−0.33	−0.16
		(−1.22)	(−0.45)	(−0.77)	(−0.24)	(−2.46)	(−0.68)	(−0.27)
Value-weighted	High ΔVol	−0.65	−0.77	−1.39	−2.83	−2.35	−1.70	−2.01
		(−0.97)	(−1.09)	(−2.18)	(−4.43)	(−2.65)	(−1.70)	(−1.74)
	Low ΔVol	−0.40	−0.09	0.09	−0.55	−1.14	−0.74	−0.39
		(−0.80)	(−0.26)	−0.14	(−0.91)	(−2.22)	(−1.23)	(−0.63)

Note(s): This table presents the average monthly returns and Fama and French (1993) three-factor alphas for each MAX-MIS stock group of high and low ΔVol. At the end of each month (t), we sort stocks into high and low ΔVol, the change in total trading volume relative to the average of the previous 12 months. Within each ΔVol group, stocks are further sorted into quintiles based on MIS. Subsequently, stocks are sorted into quintiles based on MAX. The table reports equal-weighted and value-weighted average alphas of the MAX-MIS-ΔVol groups in the month ($t + 1$). The row labeled "5–1" and "5–1 alpha" presents the MAX spread difference, calculated as the average returns and alphas between the top and bottom MAX quintiles, between the high MIS and low MIS quintiles. The t-statistics corrected by Newey and West (1987) with 12 lags are shown in parentheses. The sample period is from July 2000 to December 2020
Source(s): Created by the authors

6. Robustness tests

In this section, we conduct a series of robustness tests to validate our main results with various specifications. The results are presented in Table 9.

First, we conduct a sub-sample analysis. We reexamine our results by dividing the total sample into two 10-year sample periods of 2001–2010 and 2011–2020. We report the results of the bivariate sorted portfolio based on MIS and MAX in the two sub-sample periods. The results of the returns and factor-adjusted alphas show that our main findings of a strong MAX effect among overpriced stock groups are not sample-period driven. For example, when we use the sample period of 2011–2020 for the analysis, the differences in the return (three-factor alpha) spread between high-MAX and low-MAX stocks among overpriced firms and underpriced firms is −1.84% (2.08%) with a *t*-statistic of −5.60 (−5.20).

Second, one concern of the lottery-related anomalies is that the MAX effect is mainly driven by small-size firms (e.g. Bali *et al.*, 2011). To address this concern, we separate the stocks into three groups based on firm size. Firm sizes in the highest, middle, and lowest 33% are classified as big, medium, and small stocks, respectively. We reexamine whether the bivariate sort portfolio analysis based on MIS and MAX is consistent in these three stock groups categorized by firm size. The results show that the strong MAX effect among overpriced stock groups is reported in every stock group classified based on firm size. Specifically, the differences in returns and three-factor alphas in the MAX spread between high-MIS stocks and low-MIS stocks are −1.67% (*t*-stat = −2.64) and −1.83% (*t*-stat = −2.84), even for big stocks. These results provide evidence that small stocks do not drive our findings.

Finally, we exclude outlier samples where the monthly return exceeds 500%, as opposed to the previously specified threshold of 50,000%. We reexamine the bivariate sort portfolio analysis based on MIS and MAX and find the results to be consistent and even more

		MIS quintile						
		1 (Low)	2	3	4	5 (High)	5–1	5–1 alpha
Sub-sample period	2000~2010	−1.14	−1.62	−2.24	−2.82	−3.22	−2.08	−2.30
		(−1.95)	(−2.76)	(−5.63)	(−5.26)	(−5.10)	(−2.89)	(−2.82)
	2011~2020	−0.06	−0.67	−0.06	−1.11	−1.90	−1.84	−2.08
		(−0.20)	(−1.37)	(−0.12)	(−1.47)	(−5.56)	(−5.60)	(−5.20)
Sub-sample size	Small	−0.52	−0.98	−2.10	−0.93	−3.00	−2.46	−2.48
		(−0.93)	(−1.93)	(−3.51)	(−1.45)	(−5.01)	(−4.11)	(−3.50)
	Medium	−0.84	−1.64	−2.35	−2.34	−2.83	−1.99	−2.15
		(−1.35)	(−4.07)	(−4.06)	(−3.44)	(−5.41)	(−2.49)	(−2.82)
	Big	−0.78	−1.26	−0.85	−1.83	−2.44	−1.67	−1.83
		(−1.58)	(−3.26)	(−1.87)	(−2.74)	(−3.81)	(−2.64)	(−2.84)
Outlier 500%		−0.61	−1.15	−1.18	−1.97	−2.63	−2.01	−2.21
		(−1.88)	(−3.00)	(−3.01)	(−3.70)	(−6.71)	(−4.82)	(−4.79)

Note(s): This table reports the additional robustness checks for our results. The main results from the bivariate sort analysis in Table 3 are repeated while considering the following three additional conditions. First, we analyze the sub-sample period by dividing the sample period into two sub-period, 2000–2010 and 2011–2020. Additionally, we employ the sub-sample size analysis by classifying stocks into three categories, small, medium and large, based on their firm size. Third, we perform the alternative outlier huddle by excluding outlier samples whose monthly return exceeds 500%. The columns labeled "1" to "5" present the difference in equal-weighted average returns between the high- and low-MAX quintiles among each MIS quintile. The columns labeled "5–1" and "5–1 alpha" show the difference in MAX spread, where the MAX spread is calculated by the average returns and the Fama and French (1993) three-factor alphas of high-low MAX portfolios between the overpriced and underpriced groups. The *t*-statistics corrected by Newey and West (1987) with 12 lags are shown in parentheses. The sample period is from July 2000 to December 2020

Source(s): Created by the authors

Table 9. Robustness tests

substantial compared to our main results in Table 3. For example, the differences in returns and three-factor alphas in the MAX effect between high-MIS stocks and low-MIS stocks are -2.01% (t-stat $= -4.82$) and -2.21% (t-stat $= -4.79$), respectively.

In sum, the results of Table 9 provide evidence that our main results from Tables 3 and 4 are robust when we consider the different sub-sample groups.

7. Conclusion

This study uncovers a pronounced negative relationship between MAX and expected stock returns in the South Korean stock market, identified by Bali *et al.* (2011). We employ a bivariate sort analysis and a Fama and MacBeth (1973) cross-sectional regression and find additional evidence of the predictive power of MAX and MIS. High–low MAX portfolios exhibit negative returns and three-factor alphas for overpriced and underpriced stocks. However, the negative values lack statistical significance for underpriced stocks, and the spread's magnitude increases as stocks lean toward the overpriced side. Furthermore, we find that the MAX effect is particularly significant for overpriced stocks. This contrasts with findings from Zhong and Gray (2016) in the Australian stock market and Van Hai *et al.* (2020) in the Chinese stock markets, attributing the MAX effect to arbitrage asymmetry due to the strong positive link between MAX and IVOL. Our results suggest the potential influence of overlapping demand for lottery-like stocks and the presence of an arbitrage risk effect.

Furthermore, we establish that while the MAX effect and the IVOL puzzle share a connection, they do not mutually explain each other. The MAX effect, exclusive among overpriced stocks, is not solely a result of the high positive correlation between IVOL and MAX. Our findings further suggest that MAX and IVOL have predictive ability for stock returns in the South Korean stock market due to their provision of distinct information.

Finally, by analyzing direct trading activity data categorized by investor type, we discover that investors – especially individual investors – prefer high-MAX stocks over low-MAX stocks and are concentrated within overpriced stock groups. Using changes in trading volume as a proxy for investor attention and individual investors' trading behavior, we ascertain that investors' demand for lottery-like stocks is particularly significant only among overpriced stock groups; this leads to the negative future returns of those stocks. Our results withstand a battery of robustness tests, enhancing the significance of our research in advancing investigations into the MAX effect in the South Korean stock market.

Notes

1. Building on Stambaugh *et al.* (2015), Zhong and Gray (2016) observe a pronounced MAX effect in the Australian stock market, particularly among overpriced stocks, but reversed among underpriced stocks, explaining it by high correlation between MAX and idiosyncratic volatility. Similarly, in the Chinese stock market, Van Hai *et al.* (2020) find a significant MAX effect, exclusive to overpriced stocks, attributing it to asymmetric arbitrage role of MAX.

2. Cheon and Lee (2018b) discuss the MAX effect in the Korean market, but our study differs in key aspects. Firstly, they assert that the MAX effect in the Korean market is time-varying, particularly pronounced during high market volatility states. In contrast, we focus on the impact of cross-sectional mispricing within overpriced stocks. Secondly, while Cheon and Lee (2018b) also examine the relationship between the IVOL Puzzle and the MAX effect, the empirical analysis considers different causes. They analyze IVOL together with MAX, attributing it to market volatility's impact on individual stock idiosyncratic volatility. Conversely, our analysis, inspired by Stambaugh *et al.* (2015), explores IVOL from the arbitrage risk perspective. Lastly, from an empirical standpoint, they demonstrate the IVOL Puzzle in high MAX stocks, but our critical finding underscores that MAX and IVOL are not mutually subsumable. This is essential as our results are not merely implied by Stambaugh *et al.* (2015) but require a distinct argument.

3. The results when considering outliers as 500% is reported in Table 9 for the robustness checks.
4. We adhere to the construction of ΔVol as Barber and Odean (2008) outlined, where it is defined relative to the past 12-month average volume.

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Appendix

In this appendix, we provide the details of variables that are used in the main text of the paper. In Section A.1, we supplement the description in the text of how we construct the stock-level variables. In Section A.2, we provide the details of composite mispricing index construction.

A.1. Construction of stock-level variables

The key variable in this study is a maximum daily return of a stock over the past month (MAX), by following Bali *et al.* (2011). Specifically, MAX is defined as

$$MAX_{i,t} = MAX\left(r_{i,d}\right), d \in \left\{1, .., D_{i,t}\right\}, \tag{A.1}$$

where $r_{i,d}$ is stock i's return on day d and D_t is the number of trading days in month t.

Following Ang *et al.* (2006), IVOL is defined as the standard deviation of residuals from the single-factor model. Excess stock returns are regressed on the market risk premiums, by using daily returns over the previous 252 trading days, where returns are available for a minimum of 65 days. We run the following regression:

$$r_{i,d} - r_{f,d} = \alpha_i + \beta_i(r_{m,d} - r_{f,d}) + \varepsilon_{i,d}, \tag{A.2}$$

where $r_{i,d}$, $r_{m,d}$, and $r_{f,d}$ are the daily return of stock i, daily market return, and risk-free return on day d, respectively.

The systematic risk, beta (BETA), is estimated using the approach of Scholes and Williams (1977) to account for non-synchronous trading. At the end of month t, daily excess stock returns are regressed on the contemporaneous market risk premium, with one lead and one lagged value. The monthly beta is calculated by adding three sensitivities of the independent variables.

Size (ME) is the logged value of stock i's market value of equity in month t. The book-to-market ratio (BM) is the logged value of the book value divided by the market value of equity at the end of December of the previous year, by following Fama and French (1992).

The momentum (MOM) is computed as the buy-and-hold return over the previous 11-months with a one-month lag, by following Jegadeesh and Titman (1993).

The short-term reversal (REV) is computed as the stock return in the previous month, by following Jegadeesh (1990).

	MIS decile										
	1 (Underpriced)	2	3	4	5	6	7	8	9	10 (Overpriced)	10–1
Panel A: equal-weighted portfolios											
Excess	1.49	1.34	1.29	1.09	1.13	1.24	1.06	1.00	0.92	−0.16	−1.65
return	(3.63)	(3.33)	(2.89)	(2.48)	(2.40)	(2.63)	(2.05)	(1.98)	(1.81)	(−0.26)	(−3.93)
3-factor	1.49	1.35	1.32	1.13	1.21	1.33	1.11	1.10	0.98	−0.07	−1.56
alpha	(3.27)	(3.11)	(2.74)	(2.34)	(2.43)	(2.65)	(2.05)	(1.99)	(1.79)	(−0.10)	(−3.80)
Panel B: value-weighted portfolios											
Excess	1.06	0.73	0.74	0.29	0.37	0.37	0.13	0.41	0.65	−0.68	−1.75
return	(2.72)	(2.25)	(1.50)	(0.64)	(0.79)	(0.75)	(0.26)	(1.00)	(1.13)	(−1.00)	(−2.98)
3-factor	1.11	0.65	0.74	0.37	0.39	0.54	0.11	0.66	0.86	−0.40	−1.51
alpha	(2.79)	(2.10)	(1.51)	(0.82)	(0.84)	(1.06)	(0.22)	(1.47)	(1.44)	(−0.56)	(−2.45)

Note(s): This table represents the average of monthly excess returns and Fama and French (1993) three-factor alpha for each decile sorted by constructed mispricing index (MIS) by following the methodology of Stambaugh *et al.* (2015). MIS is created by aggregating the seven percentile rankings assigned by seven anomalies (z-score, net operating assets, momentum, gross profitability premium, asset growth, accrual, and return on assets). We report the equal-weighted (value-weighted) returns and Fama and French (1993) three-factor alpha of each MIS decile in Panel A (B). The column labeled "10–1" reports the difference in average returns and alphas between the top and the bottom MIS deciles. The t-statistics corrected by Newey and West (1987) with 12 lags are shown in parentheses. The sample period is from July 2000 to December 2020
Source(s): Created by the authors

Table A1.
MIS portfolio returns

A.2. Construction of mispricing index and stock return anomalies

Stambaugh *et al.* (2015) construct the mispricing index by calculating a composite rank of each stock based on a number of firm-level characteristics associated with eleven well-known anomalies. They build a single proxy for mispricing that allows the classification of stocks by direction and degree of mispricing associated with anomalous returns. Due to the lack of available data, we follow the methodology of Chang *et al.* (2016), who measure the mispricing index in the Korean stock market using seven anomalies among Stambaugh *et al.*'s (2015) eleven. Altman (1968) z-score, net operating asset (NOA), momentum (MOM), gross profitability premium (GPP), asset growth (AG), accrual (ACC), and return-on-assets (ROA) are used as well-known stock return anomalies in constructing the composite mispricing index in this study. Each variable is estimated in December and used for the following 12 months from July. For instance, after calculating AG using total assets of December 2000, this AG corresponds to the period from July 2001 to June 2002. This ensures that the financial statements are publicly announced and available when the variables are estimated.

First, Altman (1968) z-score is defined by the following formula:

$$z-score = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5, \tag{A.3}$$

where $X_1 = \frac{Current\ Asset - Current\ Liabilities}{Total\ Assets}, X_2 = \frac{Retained\ Earnings}{Total\ Assets}, X_3 = \frac{Operating\ Income}{Total\ Assets},$

$$X_4 = \frac{Market\ Capitalization}{Total\ Liabilities},\ X_5 = \frac{Sales}{Total\ Assets}$$

Second, net operating profit ($NOA_{i,t}$) is defined as operating assets ($OA_{i,t}$) minus operating liabilities ($OL_{i,t}$) scaled by lagged total assets ($TA_{i,t-1}$):

$$NOA_{i,t} = \frac{OA_{i,t} - OL_{i,t}}{TA_{i,t-1}} \tag{A.4}$$

Third, momentum ($\text{MOM}_{i,t}$) is defined as stock i's momentum at time t.
Fourth, the gross profitability premium ($GPP_{i,t}$) is defined as earnings before interest, tax, depreciation, and abnormals ($GP_{i,t}$) scaled by lagged total assets ($TA_{i,t-1}$):

$$GPP_{i,t} = \frac{GP_{i,t}}{TA_{i,t-1}} \tag{A.5}$$

Fifth, asset growth ($AG_{i,t}$) is defined as the year-on-year growth rate of the total assets ($TA_{i,t}$):

Control variable	BETA	ME	BM	MOM	REV
Panel A: equal-weighted portfolios					
1 (Low)	1.66	1.61	1.43	1.63	1.59
2	1.57	1.56	1.44	1.43	1.38
3	1.15	1.32	1.32	1.18	1.25
4	0.97	0.89	1.01	0.87	0.89
5 (High)	−0.09	−0.10	0.08	0.13	0.17
5–1	−1.75	−1.71	−1.35	−1.50	−1.42
	(−5.46)	(−5.13)	(−4.47)	(−4.98)	(−4.76)
5–1 alpha	−1.78	−1.68	−1.36	−1.51	−1.32
	(−5.98)	(−4.98)	(−4.31)	(−4.75)	(−4.51)
Panel B: value-weighted portfolios					
1 (Low)	0.74	1.47	0.84	0.68	0.76
2	0.99	1.51	1.02	0.67	0.75
3	0.55	1.30	0.93	0.48	0.78
4	0.49	0.81	0.92	0.28	0.41
5 (High)	−0.96	−0.11	−0.37	−0.60	−0.56
5–1	−1.71	−1.58	−1.20	−1.28	−1.32
	(−4.17)	(−4.93)	(−3.22)	(−3.46)	(−3.43)
5–1 alpha	−1.67	−1.53	−1.22	−1.24	−1.28
	(−4.34)	(−4.89)	(−3.12)	(−3.30)	(−3.38)

Note(s): This table represents the results of the MAX effect after controlling for various firm-characteristics by performing dependent bivariate sort analysis. Each month, stocks are sorted into quintiles based on one of the firm-characteristic variables as the control variable. Then, stocks are further sorted into quintiles within each quintile based on MAX. We report the average monthly excess returns across quintiles sorted by control variable for each MAX quintile. The raw labeled "5–1" and "5–1 alpha" reports the difference in average returns and Fama and French (1993) three-factor alphas between the top and the bottom MAX quintile portfolio. The t-statistics corrected by Newey and West (1987) with 12 lags are shown in parentheses. The sample period is from July 2000 to December 2020
Source(s): Created by the authors

Table A2.
MAX effect after controlling firm-characteristics

$$AG_{i,t} = \frac{TA_{i,t} - TA_{i,t-1}}{TA_{i,t-1}} \tag{A.6}$$

Sixth, accrual ($ACC_{i,t}$) is defined as earnings before interest and tax ($NI_{i,t}$) minus cash flow from operations ($CFO_{i,t}$) scaled by lagged total assets ($TA_{i,t-1}$):

$$ACC_{i,t} = \frac{NI_{i,t} - CFO_{i,t}}{TA_{i,t-1}} \tag{A.7}$$

Finally, return on assets ($ROA_{i,t}$) is defined as earnings before interest and taxes ($NI_{i,t}$) scaled by lagged total assets ($TA_{i,t-1}$):

$$ROA_{i,t} = \frac{NI_{i,t}}{TA_{i,t-1}} \tag{A.8}$$

Table A3.
IVOL portfolio returns

	IVOL decile										
	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	10–1
Panel A: equal-weighted portfolios											
Excess	1.48	1.55	1.60	1.64	1.46	1.36	1.36	0.74	0.57	−1.32	−2.80
return	(3.82)	(3.65)	(3.75)	(3.64)	(3.16)	(2.85)	(2.70)	(1.56)	(1.06)	(−1.75)	(−5.11)
3-factor	1.46	1.62	1.67	1.71	1.45	1.46	1.49	0.89	0.60	−1.37	−2.83
alpha	(3.83)	(3.74)	(3.70)	(3.49)	(2.94)	(2.76)	(2.70)	(1.65)	(0.98)	(−1.69)	(−4.65)
Panel B: value-weighted portfolios											
Excess	0.45	0.57	0.86	0.86	0.78	0.55	1.06	0.33	−0.33	−2.49	−2.94
return	(1.31)	(1.34)	(2.00)	(1.73)	(1.55)	(1.09)	(1.96)	(0.68)	(−0.59)	(−3.27)	(−4.25)
3-factor	0.51	0.65	0.95	0.94	0.79	0.60	1.18	0.44	−0.24	−2.44	−2.95
alpha	(1.55)	(1.42)	(2.26)	(1.84)	(1.51)	(1.18)	(2.13)	(0.77)	(−0.40)	(−2.99)	(−3.93)

Note(s): This table represents the average monthly excess returns and Fama and French (1993) three-factor alphas for each decile portfolio sorted by idiosyncratic volatility (IVOL). IVOL is defined as the standard deviation of residuals from a single-factor model, following Ang *et al.* (2006). We report the equal-weighted (value-weighted) returns and Fama and French (1993) three-factor alphas for each IVOL decile in Panel A (B). The column labeled "10–1" reports the average returns and alpha difference between the top and the bottom IVOL decile portfolio. The *t*-statistics corrected by Newey and West (1987) with 12 lags are shown in parentheses. The sample period is from July 2000 to December 2020
Source(s): Created by the authors

Corresponding author
Donghoon Kim can be contacted at: kdh9406@kaist.ac.kr