The MAX effect at the turn-of-the-month: Evidence from the Korean stock market*

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Abstract

We investigate how the MAX effect interacts with the turn-of-month effect in the Korean stock market. Prior studies at a monthly frequency have shown that stocks with an extremely high return on a day in the previous month tend to have low returns in the following month, known as the MAX anomaly. Our daily frequency study, however, finds that there exists a cyclicality of the MAX anomaly within a month. Specifically, a MAX long-short portfolio earns positive returns over a few days at the beginning of each month (at the turn of the month), but the profit is completely subdued by negative returns over the rest days of the month, resulting in the monthly negative return of the MAX anomaly in the monthly frequency literatures. Constructing a lottery stock index based on lottery characteristics, we find that a lottery-index long-short portfolio also exhibits similar results. This suggests that the cyclicality of the MAX effect possibly comes from a variation in individual investors' demand for lottery-type stocks depending on their personal funding liquidity over the course of the month.

Keywords: FnGuide; Korean stock market; lottery-type stocks; MAX anomaly; turn-of-month effect

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1 Introduction

Changes in investor sentiment and personal funding liquidity around the beginning of the month (or turn-of-the-month, hereafter TOM) may contribute to mispricing of lottery-type stocks. This intuition leads us to investigate the relationship between two well-known anomalies. One is the TOM anomaly that stock returns are higher at the beginning of the month relative to the rest of days in the month. Literatures indicate that the investor sentiment becomes more optimistic around the beginning of a month during which returns are positive. The other is the MAX anomaly that stocks with a high historical maximum return earn lower returns in the future. Literatures on MAX anomaly argue that preferences for positive skewness leads stocks with a high MAX return to be overpriced and subsequently those stocks realize negative future returns. See the literature review section for more details.

Taken together, we hypothesize that preferences for positive skewness (e.g., high MAX return) can be magnified during the period when sentiment is optimistic. Thus, even though high MAX stocks have negative returns in the following month, we expect high MAX stocks to have positive (rather than negative) returns during TOM days (a few days at the beginning of a month). Our research can contribute to uncover why the MAX anomaly exists or what causes it. Even though many studies have examined the MAX anomaly and the TOM anomaly separately, few paper focuses on the interaction between the two anomalies. This study can provide new insight and implications about the relationship between investors' mentality and preferences for return skewness. In addition, while previous studies on anomaly typically have employed monthly return data, we explore the anomalies at higher frequency, that is, using daily return data. As shown in our preliminary test, anomaly profit is not even over days in a month. The profit may be concentrated on specific days. Interestingly, we find positive returns of high MAX stocks during TOM periods, which is opposite to the findings of previous studies using monthly stock data.

This cyclicality of the MAX anomaly is attributed to a common feature of lottery-type stocks. When we conduct the same analysis with alternative measures of lottery characteristics such as low price, high idiosyncratic volatility, and high idiosyncratic skewness, we find qualitatively similar patterns. In particular, the overpricing of lottery-like stocks during the TOM period is very robust to alternative measures. In order to generalize and summarize the experiment, we construct a lottery index using all the measures of lottery characteristics and confirm that lottery-type stocks have the within-month cycle of daily returns; that is, lottery-type stocks are gradually overpriced over a few days at the beginning of the month and all the profits are completely subdued by the negative returns over the rest days, eventually producing the monthly negative return as shown in the literatures.

To our knowledge, our paper is the first to uncover the MAX effect at the TOM in the Korean stock market. South Korea is a country where retail investors account for the majority of total trading. According to data from FnGuide, the retail trading proportion ranges from 65% to 90% in our sample. Retail investors who have a high tendency to gamble are known to prefer to invest more in the lottery-like stocks that have a low probability of winning but reap enormous returns if they win (Han and Kumar 2013). The emotions, thoughts and aspirations to rise in life can be the reasons that investors still invest in lottery-like stocks even if expected returns are negative (Statman 2002). Investors' preference for lottery-like stocks has been modeled in many papers (Brunnermeier, Gollier, and Parker 2007; Mitton and Vorkink 2007; Barberis and Huang 2008). An interesting finding in (Evans and Moore (2012) shows that lottery sales tend to peak during the first few trading days of the month. Lottery buyers and lottery-like stock investors, on the other hand, share similar characteristics (Kumar 2009). Therefore, the demand for investing in lottery-like stocks also soars at the TOM. The reason is that, as explained by Ogden (1990), retail investors with low income are likely to have the strongest liquidity position at the TOM, the demand thus increase and returns on lottery-like stocks skyrocket at the TOM higher than those on non-lottery-like stocks. Therefore, South Korea with a high concentration of retail traders is an ideal choice to investigate the long-short strategy of MAX anomaly (i.e. the difference between the highest MAX stocks and the lowest MAX stocks) at the TOM.

Our study indicates that the MAX effect on the cross-section of stock returns, which has been clearly demonstrated to be negative in prior papers, changes to positive around the beginning of the month. Stocks with extreme positive returns (i.e. high MAX stocks, lottery-like stocks) are poor long-term investment option that is suggested in previous studies. However, we observe that these stocks outperform at the TOM, which may be useful for practitioners to maximize the profit from an anomaly strategy. Our result indicates that a strategy of buying a portfolio consisting of stocks with high maximum daily returns and selling a portfolio consisting of stocks with low maximum daily returns can be obtained approximately 0.4% per month.

2 Literature review

Researchers around the world have found evidence of the presence of the MAX effect on the cross-section of stock returns. First, Bali, Cakici, and Whitelaw (2011) explore the new anomaly, known as the MAX effect. They observe the data in the US stock market from January 1926 to December 2005 and define MAX as the maximum daily return over the previous month. They prove that stocks with high MAX tend to have expected higher returns than stocks with low MAX. Specifically, long-short strategy generate an average return of approximately -1% per month. They attempt to interpret this effect as a new assumption about investor preference. Investors prefer lottery-like stocks (i.e. stocks with high extreme positive returns), leading to a spike in the stock price and thus the expected return is relatively low. This effect is confirmed to be significant even after controlling for various firm characteristics known to be related to stock returns, such as firm size, book to market ratio, momentum, short-term reversal, and liquidity. The persistence of MAX effect in the US market is also confirmed in the study of Fong and Toh (2014). Meanwhile, outside the US, Walkshäusl (2014) and Annaert, De Ceuster, and Verstegen (2013) also present the evidence of negative MAX effect in the European stock markets. However, in the study of Annaert, De Ceuster, and Verstegen (2013), the MAX effect is only apparent after controlling for other factors in double-sorted portfolio analysis and cross-sectional regressions. Exploring emerging markets, Zhong and Gray (2016) discover that the negative MAX effect is economically significant in the Australian market by using a variety of approaches over the period 1991-2003. In addition, they prove that the MAX effect is not due to a common risk factor in returns, but due to mispricing. Nartea, Wu, and Liu (2014) and Kang and Sim (2014) indicate that high MAX stocks underperform low MAX stocks in the South Korean market and this phenomenon is not driven by well-known cross-sectional effects. They also explain that investor preference for high MAX stocks is the reason for this effect. Therefore, the behavior of investors in the South Korea market is similar to that of investors in the US market despite the difference in the level of development. However, this effect is only apparent in equal-weighted portfolios.

A growing body of papers have documented the TOM anomaly. Ariel (1987) is generally recognized as the first academic researcher to record a monthly cycle in stock returns from 1963 to 1981. He notices that stocks tend to have higher returns in the first half of the month compared to the rest of the month. However, he cannot give a complete explanation for this phenomenon. An explanation is later given in Penman (1987)'s research paper, which suggests that companies tend to announce good news during the first half of the month and keep bad news until the second half of the month. Unlike Ariel, Lakonishok and Smidt (1988) define the TOM period as four consecutive days starting from the last trading day of the previous month to the first three trading days of the month and find a strong evidence of positive returns around the turn of the month during the period 1897-1986 using the Dow Jones Industrial Average. Ogden (1990) also offers evidence and explanation for the TOM anomaly. He argues that since the "standardization of payments system" in the US often pays dividends and salaries at the end of the month, the cash flow focuses around the TOM period, making the liquidity position of investors at the highest level, leading to a high demand for stock investment, which make returns increase in the short time.

Combining these two aspects, we speculate that the well-known MAX effect on stock returns may change around the TOM period. An interesting finding presented in Meng and Pantzalis (2018) is that the performance of lottery-like stocks is higher than that of non-lottery like stocks at the TOM due to high demand from retail investors on the days around the beginning of the month for lottery-like stocks with attributes such as low price, high idiosyncratic volatility and high idiosyncratic skewness. Since stocks with the extreme positive returns can be considered as lottery-like stocks, we conjecture that the MAX effect on future returns changes from negative to positive at the TOM. Therefore, we hypothesize that high MAX stocks earn higher returns than low MAX stocks around the turn of the month.

Motivated by these studies, we investigate the role of the extreme positive returns in stock returns on the TOM trading days. Most of previous studies (Bali, Cakici, and Whitelaw 2011; Walkshäusl 2014; Annaert, De Ceuster, and Verstegen 2013; Nartea, Wu, and Liu 2014; Kang and Sim 2014) suggest that high MAX stocks underperform low MAX stocks in the long run. In other words, the long-short strategy from MAX anomaly produces negative average returns. However, we explore that this MAX effect changes around the turn-of-month period. Specifically, we find that high MAX stocks earn higher returns than low MAX stocks on four consecutive trading days, starting from the last trading days of previous month. A similar result is found in the study of Meng and Pantzalis (2018). They show that lottery-like stocks outperform non-lottery-like stocks at the TOM. In the research, they use three criteria which are low price, high idiosyncratic volatility and high idiosyncratic skewness to classify stocks as lottery-like stocks. In our study, however, we focus on the effect of MAX, another characteristic of a lottery-like stock. Furthermore, we examine the MAX anomaly around the TOM in a representative emerging market, South Korea, which makes our study distinct from Meng and Pantzalis (2018).

3 Methodology

3.1 Data

Our sample includes information of common stocks traded in the Korea Composite Stock Price Index (KOSPI) market, taken from DataGuide provided by FnGuide over the period from December 1998 to May 2020. In the sample, we require stocks to have a closing price higher than KRW 1000. To extenuate the impact of outliers, observations of 15 days prior to the delisting date of the stock are excluded. In addition, the days when stocks have absolute returns higher than 30% and zero trading amount are also excluded. After filtering data, there are 3,468,275 firm-day observations in the sample. In our sample, daily returns are employed to estimate returns on the trading days around the beginning of the month, the maximum daily return of each month and control variables such as illiquidity ratio, systematic and idiosyncratic skewness. The CD-91 rate is assigned to the risk-free rate for calculating excess return. Monthly returns are used to construct momentum and short-term reversal variables. Trading amount for calculating illiquidity variable and accounting information such as book equity are also available in DataGuide.

3.2 Variable definitions

The aim of this study is to examine the MAX effect in the turn-of-month period. Therefore, the main variable in our study is MAX. According to Bali, Cakici, and Whitelaw (2011), we assign the maximum daily return of each month to the MAX variable. One month requires at least 15 daily observations available. For consistency with previous studies (Lakonishok and Smidt 1988; Kunkel, Compton, and Beyer 2003; McConnell and Xu 2008; Meng and Pantzalis 2018), the turn-of-month period is from the last trading day of the previous month to the first three trading days of the month. We calculate the turn-of-the-month return as the cumulative excess return on trading days from -1 to +3 of each month.

To separate the effect of other characteristics in cross-sectional returns, we control for several other variables in portfolio analysis and cross-sectional regression. Control variables are estimated at the beginning of month t as follows: The momentum variable (MOM) in month t estimated according to Jegadeesh and Titman (1993) is the cumulative returns in the previous 11 months after skipping 1 month prior to that month (i.e. from month $t-12$ to month $t-2$). We use the return in month $t-1$ to proxy for the short-term reversal variable (STR) of each stock in month t, following Jegadeesh (1990). Size in month t is the logarithmic market equity computed by share price multiplied by the number of shares outstanding in month $t-1$. According to Fama and French (1992), book-to-market (BM) ratio of each stock in March of year T is calculated by book equity in December of year $T-1$ divided by market equity in December of year $T-1$. Then, this ratio is assigned for the period from April of year T to March of year $T+1$ to match monthly data. Accordingly, the BM ratio of each month is taken from the most recent March. Using the approach of Amihud (2002), the illiquidity (ILLIQ) of each stock in month t is measured by the absolute daily return divided by the trading amount and then averaged in month $t-1$. In light of Harvey and Siddique (2000), idiosyncratic skewness (ISKEW) of each stock in month t is defined as the skewness of daily residuals in the previous year from month $t-12$ to month $t-1$, estimated from daily regressions of excess stock returns on market excess returns and the square of the market excess returns. The coefficient of the square of the market excess returns in the above regressions is assigned to systematic skewness (SSKEW) variable. While estimating ISKEW and SSKEW variables, a year must have at least 180 daily observations per year.

3.3 Portfolio analysis

First, we examine the effect of MAX on the cross-section of returns around the beginning day of the month at the portfolio level. At the beginning of month t, quintile portfolios are constructed by sorting stocks based on MAX defined as the maximum daily return in month $t-1$. We reform portfolios every month. Then, we calculate both equal- and value-weighted average excess returns and abnormal returns (the CAPM and the Fama-French-three-factor (FF3) alphas) of portfolios only on turn-of-month trading days from the last trading day in month t to the first three trading days in month $t+1$. We also check the pattern of MAX-sorted portfolio returns on the remaining trading days of month $t+1$, except the last trading day of that month. CAPM alphas or FF3 alphas are intercepts estimated from regressions of the average excess returns of portfolios on market excess return or three factors in Fama and French (1993) such as market excess return, size (SMB) and book-to-market (HML) factors.

To control for other known firm characteristics, we use double-sorts. First, we sort stocks into quintile portfolios based on the control variables estimated in month t, detailed in Section 3.2. Within each portfolio, we continue to divide stocks into quintiles on MAX, described in Section 3.2. Then, similar to single-sorted portfolio analysis, we also calculate value- and equal-weighted average excess returns, the CAPM alphas and the FF3 alphas of 25 portfolios on turn-of-month trading days from the last trading day in month t to the first three trading days in month $t+1$. The average return across the five control portfolios within each MAX portfolio is computed. From there, we can observe the fluctuation of average return in MAX-sorted portfolios after controlling for the effects of other characteristics and report a MAX effect at the TOM.

3.4 Cross-sectional regression

Finally, we run the following cross-sectional regressions to confirm the MAX effect around the turn-of-month period after controlling for other characteristics simultaneously.

$$R_{i,t+1} = \beta_0 + \beta_1 MAX_{i,\mathrm{t}-1} + \sum_{k=1}^{n} \beta_k F_{k,i,\mathrm{t}-1} + \varepsilon_{i,t+1} \tag{1}$$

where $R_{i,t+1}$ is the cumulative excess return of stock i (or portfolio) from the last trading day of month t to the first three trading days of month $t+1$, i.e., over turn-of-month trading days. $MAX_{i,t-1}$ is the daily maximum return in month $t-1$. $F_{k,i,t-1}$ are the control variables of stock i estimated at the end of month $t-1$. Thus, one month is skipped between the measurement period of dependent and independent variables in order to avoid a micro-market structure effect as well as a look-ahead bias due to the otherwise overlap of one trading day. The monthly regression results are averaged in the same manner of Fama and MacBeth (1973).

4 Empirical Results

4.1 Summary statistics

Some basic statistical indicators of the variables used in our study are presented in Table 1. In which, panel A displays the statistics such as mean, standard deviation, 25th percentile, median and 75th percentile. Panel B reports correlations between variables. Correlations between the variables with cross-sectional data are estimated monthly and then averaged over time. As shown in panel A, the mean value of MAX is approximately 1% higher than the median value, indicating that the distribution of extreme positive returns is right-skewed or a few stocks have very high returns.

Table 1: Descriptive statistics

Panel A displays the statistics of variables in this study. Panel B reports correlations between variables. Correlations between the variables with cross-sectional data are estimated monthly and then averaged over time.

Panel A: Summary statistics

Variable	Mean	STD	P25	Median	P75
MAX	6.49	4.02	3.72	5.50	8.23
SSKEW	-0.05	0.10	-0.10	-0.04	0.01
ISKEW	0.75	0.75	0.30	0.66	1.13
MOM	14.26	60.64	-17.38	3.31	31.04
STR	1.22	15.75	-6.36	-0.43	6.48
SIZE	11.91	1.68	10.70	11.58	12.82
BM	2.63	21.86	0.86	1.46	2.28
ILLIQ	0.33	1.01	0.01	0.05	0.21

Panel B: Correlation

	BM	MOM	ILLIQ	ISKEW	MAX	SIZE	SSKEW
MOM	0.02						
ILLIQ	0.18	-0.06					
ISKEW	0.08	0.08	-0.04				
MAX	-0.02	0.11	-0.02	0.16			
SIZE	-0.30	0.13	-0.29	-0.21	-0.12		
SSKEW	-0.05	0.00	-0.01	-0.09	-0.07	0.24	
STR	0.02	-0.01	-0.01	0.09	0.38	0.05	0.00

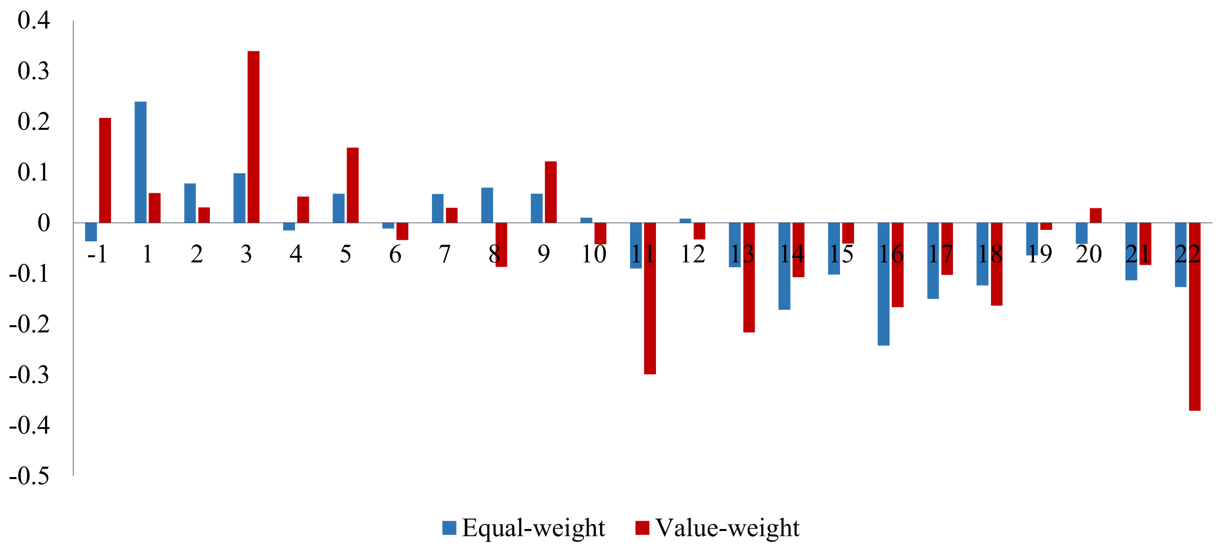

Figure 1: Average daily returns on zero-cost portfolio formed on MAX

The equal-weighted and value-weighted excess return of the zero-cost portfolio on each trading day of the month is illustrated. The zero-cost portfolio is determined by the highest MAX-sorted portfolio minus the lowest MAX-sorted portfolio. MAX is defined as the maximum daily return in previous month.

Figure 1 shows the equal-weighted and value-weighted excess returns of the high-low portfolio, as determined by MAX quintile 5 minus MAX quintile 1, on each trading day of the month. Due to the definition of the TOM period, a month starts from the last trading day of the previous month. In the figure, the number -1 means the last trading day of the month. The numbers 1, 2, 3 mean the first, second and third trading day of the month, etc. As illustrated in the figure in both the equal-weight and value-weight cases, the excess returns of the high-low portfolio on the TOM trading days are relatively higher than for the rest of the month. In the case of the equal-weight, the MAX return spread (the difference in excess return between the highest MAX quintile and the lowest MAX quintile) is positive and is the highest in the first three trading days of the month. However, this spread decreases and is mostly negative on the remaining days of the month. In the case of the value-weight, the MAX return spread is positive and high from day -1 to day 3 and reaches its highest value on day 3. After that time, the spread diminishes and is mostly negative. Based on the figure, it is clearly that the MAX return spread is not evenly distributed across trading days of the month. Interestingly, the well-known MAX anomaly suggested by Bali, Cakici, and Whitelaw (2011) changes across the month. According to previous research on the MAX effect, a hedge portfolio is created by taking long positions on low MAX stocks and short positions on high MAX stocks. Nevertheless, according to the research results shown in the figure, the effect of MAX on the cross-sectional stock returns is not consistent over the month, it changes on specific days.

Specifically, this effect is reversed during the first trading days of the month or during the TOM period. In other words, high MAX stocks earn higher returns than low MAX stocks for a few days around the beginning of the month, as opposed to the rest of the month.

4.2 Portfolio analysis

Intuitively, we can observe that the MAX effect on cross-sectional stock returns during the first few days of the month differs from the rest of the month, based on the results in Figure 1. To demonstrate this anomaly more clearly, we apply the method of portfolio analysis. Table 2 presents the results of single-sorted portfolios formed on value of MAX. The stocks with the lowest MAX value are classified into portfolio 1 and portfolio 5 contains the stocks with the highest MAX value. The row labeled 'High-Low' indicates the different values of the two extremes, portfolio 5 and portfolio 1. In the table, we show both equal-weighted and value-weighted calculations. For each calculation method, average excess returns and abnormal returns (CAPM alphas and FF3 alphas) of portfolios are reported. The numbers in parentheses display Newey and West (1987) t-statistics with a lag of 12. We observe the pattern in portfolio returns in two periods of the month. In panel A, we calculate the cumulative excess returns of each stock on the turn-of-month trading days of each month, then average excess returns of portfolios are computed each month. CAPM alphas or FF3 alphas are intercepts estimated from regressions of portfolio excess returns on market excess returns or three factors. Panel B is similar to panel A, except that we calculate the cumulative excess returns of each stock for the rest of the month, except for the days in the TOM period. Therefore, we can examine an unusual change in the MAX effect on cross-sectional stock returns on the TOM trading days of the month compared to the rest of the month.

Considering for details in panel A, we observe that the pattern of return does not increase monotonously with an increase in the MAX value. In the case of equal-weighted calculation, although the average excess returns and alphas decrease slightly in portfolio 3, they generally tend to increase with the MAX value. The stocks with the highest MAX value in quintile 5 have higher average excess return and alphas than stocks with lower MAX value. As reported in panel A, the difference in average excess return between quintile 5 (high MAX) and quintile 1 (low MAX) is 0.41% and strongly significant at 1% level. The results are similar for alphas, where the CAPM alpha spread is 0.4% and the FF3 alpha spread is 0.34% and both are significant at 1% level. For value-weighted calculation, average excess return and alphas increase steadily from the portfolio with the lowest MAX stocks to the portfolio with the highest MAX stocks. The MAX return spread is reported to be in the range of 0.63%-0.67%. As proved by Bali, Cakici, and Whitelaw (2011), stocks with high extreme positive returns (MAX) in the past are likely to continue to have high MAX value in the following month. Therefore, investors prefer stocks with high extreme positive returns or high MAX, which have a low probability of winning but can reap enormous returns, because investors expect the persistence of the MAX effect. Moreover, the TOM period is the time when investors have abundant cash flow and financial resources, optimistic sentiment that makes investment potential increase. Hence, during the first few trading days of the month, a surge in investor demand for lottery-like stocks or high MAX stocks, causing these stocks to overprice for a short period of the month.

Looking at panel B, the result of the MAX effect for the rest of the month is found to be reversed compared to the TOM trading days. This result is consistent with the suggestions of previous researchers when they use monthly frequency to investigate the MAX effect on stock returns, which is reviewed in detail in the literature section. In both ways of calculation, the MAX return spread and alpha spread are significantly negative.

However, the significance level in the case of value-weighted calculation decreases compared to the case of equal-weighted calculation in both panel, suggesting that the strong MAX effect focuses mainly on small stocks.

Overall, we observe a difference in the MAX effect over two periods in the same month. Specifically, the MAX return spread made up of the highest portfolio return minus the lowest portfolio return is significantly positive in the TOM period. However, this spread becomes negative during the latter part of the month. The positive return spread in the TOM period is less than the negative return spread for the rest of the month, suggesting that the cumulative return spread for the whole month is likely to be negative, similar to the results found in previous studies using monthly return data.

Table 2: MAX-sorted portfolios

Quintile portfolios are constructed at the beginning of month t by sorting stocks based on MAX defined as the maximum daily return in month $t-1$. Portfolios are reconstructed every month. The stocks with the lowest MAX value are classified into portfolio 1 and portfolio 5 contains the stocks with the highest MAX value. Both equal- and value-weighted average excess returns and abnormal returns (CAPM and Fama-French-three-factor alphas) of portfolios are calculated and then averaged across the months. The row labeled 'High-Low' indicates the different values of the two extremes, portfolio 5 and portfolio 1. The numbers in parentheses display Newey and West (1987) t-statistics with a lag of 12. In panel A, the average excess returns and alphas of portfolios are calculated only on turn-of-month trading days from the last trading day in month t to the first three trading days in month $t+1$. In panel B, the average excess returns and alphas of portfolios are calculated on the remaining trading days of month $t+1$, except the last trading day of that month.

	Equal-weight			Value-weight		
Portfolio	Excess return	CAPM-Alpha	FF3-Alpha	Excess return	CAPM-Alpha	FF3-Alpha
Panel A: Turn-of-month						
1 (Low)	0.66***	0.62***	0.49***	0.20	0.13	0.08
	(3.46)	(3.12)	(2.68)	(0.97)	(0.70)	(0.42)
2	0.79***	0.73***	0.58***	0.53**	0.45*	0.34
	(3.69)	(3.28)	(2.92)	(2.07)	(1.68)	(1.44)
3	0.76***	0.70***	0.55***	0.66**	0.58*	0.52*
	(3.63)	(3.21)	(2.65)	(2.11)	(1.84)	(1.66)
4	0.93***	0.86***	0.71***	0.68**	0.58**	0.51*
	(3.66)	(3.24)	(2.91)	(2.37)	(2.04)	(1.82)
5 (High)	1.08***	1.01***	0.84***	0.88***	0.76***	0.71**
	(4.23)	(3.79)	(3.45)	(3.01)	(2.64)	(2.37)
High-Low	0.41***	0.40***	0.34***	0.67***	0.63***	0.63***
	(3.95)	(3.64)	(3.20)	(2.98)	(2.64)	(2.65)
Panel B: Non turn-of-month						
1 (Low)	0.64*	0.41**	-0.04	0.02	-0.21	-0.24
	(1.92)	(2.04)	(-0.25)	(0.05)	(-0.92)	(-0.93)
2	0.65*	0.38*	-0.11	0.16	-0.08	-0.09
	(1.68)	(1.85)	(-0.56)	(0.46)	(-0.47)	(-0.44)
3	0.55	0.27	-0.16	-0.22	-0.52*	-0.46
	(1.37)	(1.29)	(-0.71)	(-0.46)	(-1.71)	(-1.65)
4	0.47	0.17	-0.25	0.03	-0.31	-0.44
	(1.14)	(0.70)	(-1.11)	(0.06)	(-1.03)	(-1.22)
5 (High)	-0.10	-0.39	-0.86***	-0.76	-1.11***	-1.26***
	(-0.23)	(-1.36)	(-2.83)	(-1.28)	(-2.89)	(-2.72)
High-Low	-0.74***	-0.80***	-0.82***	-0.78**	-0.90***	-1.03***
	(-3.20)	(-3.75)	(-3.61)	(-2.17)	(-2.89)	(-2.66)

*, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

As suggested in previous papers on the MAX effect, they point out that the MAX effect can be attributed to firm characteristics. To see more clearly the attributes of the high MAX stocks, we report summary statistics for MAX-sorted portfolios in Table 3. Specifically, we sort stocks into quintiles based on their MAX values for each month. We then estimate the median value of each characteristic in each portfolio within each month and average across the months. The calculation of these characteristics is detailed in Section 3.2.

Table 3: Firm characteristics of MAX-sorted portfolios

Quintile portfolios are constructed at the beginning of month t by sorting stocks based on MAX defined as the maximum daily return in month $t-1$. Portfolios are reconstructed every month. Portfolio 1 contains the stocks with the lowest MAX value and portfolio 5 contains the stocks with the highest MAX value. The median value of each characteristic in each portfolio is estimated at the beginning of month t. The time-series average of these median values is calculated for each portfolio.

Portfolio	MOM	STR	SIZE	BM	ILLIQ	SSKEW
1 (Low)	0.652	-3.311	11.528	1.676	0.102	-0.040
2	3.518	-1.964	11.832	1.487	0.059	-0.041
3	6.839	-0.223	11.971	1.374	0.039	-0.042
4	10.157	2.117	11.929	1.365	0.034	-0.045
5 (High)	9.739	7.235	11.363	1.473	0.046	-0.059

The first two columns in the table show movement in the MAX-sorted portfolios of the cumulative return in the previous 11 months and the return for the month in which the portfolios are formed. The patterns found in the table show the extent to which the momentum and short-term reversal characteristics affect the portfolios. Specifically, the pattern in MOM increases across the quintiles as their MAX increases. Although MOM decreases slightly in portfolio 5 compared to portfolio 4, in general, stocks with high MAX values in portfolio 5 also have high cumulative returns in the previous 11 months. As proposed by Jegadeesh and Titman (1993), the past long-term winners continue to perform well into the future. Therefore, the high return on the high MAX portfolio during the first few days of the month can be attributed to MOM phenomenon. Looking at the pattern of STR, it is clear that stocks with highly extreme positive returns tend to have high returns in the portfolio formation month. Therefore, MAX can also be considered to represent the short-term reversal phenomenon. In terms of size, the numbers are quite similar across the portfolios. However, the highest MAX portfolio consists of small stocks. The characteristics of small size can make these stocks earn higher returns than others, thus affecting the MAX phenomenon during the month. For the BM and ILLIQ ratios, the pattern is not clear across the portfolios. The MAX is considered to be an attribute related to lottery-like stocks, so it may be related to another attribute of lotter-like stocks, such as skewness. The patterns in both ISKEW and SSKEW also move clearly across the portfolios. Stocks with a high MAX also have a high ISKEW, so the MAX effect can be attributed to the ISKEW phenomenon. Therefore, we control them in our study to see more clearly whether the abnormal MAX effect on the TOM trading days is due to the stock characteristics. We use the double-sorted portfolio method, detailed in Section 3.3 and report the results in Table 4.

Table 4: MAX-sorted portfolios after controlling for cross-sectional effects

Double-sorted portfolios are constructed by first sorting stocks into quintiles based on the control variables estimated at the beginning of month t and then dividing stocks within each portfolio into quintiles based on MAX defined as the maximum daily return in month $t-1$. The equal- and value-weighted average excess returns, the CAPM alphas and the FF3 alphas of 25 portfolios are computed on turn-of-month trading days from the last trading day in month t to the first three trading days in month $t+1$. We then compute time-series average excess return and alphas for 25 portfolios and average across 5 portfolios sorted on firm-characteristics within each MAX portfolio. The numbers in the table display the hedge portfolios defined as the differences in average excess returns and alphas between the highest MAX portfolio and the lowest MAX portfolio. Newey and West (1987) t-statistics with a lag of 12 are shown in parentheses.

	Equal-weight			Value-weight		
	Excess return	CAPM-Alpha	FF3-Alpha	Excess return	CAPM-Alpha	FF3-Alpha
BM	0.42***	0.41***	0.36***	0.47***	0.43***	0.42***
	(4.07)	(3.71)	(3.29)	(3.11)	(2.60)	(2.63)
ILLIQ	0.50***	0.48***	0.45***	0.39***	0.36**	0.34***
	(4.78)	(4.40)	(4.21)	(3.12)	(2.59)	(2.60)
MOM	0.28***	0.26***	0.22**	0.21	0.18	0.21
	(3.34)	(3.11)	(2.55)	(1.51)	(1.20)	(1.37)
SIZE	0.42***	0.40***	0.36***	0.46***	0.44***	0.40***
	(3.93)	(3.52)	(3.16)	(3.98)	(3.50)	(3.17)
SSKEW	0.33***	0.32***	0.26**	0.37**	0.33*	0.31*
	(3.00)	(2.74)	(2.25)	(2.04)	(1.73)	(1.65)
STR	0.43***	0.41***	0.39***	0.40**	0.37*	0.41*
	(3.72)	(3.50)	(3.33)	(2.12)	(1.84)	(1.96)

*, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

The numbers in the Table 4 show the differences in average excess returns and alphas between the highest MAX portfolio and the lowest MAX portfolio after controlling for firm characteristics. Newey and West (1987) t-statistics with a lag of 12 are shown in parentheses. According to the results in both equal-weighted and value-weighted calculations, after controlling for firm characteristics such as BM, ILLIQ, SIZE and STR, the MAX return spreads do not change much in magnitude from those reported in Table 2 and have strongly statistical significance, confirming the significance of the MAX phenomenon on the TOM trading days without being affected by these firm characteristics. However, after controlling for ISKEW and SSKEW, the differences in equal-weighted average excess returns and alphas between the two extreme portfolios have a quantitative decrease but remain significantly positive. ISKEW is also considered to be an attribute of lottery-like stocks, and stocks with a high MAX also have a high ISKEW, as shown in Table 3. Therefore, the ISKEW effect can be similar to the MAX effect on the TOM trading days, meaning that high ISKEW stocks may earn higher returns than low ISKEW stocks. Controlling for ISKEW can reduce the effect on stock returns at the TOM period. However, hedge portfolio by holding a long (short) position in high (low) MAX stocks still generates significantly positive return in the

TOM period, confirming the significance in the MAX anomaly around the turn of the month. When controlling for MOM, equal-weighted average excess return and alphas of the high-low portfolio are of a smaller magnitude than the results reported in Table 2 but are still statistically significant. It is conceivable when observing a clear movement in MOM across the MAX-sorted portfolios. As explained in Table 3, high MAX stocks have high cumulative returns in the previous 11 months. Hence, the high MAX stocks that can earn high returns around the turn of the month may be partly explained by the MOM effect. In general, the spreads decrease in magnitude but are still statistically significant, so the MAX anomaly in the TOM period persists after controlling the variables. In the case of value-weighted calculation, after controlling for MOM, ISKEW, SSKEW and STR, the significance level decreases but the number remains positive. As mentioned in Table 2, the MAX effect seems to concentrate primarily on small stocks, so in this table, the significance level in the case of value-weighted calculation is also reduced compared to the case of equal-weighted calculation. In summary, high returns on high MAX stocks around the turn of the month cannot be attributed to the well-known cross-sectional effects.

4.3 Cross-sectional regression

In the previous section, we use the method of portfolio analysis and test for the MAX anomaly around the turn of the month, besides that firm characteristics are also in turn controlled. We now use daily cross-sectional regression at the firm level only in the TOM period to recheck results found in portfolio analysis and control for firm characteristics simultaneously. We report the time-series averages of the coefficients from the regressions of model in Equation (1). The Newey-West t-statistics with a lag of 12 are presented in parentheses. Column 1 in Table 5 shows the result of daily univariate regressions of cross-sectional excess returns on the MAX value only on the TOM trading days. The coefficient on MAX is 0.007 and statistical significant, confirming that a high MAX stock earn higher return around the turn of the month than a low MAX stock. Column 2 shows the result after controlling for characteristics that cannot explain high returns on high MAX stock in portfolio analysis. Columns 3, 4, and 5 add the control variables MOM, ISKEW and SSKEW to the model that are found in the portfolio analysis to reduce slightly the magnitude of the MAX effect during the turn of the month. The result in column 6 is of our interest, showing the MAX effect around the turn of the month after controlling for all firm characteristics. Controlling these variables simultaneously in the model does not significantly change the MAX coefficient. Therefore, the cross-sectional effects do not explain a positive relation between MAX and stock returns during the turn of the month.

Table 5: Cross-sectional regressions on turn-of-month period

We run daily cross-sectional regressions of excess returns on lagged MAX and lagged control variables according to Equation (1) on turn-of-month trading days. The time-series averages of the coefficients from the regressions are reported. The Newey-West t-statistics with a lag of 12 are presented in parentheses.

	1	2	3	4	5	6
			Panel A: Firm-level regressions			
MAX	0.030***	0.026**	0.034***	0.022**	0.026**	0.029**
	(3.04)	(2.59)	(2.78)	(2.45)	(2.57)	(2.46)
BM		-0.017	-0.014	-0.018	-0.018	-0.013
		(-0.70)	(-0.59)	(-0.66)	(-0.74)	(-0.53)
SIZE		-0.119***	-0.113***	-0.120***	-0.122***	-0.116***
		(-3.47)	(-3.19)	(-3.67)	(-3.56)	(-3.50)
ILLIQ		-0.131**	-0.126**	-0.126*	-0.136**	-0.127*
		(-2.03)	(-2.01)	(-1.92)	(-2.08)	(-1.93)
STR			-0.007**			-0.007*
			(-2.10)			(-1.87)
MOM				-0.005		-0.009
				(-0.30)		(-0.54)
SSKEW					-0.118	0.293
					(-0.15)	(0.49)
Adj. R^2	0.012***	0.034***	0.042***	0.044***	0.036***	0.053***
	(7.70)	(17.62)	(17.85)	(21.33)	(18.37)	(19.99)
			Panel B: Portfolio-level regressions			
			B1: Equal-weight			
MAX	0.023**	0.023**	0.048***	0.019*	0.023**	0.041***
	(2.19)	(2.22)	(3.61)	(1.92)	(2.13)	(3.14)
BM		0.054	0.083*	0.066	0.057	0.091
		(1.19)	(1.84)	(1.14)	(1.26)	(1.63)
SIZE		-0.100***	-0.081**	-0.085**	-0.116***	-0.076**
		(-2.83)	(-2.16)	(-2.39)	(-3.43)	(-2.15)
ILLIQ		0.001	0.027	-0.001	-0.013	0.016
		(0.01)	(0.20)	(-0.01)	(-0.11)	(0.14)
STR			-0.016***			-0.014***
			(-3.18)			(-3.01)
MOM				-0.013		-0.019
				(-0.48)		(-0.68)
SSKEW					2.105	2.151
					(1.12)	(1.15)
Adj. R^2	0.042***	0.121***	0.136***	0.139***	0.127***	0.157***

	(7.63)	(17.09)	(18.09)	(19.23)	(17.97)	(21.34)
			B2: Value-weight			
MAX	0.025**	0.025**	0.049***	0.020**	0.024**	0.040***
	(2.36)	(2.40)	(3.61)	(2.08)	(2.28)	(3.02)
BM		0.032	0.054	0.043	0.031	0.056
		(0.73)	(1.28)	(0.77)	(0.72)	(1.05)
SIZE		-0.092***	-0.075**	-0.075**	-0.105***	-0.068**
		(-2.70)	(-2.12)	(-2.18)	(-3.41)	(-2.11)
ILLIQ		0.105	0.139	0.097	0.092	0.123
		(0.62)	(0.84)	(0.64)	(0.58)	(0.84)
STR			-0.016***			-0.014***
			(-3.09)			(-2.79)
MOM				-0.012		-0.017
				(-0.42)		(-0.57)
SSKEW					2.325	2.602
					(1.12)	(1.29)
Adj. R^2	0.041***	0.115***	0.129***	0.134***	0.121***	0.151***
	(7.64)	(17.62)	(18.35)	(18.93)	(18.36)	(20.72)

*, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 6: Cross-sectional regressions in the non-turn-of-month period

We run daily cross-sectional regressions of excess returns on lagged MAX and lagged control variables according to Equation (1) on turn-of-month trading days. The time-series averages of the coefficients from the regressions are reported. The Newey-West t-statistics with a lag of 12 are presented in parentheses.

	1	2	3	4	5	6
			Panel A: Firm-level regressions			
MAX	-0.064***	-0.073***	-0.069***	-0.071***	-0.071***	-0.065***
	(-3.29)	(-3.51)	(-3.19)	(-3.52)	(-3.41)	(-3.08)
BM		0.109	0.108	0.095	0.109	0.089
		(1.20)	(1.19)	(1.11)	(1.21)	(1.05)
SIZE		-0.172**	-0.168**	-0.175***	-0.174**	-0.176***
		(-2.37)	(-2.39)	(-2.61)	(-2.34)	(-2.62)
ILLIQ		0.311**	0.305**	0.312**	0.300**	0.294**
		(2.34)	(2.43)	(2.42)	(2.30)	(2.42)
STR			-0.006			-0.007
			(-1.23)			(-1.63)
MOM				0.008		0.005
				(0.54)		(0.33)
SSKEW					1.590	2.437*
					(1.27)	(1.97)
Adj. R^2	0.009***	0.029***	0.036***	0.039***	0.032***	0.048***
	(7.56)	(17.50)	(19.91)	(20.47)	(17.72)	(22.19)

Panel B: Portfolio-level regressions

B1: Equal-weight

MAX	-0.066***	-0.068***	-0.041	-0.069***	-0.067***	-0.045
	(-3.13)	(-3.11)	(-1.54)	(-3.05)	(-2.83)	(-1.63)
BM		0.140	0.151	0.136	0.127	0.117
		(0.97)	(1.03)	(1.06)	(0.90)	(0.94)
SIZE		-0.093	-0.092	-0.078	-0.109	-0.094
		(-1.26)	(-1.31)	(-1.07)	(-1.24)	(-1.19)
ILLIQ		1.124***	1.113***	1.104***	1.081***	1.034**
		(2.72)	(2.71)	(2.71)	(2.66)	(2.57)
STR			-0.011			-0.012
			(-0.98)			(-1.17)
MOM				-0.032		-0.027
				(-1.03)		(-0.83)
SSKEW					5.174	4.705
					(1.18)	(1.15)
Adj. R^2	0.032***	0.105***	0.120***	0.125***	0.114***	0.146***
	(8.25)	(14.62)	(15.85)	(16.41)	(15.24)	(18.46)

B2: Value-weight

MAX	-0.069***	-0.068***	-0.045*	-0.070***	-0.066***	-0.048*
	(-3.24)	(-3.13)	(-1.77)	(-3.10)	(-2.82)	(-1.82)
BM		0.190	0.192	0.189	0.179	0.170
		(1.37)	(1.34)	(1.55)	(1.31)	(1.42)
SIZE		-0.056	-0.057	-0.043	-0.059	-0.044
		(-0.84)	(-0.91)	(-0.68)	(-0.74)	(-0.61)
ILLIQ		1.267***	1.264***	1.245***	1.231***	1.185**
		(2.66)	(2.67)	(2.68)	(2.61)	(2.59)
STR			-0.007			-0.008
			(-0.69)			(-0.82)
MOM				-0.014		-0.011
				(-0.52)		(-0.39)
SSKEW					3.729	3.050
					(0.84)	(0.73)
Adj. R^2	0.032***	0.103***	0.118***	0.122***	0.111***	0.143***
	(8.06)	(15.68)	(17.02)	(16.96)	(15.95)	(18.92)

*, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

5 Cyclicality of daily returns on lottery-type stocks

What can be a reason for the pattern that high MAX stocks are gradually overpriced during the TOM period and then the mispricing is resolved over the rest days each month? Bali, Cakici, and Whitelaw (2011) argue that high MAX stocks can be viewed as a lottery to retail investors. Meng and Pantzalis (2018) find that lottery-type stocks have the within-month cyclicality in the U.S. stock market. As such, we examine if the pattern of the MAX effect in Korea is generalized as a common feature of lottery-type stocks.

Several variables have been used to define lottery-type stocks in the literature. Kumar (2009) defines a lottery feature as a cheap bet with very unlikely extreme profits. According to this definition, previous studies classify stocks with high MAX, low price, high idiosyncratic volatility and high idiosyncratic skewness as lottery-type stocks (Harvey and Siddique 2000; Barberis and Huang 2008; Kumar 2009; Han and Kumar 2013; Meng and Pantzalis 2018; Liu et al. 2020; Meng and Pantzalis 2020). Thus, we choose closing price, idiosyncratic volatility and idiosyncratic skewness as alternative measures of lottery-feature and repeat the main analyses of the previous section with these alternative variables in order. At the end of this section, we construct a lottery index to summarize all the measures following Kumar, Page, and Spalt (2016) and repeat the same analyses.

5.1 Results with alternative measures of lottery-type stocks

Before displaying the details of results, figures 2-4 visualize the monthly cycle of returns on the zero-cost portfolio at a glance. We see that the patterns are similar with that of MAX long-short portfolio returns; lottery-type stocks are gradually overpriced and earn positive cumulative returns during the TOM period. Slightly different results are observed as well. First, the ISKEW long-short portfolio is overpriced but not as much as the MAX and other cases. Second, the PRICE long-short portfolio is highly overpriced during the TOM period and the overpricing last much longer than the other lottery measure cases. The positive returns persist almost half a month. As will be shown in the portfolio analysis result, PRICE anomaly has a monthly positive return. Although there are subtle differences, we confirm that the cyclical patterns are qualitatively similar in the use of alternative measures.

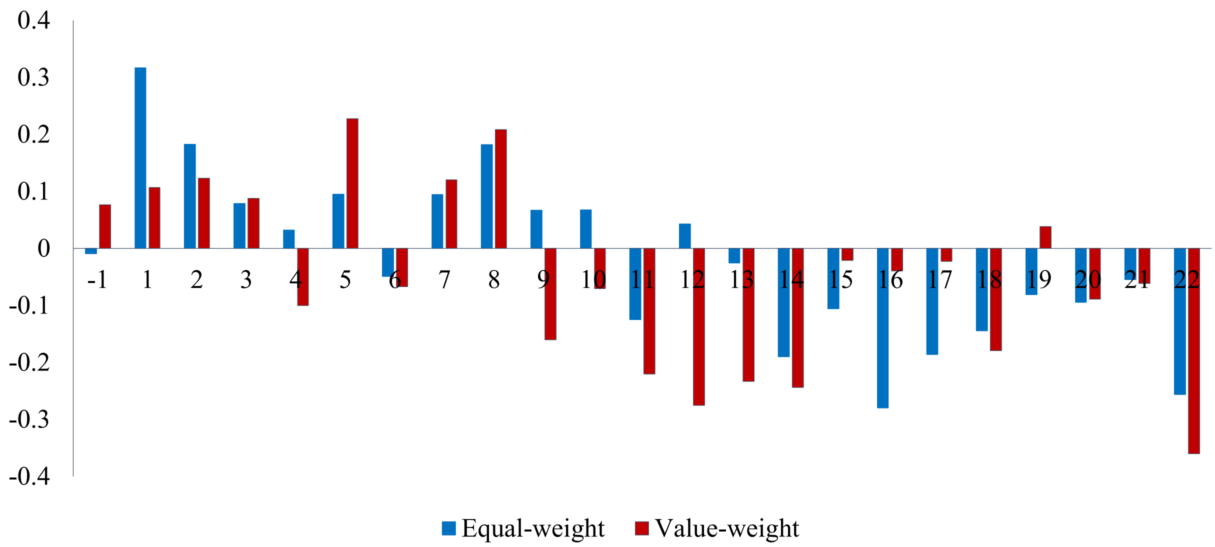

Figure 2: Average daily returns on the zero-cost portfolio formed by IVOL

The equal-weighted and value-weighted excess return of the zero-cost portfolio on each trading day of the month is illustrated. The zero-cost portfolio is determined by the highest IVOL-sorted portfolio minus the lowest IVOL-sorted portfolio. IVOL is defined as the standard deviation of daily residuals in regressions of Fama and French (1993) three-factor model over the past 12 months.

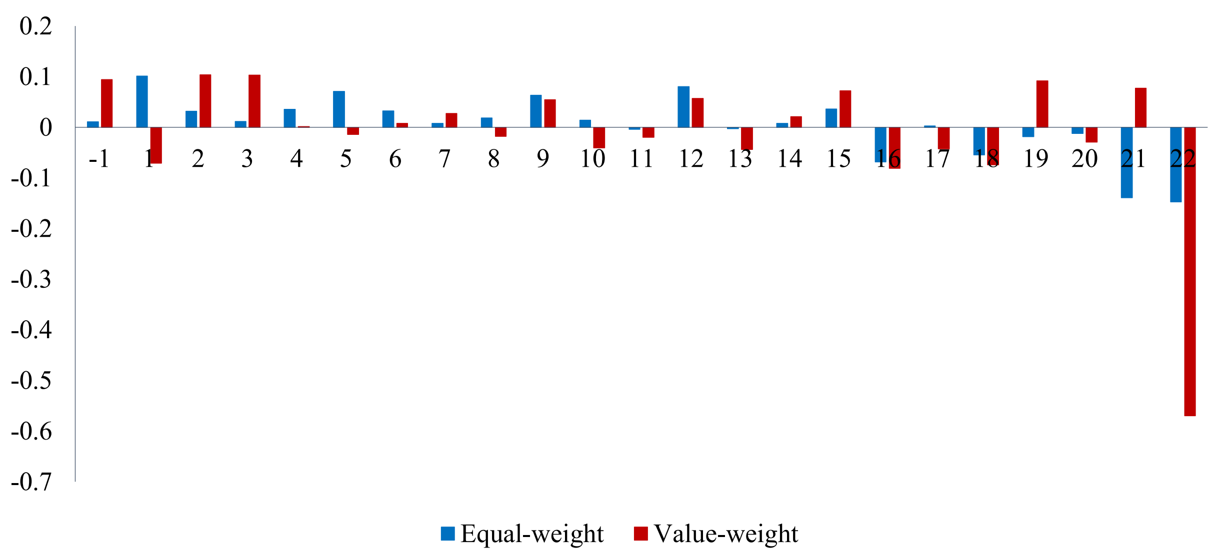

Figure 3: Average daily returns on the zero-cost portfolio formed by ISKEW

The equal-weighted and value-weighted excess return of the zero-cost portfolio on each trading day of the month is illustrated. The zero-cost portfolio is determined by the highest ISKEW-sorted portfolio minus the lowest ISKEW-sorted portfolio. ISKEW is defined as the skewness of daily residuals in regressions of excess returns on market excess returns and squared market excess returns over the past 12 months.

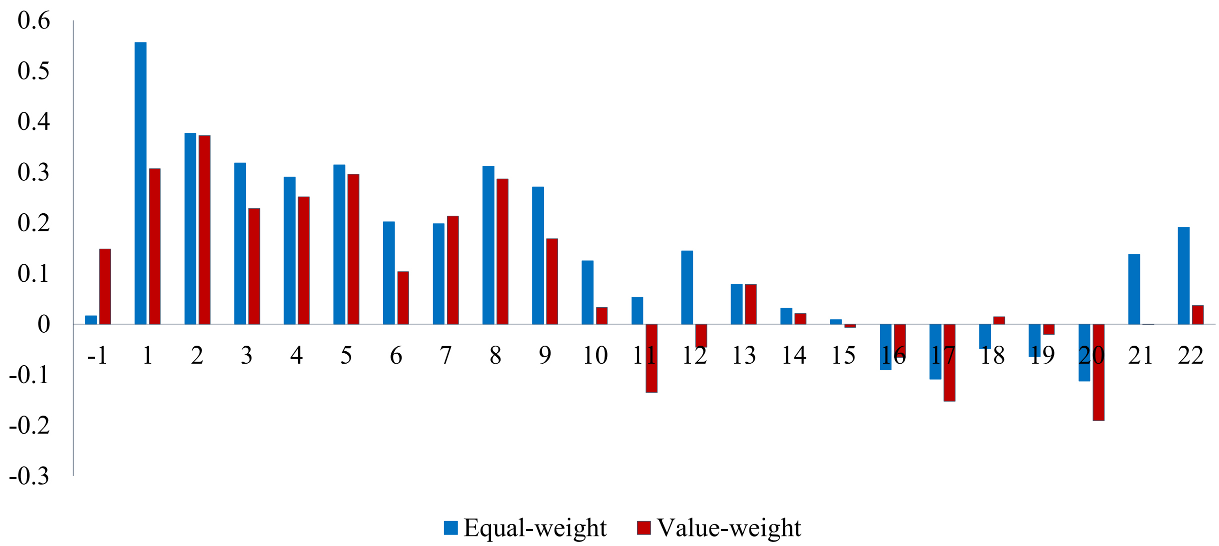

Figure 4: Average daily returns on the zero-cost portfolio formed by PRICE

The equal-weighted and value-weighted excess return of the zero-cost portfolio on each trading day of the month is illustrated. The zero-cost portfolio is determined by the highest PRICE-sorted portfolio minus the lowest PRICE-sorted portfolio. PRICE is the logarithm of closing price at the end of the previous month.

Now, tables 7-9 present the results of single-sorted portfolio analyses using IVOL, ISKEW, and PRICE measures, respectively. For the methodological details, refer to the MAX case in the previous sections.

Several findings are worth noting. First, the long-short portfolios formed by the alternative measures are all positive at TOM, although their statistical significance is mixed depending on the measure and the weighting scheme. While PRICE portfolio returns are highly significant both statistically and economically, IVOL portfolio returns statistically significant only for the equal-weight case and ISKEW portfolio returns are positive but statistically insignificant. Second, the non-TOM period results are also mixed. While IVOL portfolios have negative returns in the NTOM period, ISKEW and PRICE portfolios do not show such a pattern. Finally, in spite of the mixed results, the most lottery-like stocks (i.e., portfolio 5) have highly significant, positive returns at TOM regardless of the weight scheme, the lottery characteristic measures, and the asset pricing models. Therefore, at least, stocks with highly lottery-like characteristics are gradually overpriced over TOM trading days.

Tables 10-12 present the result of double-sorted portfolio analyses. Even after controlling for other stock characteristics, we confirm that the findings in the single-sorted portfolio analysis remains the same.

All in all, even though some results are not robust as much as the case of the MAX anomaly, the overpricing during the TOM period is very robust to other lottery measures. This finding supports the view that the overpricing of MAX long-short portfolio during the TOM period is attributed to a general behavior of lottery-type stocks.

Table 7: IVOL-sorted portfolios

Quintile portfolios are constructed at the beginning of month t by sorting stocks based on IVOL estimated as the standard deviation of daily residuals in regressions of Fama and French (1993) three-factor model in the previous year from month $t-12$ to month $t-1$. Portfolios are reconstructed every month. The stocks with the lowest IVOL value are classified into portfolio 1 and portfolio 5 contains the stocks with the highest IVOL value. Both equal- and value-weighted average excess returns and abnormal returns (CAPM and Fama-French-three-factor alphas) of portfolios are calculated and then averaged across the months. The row labeled 'High-Low' indicates the different values of the two extremes, portfolio 5 and portfolio 1. The numbers in parentheses display Newey and West (1987) t-statistics with a lag of 12. In panel A, the average excess returns and alphas of portfolios are calculated only on turn-of-month trading days from the last trading day in month t to the first three trading days in month $t+1$. In panel B, the average excess returns and alphas of portfolios are calculated on the remaining trading days of month $t+1$, except the last trading day of that month.

	Equal-weight			Value-weight		
Portfolio	Excess return	CAPM-Alpha	FF3-Alpha	Excess return	CAPM-Alpha	FF3-Alpha
Panel A: Turn-of-month						
1 (Low)	0.58***	0.53***	0.40**	0.47*	0.39	0.35
	(3.25)	(2.90)	(2.51)	(1.90)	(1.62)	(1.52)
2	0.67***	0.60***	0.48**	0.62**	0.53*	0.48
	(3.11)	(2.72)	(2.26)	(2.15)	(1.83)	(1.59)
3	0.80***	0.73***	0.57**	0.87***	0.77**	0.66**
	(3.41)	(3.01)	(2.50)	(2.71)	(2.31)	(2.15)
4	0.94***	0.87***	0.72***	0.79***	0.66**	0.66*
	(3.88)	(3.39)	(2.97)	(2.69)	(2.28)	(1.93)
5 (High)	1.18***	1.12***	0.95***	0.88***	0.79**	0.69**
	(4.38)	(3.94)	(3.67)	(2.78)	(2.42)	(2.30)
High-Low	0.60***	0.59***	0.55***	0.41	0.40	0.34
	(4.82)	(4.50)	(4.19)	(1.63)	(1.58)	(1.40)
Panel B: Non turn-of-month						
1 (Low)	0.61*	0.39**	-0.05	0.05	-0.19	-0.08
	(1.70)	(1.97)	(-0.27)	(0.14)	(-0.75)	(-0.34)
2	0.59	0.32	-0.14	-0.06	-0.35	-0.42
	(1.43)	(1.50)	(-0.66)	(-0.13)	(-1.35)	(-1.39)
3	0.46	0.18	-0.25	0.26	-0.07	-0.07
	(1.14)	(0.90)	(-1.22)	(0.59)	(-0.34)	(-0.34)
4	0.53	0.24	-0.26	-0.22	-0.58	-0.77*
	(1.25)	(0.97)	(-1.09)	(-0.36)	(-1.51)	(-1.79)
5 (High)	0.18	-0.09	-0.58**	-0.75	-1.07***	-1.23***

	(0.49)	(-0.28)	(-2.21)	(-1.38)	(-2.64)	(-2.65)
High-Low	-0.43*	-0.47*	-0.53**	-0.80**	-0.88**	-1.15***
	(-1.82)	(-1.82)	(-2.56)	(-2.26)	(-2.55)	(-3.10)

*, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 8: ISKEW-sorted portfolios

Quintile portfolios are constructed at the beginning of month t by sorting stocks based on ISKEW estimated as the skewness of daily residuals in regressions of excess returns on market excess returns and squared market excess returns in the previous year from month $t-12$ to month $t-1$. Portfolios are reconstructed every month. The stocks with the lowest ISKEW value are classified into portfolio 1 and portfolio 5 contains the stocks with the highest ISKEW value. Both equal- and value-weighted average excess returns and abnormal returns (CAPM and Fama-French-three-factor alphas) of portfolios are calculated and then averaged across the months. The row labeled 'High-Low' indicates the different values of the two extremes, portfolio 5 and portfolio 1. The numbers in parentheses display Newey and West (1987) t-statistics with a lag of 12. In panel A, the average excess returns and alphas of portfolios are calculated only on turn-of-month trading days from the last trading day in month t to the first three trading days in month $t+1$. In panel B, the average excess returns and alphas of portfolios are calculated on the remaining trading days of month $t+1$, except the last trading day of that month.

	Equal-weight			Value-weight		
Portfolio	Excess return	CAPM-Alpha	FF3-Alpha	Excess return	CAPM-Alpha	FF3-Alpha
Panel A: Turn-of-month						
1 (Low)	0.75***	0.69***	0.55**	0.59**	0.49*	0.45
	(3.12)	(2.73)	(2.36)	(2.17)	(1.81)	(1.62)
2	0.75***	0.69***	0.55**	0.43*	0.34*	0.31
	(3.36)	(2.94)	(2.58)	(1.93)	(1.67)	(1.47)
3	0.88***	0.81***	0.68***	0.77***	0.69**	0.62**
	(3.57)	(3.17)	(2.79)	(2.64)	(2.29)	(2.09)
4	0.86***	0.80***	0.65***	0.56**	0.49*	0.35
	(4.01)	(3.60)	(3.21)	(2.12)	(1.77)	(1.44)
5 (High)	0.91***	0.84***	0.69***	0.82***	0.74***	0.65***
	(4.26)	(3.82)	(3.30)	(3.39)	(3.04)	(2.79)
High-Low	0.16	0.15	0.14	0.22	0.25	0.21
	(1.55)	(1.50)	(1.49)	(1.41)	(1.57)	(1.29)
Panel B: Non turn-of-month						
1 (Low)	0.46	0.22	-0.17	-0.04	-0.31	-0.23
	(1.41)	(1.02)	(-0.92)	(-0.09)	(-1.25)	(-0.93)
2	0.44	0.16	-0.22	-0.13	-0.42	-0.24
	(1.08)	(0.70)	(-0.90)	(-0.26)	(-1.30)	(-0.88)
3	0.40	0.12	-0.36	0.13	-0.14	-0.31
	(0.99)	(0.58)	(-1.59)	(0.37)	(-0.70)	(-1.23)
4	0.49	0.21	-0.30	0.14	-0.16	-0.47*
	(1.21)	(0.94)	(-1.38)	(0.30)	(-0.70)	(-1.77)
5 (High)	0.61	0.34	-0.23	0.02	-0.30	-0.71**
	(1.44)	(1.33)	(-1.05)	(0.03)	(-1.02)	(-2.43)

High-Low	0.15	0.12	-0.06	0.05	0.01	-0.47*
	(0.83)	(0.71)	(-0.42)	(0.18)	(0.04)	(-1.92)

*, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 9: PRICE-sorted portfolios

Quintile portfolios are constructed at the beginning of month t by sorting stocks based on the logarithm of closing price at the end of month $t-1$. Portfolios are reconstructed every month. High (Low) represents the most (least) lottery-like quintile based on PRICE, i.e., stocks with the lowest price are allocated in portfolio 5. Both equal- and value-weighted average excess returns and abnormal returns (CAPM and Fama-French-three-factor alphas) of portfolios are calculated and then averaged across the months. The row labeled 'High-Low' indicates the different values of the two extremes, portfolio 5 and portfolio 1. The numbers in parentheses display Newey and West (1987) t-statistics with a lag of 12. In panel A, the average excess returns and alphas of portfolios are calculated only on turn-of-month trading days from the last trading day in month t to the first three trading days in month $t+1$. In panel B, the average excess returns and alphas of portfolios are calculated on the remaining trading days of month $t+1$, except the last trading day of that month.

	Equal-weight			Value-weight		
Portfolio	Excess return	CAPM-Alpha	FF3-Alpha	Excess return	CAPM-Alpha	FF3-Alpha
Panel A: Turn-of-month						
1 (Low)	0.52***	0.46**	0.36*	0.52**	0.44*	0.39*
	(2.76)	(2.36)	(1.95)	(2.15)	(1.84)	(1.72)
2	0.70***	0.64***	0.48**	0.73**	0.64*	0.55*
	(3.00)	(2.62)	(2.20)	(2.29)	(1.95)	(1.70)
3	0.79***	0.73***	0.57***	0.84***	0.76**	0.66**
	(3.40)	(3.01)	(2.64)	(2.81)	(2.53)	(2.22)
4	0.96***	0.89***	0.74***	0.83***	0.74***	0.63**
	(4.20)	(3.87)	(3.26)	(3.14)	(2.84)	(2.26)
5 (High)	1.80***	1.74***	1.58***	1.53***	1.43***	1.35***
	(5.69)	(5.26)	(5.21)	(4.76)	(4.44)	(4.25)
High-Low	1.28***	1.28***	1.21***	1.01***	1.00***	0.96***
	(6.95)	(6.90)	(7.04)	(5.12)	(5.05)	(4.88)
Panel B: Non turn-of-month						
1 (Low)	0.21	-0.03	-0.31	-0.06	-0.33	-0.19
	(0.57)	(-0.15)	(-1.43)	(-0.17)	(-1.41)	(-0.83)
2	0.36	0.09	-0.33	0.09	-0.21	-0.41
	(0.88)	(0.37)	(-1.32)	(0.19)	(-0.77)	(-1.31)
3	0.33	0.05	-0.47*	-0.11	-0.45*	-0.77***
	(0.77)	(0.20)	(-1.87)	(-0.22)	(-1.71)	(-2.70)
4	0.28	-0.02	-0.57***	-0.24	-0.58**	-0.95***
	(0.67)	(-0.08)	(-2.61)	(-0.46)	(-1.97)	(-2.97)
5 (High)	2.12***	1.88***	1.27***	1.08**	0.77**	0.32
	(4.82)	(4.76)	(4.70)	(2.50)	(2.29)	(1.05)
High-Low	1.91***	1.91***	1.58***	1.15***	1.10**	0.51
	(4.69)	(4.70)	(4.46)	(2.62)	(2.48)	(1.31)

*, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 10: IVOL-sorted portfolios after controlling for cross-sectional effects

Double-sorted portfolios are constructed by first sorting stocks into quintiles based on the control variables estimated at the beginning of month t and then dividing stocks within each portfolio into quintiles based on IVOL estimated as the standard deviation of daily residuals in regressions of Fama and French (1993) three-factor model in the previous year from month $t-12$ to month $t-1$. The equal- and value-weighted average excess returns, the CAPM alphas and the FF3 alphas of 25 portfolios are computed on turn-of-month trading days from the last trading day in month t to the first three trading days in month $t+1$. We then compute time-series average excess return and alphas for 25 portfolios and average across 5 portfolios sorted on firm-characteristics within each IVOL portfolio. The numbers in the table display the hedge portfolios defined as the differences in average excess returns and alphas between the highest IVOL portfolio and the lowest IVOL portfolio. Newey and West (1987) t-statistics with a lag of 12 are shown in parentheses.

	Equal-weight			Value-weight		
	Excess return	CAPM-Alpha	FF3-Alpha	Excess return	CAPM-Alpha	FF3-Alpha
BM	0.56***	0.54***	0.51***	0.52***	0.48***	0.52***
	(4.87)	(4.49)	(4.10)	(3.19)	(2.79)	(2.97)
ILLIQ	0.61***	0.59***	0.57***	0.35**	0.33**	0.33**
	(4.54)	(4.25)	(4.06)	(2.32)	(2.03)	(2.10)
MOM	0.48***	0.47***	0.44***	0.23	0.22	0.26
	(4.01)	(3.92)	(3.70)	(1.26)	(1.24)	(1.41)
SIZE	0.52***	0.49***	0.49***	0.50***	0.48***	0.48***
	(4.02)	(3.59)	(3.43)	(3.42)	(3.07)	(2.99)
SSKEW	0.55***	0.53***	0.50***	0.35*	0.32*	0.28
	(4.44)	(4.11)	(3.87)	(1.93)	(1.71)	(1.49)
STR	0.53***	0.52***	0.50***	0.38**	0.38**	0.34**
	(4.34)	(4.16)	(4.06)	(2.34)	(2.32)	(2.04)

*, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 11: ISKEW-sorted portfolios after controlling for cross-sectional effects

Double-sorted portfolios are constructed by first sorting stocks into quintiles based on the control variables estimated at the beginning of month t and then dividing stocks within each portfolio into quintiles based on ISKEW estimated as the skewness of daily residuals in regressions of excess returns on market excess returns and squared market excess returns in the previous year from month $t-12$ to month $t-1$. The equal- and value-weighted average excess returns, the CAPM alphas and the FF3 alphas of 25 portfolios are computed on turn-of-month trading days from the last trading day in month t to the first three trading days in month $t+1$. We then compute time-series average excess return and alphas for 25 portfolios and average across 5 portfolios sorted on firm-characteristics within each ISKEW portfolio. The numbers in the table display the hedge portfolios defined as the differences in average excess returns and alphas between the highest ISKEW portfolio and the lowest ISKEW portfolio. Newey and West (1987) t-statistics with a lag of 12 are shown in parentheses.

	Equal-weight			Value-weight		
	Excess return	CAPM-Alpha	FF3-Alpha	Excess return	CAPM-Alpha	FF3-Alpha
BM	0.21**	0.20**	0.19**	0.25*	0.26**	0.25**
	(2.33)	(2.28)	(2.14)	(1.90)	(2.04)	(2.09)
ILLIQ	0.18**	0.17**	0.17**	0.23**	0.23**	0.21**
	(2.13)	(2.07)	(2.08)	(2.52)	(2.54)	(2.21)
MOM	0.15	0.15	0.13	0.13	0.15	0.11

	(1.58)	(1.54)	(1.50)	(1.23)	(1.43)	(1.08)
SIZE	0.09	0.08	0.07	0.10	0.09	0.07
	(1.21)	(1.16)	(0.88)	(1.18)	(1.15)	(0.78)
SSKEW	0.12	0.12	0.11	0.14	0.15	0.11
	(1.33)	(1.26)	(1.32)	(1.10)	(1.26)	(0.95)
STR	0.15	0.15	0.15	0.15	0.17	0.16
	(1.51)	(1.46)	(1.54)	(1.23)	(1.41)	(1.25)

*, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 12: PRICE-sorted portfolios after controlling for cross-sectional effects

Double-sorted portfolios are constructed by first sorting stocks into quintiles based on the control variables estimated at the beginning of month t and then dividing stocks within each portfolio into quintiles based on the logarithm of closing price at the end of month $t-1$. The equal- and value-weighted average excess returns, the CAPM alphas and the FF3 alphas of 25 portfolios are computed on turn-of-month trading days from the last trading day in month t to the first three trading days in month $t+1$. We then compute time-series average excess return and alphas for 25 portfolios and average across 5 portfolios sorted on firm-characteristics within each PRICE portfolio. The numbers in the table display the hedge portfolios defined as the differences in average excess returns and alphas between the highest PRICE portfolio and the lowest PRICE portfolio. Newey and West (1987) t-statistics with a lag of 12 are shown in parentheses.

	Equal-weight			Value-weight		
	Excess return	CAPM-Alpha	FF3-Alpha	Excess return	CAPM-Alpha	FF3-Alpha
BM	1.22***	1.21***	1.18***	0.99***	0.98***	1.02***
	(7.03)	(6.98)	(6.79)	(5.89)	(5.80)	(5.88)
ILLIQ	0.97***	0.95***	0.91***	0.84***	0.82***	0.80***
	(5.93)	(5.68)	(5.58)	(5.75)	(5.55)	(5.31)
MOM	1.31***	1.29***	1.30***	0.94***	0.93***	1.00***
	(6.60)	(6.45)	(6.35)	(5.79)	(5.79)	(5.55)
SIZE	1.27***	1.23***	1.24***	1.25***	1.22***	1.21***
	(6.39)	(6.12)	(6.21)	(6.19)	(6.04)	(5.97)
SSKEW	0.82***	0.81***	0.76***	0.62***	0.61***	0.59***
	(5.72)	(5.59)	(5.31)	(4.35)	(4.26)	(3.88)
STR	1.28***	1.27***	1.21***	1.08***	1.07***	1.03***
	(6.11)	(6.13)	(5.88)	(6.01)	(6.13)	(5.18)

*, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

5.2 Results with lottery index

In order to generalize and summarize the tests of all the lottery characteristic measures including MAX, IVOL, ISKEW, and PRICE, we construct a lottery index in a similar manner of Kumar, Page, and Spalt (2016). We use each characteristic to rank stocks into 20 groups and assign scores from 1 to 20 from low to high, and all stocks in the same group have equal scores. We then aggregate the ranking scores based on 4 characteristics for each stock. There are 4 characteristics in total, so each stock can score as low as 4 and as high as 80. LIDX is the ranking scores of each stock scaled by the formula (Score – 4)/(80 – 4). According to the definition of LIDX, stocks with a higher LIDX value are more lottery-like. Using this index, we repeat the main analyses; the plot of daily average returns within a month, the single- and double-sorted portfolio analyses, and the Fama-MacBeth type cross-sectional regressions.

In all the analyses, we confirm that LIDX long-short portfolios earn positive returns at TOM, but negative returns over the rest days result in monthly negative return, which is robust to the control of other stock characteristics and the use of weighting scheme. Fama-MacBeth regression also show consistent results. These findings support our conjecture that the cyclicality of MAX anomaly comes from an interaction of the preference for lottery characteristic and the changes in sentiment and liquidity at TOM.

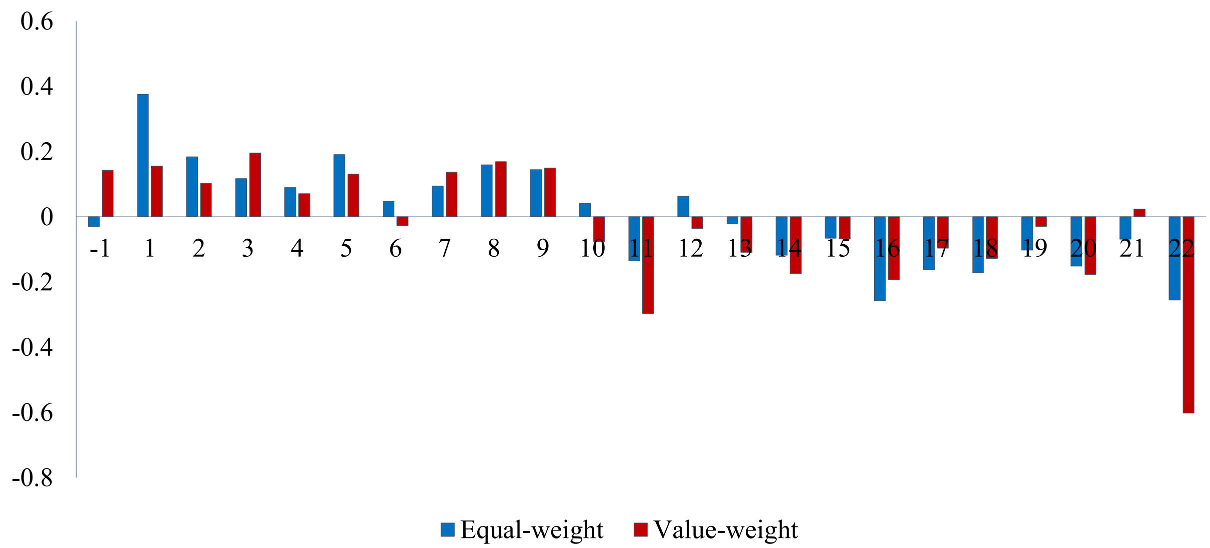

Figure 5: Average daily returns on the zero-cost portfolio formed by lottery index

The equal-weighted and value-weighted excess return of the zero-cost portfolio on each trading day of the month is illustrated. The zero-cost portfolio is determined by the highest LIDX-sorted portfolio minus the lowest LIDX-sorted portfolio. LIDX at the beginning of each month is the scaled ranking score based on 4 characteristics of lottery-like stocks such as MAX, IVOL, ISKEW and PRICE. MAX is defined as the maximum daily return in previous month. IVOL is defined as the standard deviation of daily residuals in regressions of Fama and French (1993) three-factor model in the previous year. ISKEW is defined as the skewness of daily residuals in regressions of excess returns on market excess returns and squared market excess returns in the previous year. PRICE is the logarithm of closing price at the end of last month. We use each characteristic to rank stocks into 20 groups and assign scores from 1 to 20 from low to high, and all stocks in the same group have equal scores. We then aggregate the ranking scores based on 4 characteristics for each stock. There are 4 characteristics in total, so each stock can score as low as 4 and as high as 80. LIDX is the ranking scores of each stock scaled by the formula (Score – 4)/(80 – 4).

Table 13: LIDX-sorted portfolios

Quintile portfolios are constructed at the beginning of month t by sorting stocks based on lottery index (LIDX) estimated at the beginning of month t. Portfolios are reconstructed every month. The stocks with the lowest lottery index are classified into portfolio 1 and portfolio 5 contains the stocks with the highest lottery index. Both equal- and value-weighted average excess returns and abnormal returns (CAPM and Fama-French-three-factor alphas) of portfolios are calculated and then averaged across the months. The row labeled 'High-Low' indicates the different values of the two extremes, portfolio 5 and portfolio 1. The numbers in parentheses display Newey and West (1987) t-statistics with a lag of 12. In panel A, the average excess returns and alphas of portfolios are calculated only on turn-of-month trading days from the last trading day in month t to the first three trading days in month $t+1$. In panel B, the average excess returns and alphas of portfolios are calculated on the remaining trading days of month $t+1$, except the last trading day of that month.

	Equal-weight			Value-weight		
Portfolio	Excess return	CAPM-Alpha	FF3-Alpha	Excess return	CAPM-Alpha	FF3-Alpha
Panel A: Turn-of-month						
1 (Low)	0.49***	0.44**	0.31*	0.46*	0.37	0.33
	(2.68)	(2.34)	(1.84)	(1.83)	(1.53)	(1.43)
2	0.64***	0.58***	0.45**	0.63**	0.53**	0.45*
	(2.98)	(2.63)	(2.20)	(2.35)	(2.05)	(1.76)
3	0.79***	0.73***	0.58**	0.81***	0.71**	0.65**
	(3.38)	(2.95)	(2.54)	(2.77)	(2.37)	(2.06)
4	1.01***	0.94***	0.80***	0.82***	0.73**	0.66**
	(4.17)	(3.71)	(3.42)	(2.81)	(2.40)	(2.16)
5 (High)	1.16***	1.10***	0.91***	1.06***	0.95***	0.86***
	(4.47)	(4.01)	(3.54)	(3.63)	(3.17)	(2.71)
High-Low	0.68***	0.66***	0.60***	0.60***	0.58***	0.53***
	(5.07)	(4.80)	(4.42)	(3.06)	(2.88)	(2.66)
Panel B: Non turn-of-month						
1 (Low)	0.44	0.21	-0.14	0.01	-0.24	-0.12
	(1.27)	(1.18)	(-0.70)	(0.03)	(-1.02)	(-0.53)
2	0.49	0.23	-0.18	0.13	-0.19	-0.33
	(1.23)	(1.09)	(-0.81)	(0.25)	(-0.73)	(-1.06)
3	0.49	0.21	-0.25	-0.07	-0.41	-0.53
	(1.17)	(0.92)	(-1.21)	(-0.13)	(-1.28)	(-1.57)
4	0.46	0.18	-0.30	-0.35	-0.70**	-0.96***
	(1.16)	(0.69)	(-1.22)	(-0.64)	(-2.21)	(-2.67)
5 (High)	0.34	0.05	-0.53*	-0.42	-0.78**	-1.24***
	(0.77)	(0.17)	(-1.97)	(-0.80)	(-2.58)	(-3.54)
High-Low	-0.10	-0.16	-0.39*	-0.43	-0.54*	-1.12***
	(-0.48)	(-0.80)	(-1.94)	(-1.25)	(-1.75)	(-3.71)

*, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 14: LIDX-sorted portfolios after controlling for cross-sectional effects

Double-sorted portfolios are constructed by first sorting stocks into quintiles based on the control variables estimated at the beginning of month t and then dividing stocks within each portfolio into quintiles based on the lottery index estimated at the beginning of month t. The equal- and value-weighted average excess returns, the CAPM alphas and the FF3 alphas of 25 portfolios are computed on turn-of-month trading days from the last trading day in month t to the first three trading days in month $t+1$. We then compute time-series average excess return and alphas for 25 portfolios and average across 5 portfolios sorted on firm-characteristics within each LIDX portfolio. The numbers in the table display the hedge portfolios defined as the differences in average excess returns and alphas between the highest LIDX portfolio and the lowest LIDX portfolio. Newey and West (1987) t-statistics with a lag of 12 are shown in parentheses.

	Equal-weight			Value-weight		
	Excess return	CAPM-Alpha	FF3-Alpha	Excess return	CAPM-Alpha	FF3-Alpha
BM	0.64***	0.62***	0.57***	0.62***	0.59***	0.57***
	(4.80)	(4.50)	(4.14)	(3.65)	(3.32)	(3.31)
ILLIQ	0.65***	0.62***	0.58***	0.55***	0.52***	0.49***
	(4.53)	(4.18)	(3.85)	(3.63)	(3.27)	(3.05)
MOM	0.56***	0.55***	0.49***	0.29**	0.28**	0.27**
	(4.95)	(4.84)	(4.23)	(2.14)	(2.06)	(1.97)
SIZE	0.56***	0.52***	0.49***	0.58***	0.55***	0.51***
	(4.18)	(3.81)	(3.51)	(4.03)	(3.67)	(3.34)
SSKEW	0.66***	0.63***	0.58***	0.46***	0.43***	0.38**
	(5.34)	(5.05)	(4.57)	(3.10)	(2.93)	(2.53)
STR	0.61***	0.59***	0.54***	0.43***	0.42***	0.38**
	(4.58)	(4.42)	(3.90)	(2.86)	(2.79)	(2.51)

*, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 15: Cross-sectional regressions on turn-of-month period (LIDX)

We run daily cross-sectional regressions of excess returns on lagged MAX and lagged control variables according to Equation (1) on turn-of-month trading days. The time-series averages of the coefficients from the regressions are reported. The Newey-West t-statistics with a lag of 12 are presented in parentheses.

	1	2	3	4	5	6
			Panel A: Firm-level regressions			
LIDX	1.213***	0.987***	1.037***	0.919***	0.968***	0.958***
	(5.24)	(3.87)	(3.84)	(3.72)	(3.93)	(3.66)
BM		-0.004	0.000	-0.002	-0.005	0.003
		(-0.18)	(0.01)	(-0.06)	(-0.24)	(0.12)
SIZE		-0.067*	-0.063*	-0.070**	-0.074**	-0.071**
		(-1.85)	(-1.67)	(-2.04)	(-2.03)	(-2.00)
ILLIQ		-0.069	-0.064	-0.063	-0.073	-0.063
		(-1.16)	(-1.12)	(-1.05)	(-1.24)	(-1.09)
STR			-0.006*			-0.005*
			(-1.90)			(-1.79)
MOM				-0.008		-0.011
				(-0.51)		(-0.65)
SSKEW					0.256	0.631
					(0.40)	(1.16)
Adj. R^2	0.015***	0.037***	0.044***	0.046***	0.039***	0.055***
	(6.71)	(15.75)	(17.37)	(20.08)	(16.48)	(20.11)

Panel B: Portfolio-level regressions						
B1: Equal-weight						
LIDX	1.111***	1.101***	1.283***	0.951***	1.005***	1.080***
	(4.32)	(4.30)	(4.65)	(3.91)	(3.84)	(3.97)
BM		0.021	0.020	0.019	0.025	0.015
		(0.50)	(0.48)	(0.39)	(0.58)	(0.32)
SIZE		-0.056	-0.043	-0.065*	-0.050	-0.047
		(-1.49)	(-1.09)	(-1.75)	(-1.29)	(-1.23)
ILLIQ		0.083	0.116	0.093	0.094	0.111
		(0.42)	(0.56)	(0.48)	(0.50)	(0.57)
STR			-0.008			-0.010**
			(-1.52)			(-2.20)
MOM				-0.018		-0.019
				(-0.72)		(-0.88)
SSKEW					-1.156	-0.533
					(-0.72)	(-0.39)
Adj. R^2	0.056***	0.134***	0.153***	0.154***	0.144***	0.179***
	(8.59)	(18.70)	(17.62)	(19.82)	(21.22)	(19.41)
B2: Value-weight						
LIDX	1.122***	1.117***	1.290***	0.952***	0.998***	1.038***
	(4.24)	(4.28)	(4.60)	(3.85)	(3.78)	(3.82)
BM		0.020	0.017	0.016	0.024	0.010
		(0.46)	(0.40)	(0.31)	(0.55)	(0.21)
SIZE		-0.041	-0.030	-0.052	-0.036	-0.038
		(-1.21)	(-0.85)	(-1.50)	(-1.03)	(-1.10)
ILLIQ		0.100	0.132	0.104	0.109	0.120
		(0.49)	(0.61)	(0.51)	(0.56)	(0.59)
STR			-0.007			-0.009**
			(-1.39)			(-1.99)
MOM				-0.015		-0.014
				(-0.64)		(-0.72)
SSKEW					-0.852	-0.059
					(-0.44)	(-0.04)
Adj. R^2	0.055***	0.130***	0.149***	0.151***	0.140***	0.175***
	(8.61)	(18.24)	(17.78)	(19.50)	(19.82)	(19.23)

*, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 16: Cross-sectional regressions on non-turn-of-month period (LIDX)

We run daily cross-sectional regressions of excess returns on lagged MAX and lagged control variables according to Equation (1) on turn-of-month trading days. The time-series averages of the coefficients from the regressions are reported. The Newey-West t-statistics with a lag of 12 are presented in parentheses.

	1	2	3	4	5	6

Panel A: Firm-level regressions

LIDX	-0.255	-1.088***	-0.975***	-1.068***	-1.071***	-0.907**
	(-0.69)	(-2.95)	(-2.65)	(-2.88)	(-2.87)	(-2.38)
BM		0.113	0.116	0.100	0.112	0.098
		(1.29)	(1.32)	(1.20)	(1.28)	(1.20)
SIZE		-0.205***	-0.197***	-0.206***	-0.205***	-0.198***
		(-2.78)	(-2.80)	(-2.99)	(-2.71)	(-2.89)
ILLIQ		0.298**	0.287**	0.305**	0.289**	0.287**
		(2.31)	(2.37)	(2.41)	(2.29)	(2.44)
STR			-0.010**			-0.012***
			(-2.49)			(-2.80)
MOM				0.008		0.004
				(0.48)		(0.23)
SSKEW					1.410	2.074*
					(1.17)	(1.69)
Adj. R^2	0.014***	0.032***	0.039***	0.041***	0.035***	0.051***
	(7.16)	(16.01)	(19.46)	(19.10)	(16.54)	(21.88)

Panel B: Portfolio-level regressions

B1: Equal-weight

LIDX	-1.150***	-1.216***	-0.819**	-0.913**	-1.195***	-0.475
	(-2.97)	(-3.38)	(-2.07)	(-2.26)	(-3.19)	(-1.08)
BM		0.231*	0.254**	0.203*	0.248**	0.247**
		(1.94)	(2.11)	(1.78)	(2.14)	(2.23)
SIZE		-0.150*	-0.114	-0.128	-0.149*	-0.097
		(-1.92)	(-1.50)	(-1.64)	(-1.81)	(-1.21)
ILLIQ		0.436	0.522**	0.539*	0.485*	0.606**
		(1.63)	(1.99)	(1.91)	(1.81)	(2.15)
STR			-0.017*			-0.020**
			(-1.84)			(-2.03)
MOM				-0.016		-0.039
				(-0.53)		(-1.26)
SSKEW					2.309	3.246
					(0.77)	(1.11)
Adj. R^2	0.050***	0.113***	0.131***	0.139***	0.128***	0.167***
	(7.27)	(12.73)	(14.31)	(14.81)	(14.68)	(15.86)

B2: Value-weight

LIDX	-1.153***	-1.163***	-0.779**	-0.888**	-1.127***	-0.475
	(-2.95)	(-3.16)	(-1.97)	(-2.13)	(-2.96)	(-1.07)
BM		0.274**	0.291**	0.245**	0.281**	0.278**
		(2.24)	(2.37)	(2.11)	(2.35)	(2.47)
SIZE		-0.117	-0.086	-0.100	-0.119	-0.079
		(-1.60)	(-1.21)	(-1.37)	(-1.56)	(-1.05)

ILLIQ		0.494*	0.574**	0.599**	0.529*	0.645**
		(1.73)	(2.08)	(2.10)	(1.88)	(2.33)
STR			-0.015			-0.018*
			(-1.65)			(-1.87)
MOM				-0.019		-0.040
				(-0.63)		(-1.23)
SSKEW					2.074	3.089
					(0.73)	(1.09)
Adj. R^2	0.051***	0.110***	0.127***	0.136***	0.125***	0.164***
	(7.46)	(13.25)	(14.44)	(15.90)	(15.29)	(16.61)

*, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

6 Conclusion

Using daily return data instead of monthly returns that have often been used in previous studies, we examine the daily behavior of MAX anomaly over the course of a month. Single-sorted portfolio analyses show that the MAX effect varies across days in a month. In particular, the relationship between lagged extreme positive returns measured by maximum daily returns in the previous month and stock returns during the turn of the month is positive and statistically significant. In other words, for the short period of the first few days of the month or TOM period, high MAX stocks or lottery-like stocks produce higher returns than others. This can be explained by the surge in investors' demand for high MAX stocks during the TOM period when their cash flow and financial capacity are relatively high. We also use double-sorted portfolio analysis and cross-sectional regression to confirm that firm characteristics cannot account for high returns on high MAX stocks on the TOM trading days. In addition, we find that high MAX stocks after being overpriced due to high demand during the first few days of the month generate low returns for the rest of the month. Therefore, understanding of the MAX anomaly on the TOM trading days helps investors realize that the abnormal returns from the MAX strategy around the beginning of the month change drastically from the rest of the month and thereby make their stock investment options to achieve short-term positive returns.

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