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Article

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Lottery factor and stock returns: Evidence from India

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ABSTRACT

This study examines important aspects of lottery behavior in India using data from December 2001 to March 2021. We experiment with a new measure of lottery along with well-established measures. Our lottery measure focusing on more recent information is found to be appropriate for India. MAX has a unique role in predicting returns that is not subsumed by other risk measures. We find MAX, skewness, tail risk, and idiosyncratic volatility as relevant characteristics of lottery stocks. Using these, we construct a lottery factor representing investors' risk-seeking behavior. This behavior is an outcome of mis-weighting probability of extreme gains or losses and leads to overreaction to attention-catching events. We augment the Fama-French five-factor model with our lottery factor. Our six-factor behavioral asset pricing framework is found to be an appropriate performance benchmark. Lottery behavior is mainly the result of retail investor actions and is linked to several behavioral biases.

1. Introduction

Investors in the Indian market are continuously searching for new stock market anomalies that might reap greater profits than normal in a given market setting. A prominent anomaly that has attracted investor attention in recent years, is based on lottery behavior exhibited by investors. Kumar (2009) states that the human psyche has a deep-rooted desire to gamble. Investors who wish to profit from cheap bets prefer lottery-like stocks. Bali et al. (2011) define lottery behavior as chasing stocks with extreme positive returns in a recent period. Excess demand for these stocks pushes up their prices and consequently results in lower future returns. Walkshausl (2014), Cheon and Lee (2018), Lin and Liu (2018), and others also document the presence of lottery behavior. The evidence of the lottery anomaly makes it an exciting investment option for global investors.

Lottery behavior in stock markets might depend on certain socio-logical dimensions in a country. In recent years India has experienced a rapid increase in the urbanization rate. Because more people are moving to cities, their desire to earn quick profits might lead to lottery behavior. Investors engage in risk-seeking behavior and play the lottery through various investment avenues in the grey market, such as casinos, betting in gaming and election polls, and online betting. The availability of these options in India is limited. Moreover, not all these avenues are legal. Hence, investors may demonstrate lottery behavior through their actions in the securities market. This motivates us to study lottery behavior

in the Indian context. Most of the prior empirical evidence on lottery behavior comes from other advanced and emerging markets, but little work has been conducted on India. Our study builds on prior literature, as we comprehensively analyze various aspects of lottery behavior. Sharma and Chakraborty (2021) examine investment in lottery-like stocks in India but do not find a MAX effect. In this study, we employ alternative MAX-based measures and confirm that Indian investors engage in lottery behavior. We also construct a lottery factor and evaluate its role in enhancing the asset pricing framework. Subsequently, we offer behavioral explanations for the lottery factor.

Other prior work in India does not examine lottery behavior as the prime task. For instance, Peswani and Joshipura (2021) document that low-risk anomalies in India are driven predominantly by the leverage constraint effect, not by the lottery effect. Ali and Badhani (2023) examine the relationship between beta, tail risk, and returns after controlling for lottery effects.

In the present study, we explicitly look at lottery behavior in India and address some critical issues to understand this behavior. In particular, we focus on the following research challenges.

First, we determine the appropriate measure of lottery behavior and whether it is the same as used in prior work. Lottery behavior is believed to be driven by a memory process and is primarily an outcome of probability overweighing. In this light, we measure lottery behavior using MAX and MAX (5), as in prior literature (see Bali et al., 2011; Blau et al., 2019; Gong & Dai, 2017; Gong et al., 2021; Zhong & Gray, 2016).

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MAX is defined as the maximum daily return in the previous month, and MAX (5) is defined as the average of the highest five daily returns within the previous month. We also explore a new measure of lottery, MAX (L5), which is defined as the maximum return observed in the last five trading days in the previous month. The motivation comes from the idea that investors take a myopic view, hence they focus on more recent information, leading to overextrapolation bias. These investors may be interested in playing the lottery in stocks with extreme positive returns on the most recent trading days.

The second challenge addressed in the study is evaluating whether MAX overlaps with other risk-based anomalies. Specifically, we investigate whether MAX is a unique risk anomaly or simply proxies for the role of other risk measures in stock returns. Prior work identifies four prominent risk measures (beta, idiosyncratic volatility [IVOL], skewness, and tail risk) and states that MAX may not be the only measure of lottery, as investors can demonstrate gambling behavior in multiple ways (see Atilgan et al., 2020; Bali et al., 2017; Kumar, 2009; Zhong & Gray, 2016). We examine the relationship between MAX and expected returns in the presence of other risk measures.

Next, we identify important stock characteristics that connote lottery behavior and confirm the role of retail participants in this process. Based on the four key stock characteristics identified (i.e., MAX, skewness, tail risk, and IVOL), we construct our lottery index.

Traditionally, lottery behavior is defined as investors' risk-seeking response to low-probability positive events, such as MAX and skewness. Our findings suggest that investors can play the lottery in stock markets in other ways as well. They bet on low-probability negative events, such as left-tail risk. At the same time, their response to highly attention-catching variables such as IVOL, which does not have a role in the fundamental risk-return relationship, can lead to overreaction bias. These actions can also be classified as lottery-like behavior.

We incorporate this risk-seeking behavior into the asset pricing framework. The lottery index is then used to construct a lottery factor, which we employ to augment the Fama-French (F-F) five-factor model. We evaluate the role of the lottery factor in explaining MAX, prominent market, fundamentals-based, and other risk-based anomalies.

Finally, we examine some psychological determinants of lottery behavior. We analyze herd behavior in lottery and nonlottery stocks. Prior work shows that herding is stronger for lottery-like stocks (see Gong & Dai, 2017; Kumar et al., 2016). Next, we explore whether lottery behavior is influenced by market and firm-level sentiment and whether it is linked to investor attention. Specifically, we evaluate the performance of lottery and nonlottery stocks during market upturns and downturns. Following Aboody et al. (2018), we construct a measure of firm-level sentiment using the overnight return of stocks. To measure investor attention, we construct an index based on abnormal trading volume (see Barber & Odean, 2008) and a proxy of information discreteness, proposed by Da et al. (2014).

The present study explores these prominent aspects of lottery behavior in India. The findings are relevant for global investors who are interested in the Indian market. In particular, it contributes to the existing literature on lottery in the following ways. We introduce a novel measure of lottery behavior that demonstrates overextrapolation bias in India not seen in prior work. MAX is found to have unique information and other stock characteristics, such as skewness, tail risk, and idiosyncratic volatility, are relevant for identifying lottery stocks. The lottery factor representing investors' risk-seeking behavior, which is an outcome of mis-weighting the probability of gain- or loss-making events has the power to explain major stock market anomalies. We next confirm that lottery behavior in our sample market is mainly driven by the actions of retail investors. Lottery behavior is also linked to many behavioral biases.

After this introduction, the paper is organized as follows. In Section 2, we describe the data and construct the variables. Section 3 covers the methodology and estimation procedures. Our empirical results and discussions are in Section 4. Behavioral explanations of the lottery factor

are in Section 5, followed by conclusions in Section 6.

2. Data and variable construction

The sample comprises all companies listed on India's National Stock Exchange from December 2001 to March 2021. Stocks for which trading was discontinued during the study period were deleted. We use daily data for adjusted closing prices in local currency, which are converted into percentage returns. Returns in the prior month are used to calculate all measures of MAX. To estimate MAX and MAX (5), we use only stocks for which return data are available for at least 12 trading days in the past month. To estimate MAX (L5), we consider only stocks for which return data are available for at least three of the five most recent trading days. We use the NSE 500 Index as a market proxy, and 91-day Treasury bill yields are used to measure the risk-free rate. We check the association of MAX with other risk-based measures, namely, beta, IVOL, skewness, and tail risk. Stock beta and IVOL are calculated every month by regressing the daily returns of individual securities on the market return in the previous 12 months. Beta is estimated as the slope of this regression, whereas the variance in the error term represents IVOL. To calculate idiosyncratic skewness, we use the daily residual returns for the prior 12 months. In our analysis, we consider only stocks that have return data available for at least 100 trading days in the past 12 months to estimate these measures.

We calculate the tail risk factor every month using conditional value at risk (CVAR). It is estimated following the methodology suggested by Ling and Cao (2019). CVAR is derived by taking a weighted average of the extreme values in the left tail of the return distribution beyond the value at risk (VaR) cutoff point of 5 percent.

Next, cross-sectional estimations are performed to evaluate the impact of MAX on expected returns in the presence of other risk measures and firm characteristics. We employ firm characteristics such as size, value, and illiquidity.

Then, we evaluate the characteristics of lottery stocks to construct a lottery-based index. Prior empirical work also suggests that the lottery is primarily a retail phenomenon. To evaluate this, we check whether lottery behavior varies with the institutional holding pattern of our sample stocks. For this, we use annual data for institutional holdings for each security. Next, we evaluate the role of standard asset pricing models in explaining MAX, prominent market anomalies (size, illiquidity, and momentum), fundamentals-based anomalies (value and profitability), and other risk-based anomalies (beta, IVOL, skewness, and tail risk).

Size is measured using monthly data on market capitalization. To measure illiquidity, we take the average of the daily $\ln(\text{trading volume})$ for each month. We select only stocks for which data are available for at least 12 trading days every month. Momentum is estimated using the average of the past 12 months' returns. We select only stocks for which returns data are available for at least eight months. Value and profitability are measured using the monthly book-to-market equity ratio and the ratio of annual operating profits to total equity respectively. To employ the F-F size, value, profitability, and investment factors, we use annual data for the variables as described earlier. Change in total assets is used to estimate the investment factor.

Next, we analyze the potential determinants of lottery behavior. This involves testing herd behavior for lottery stocks and evaluating the role of the market, firm-level sentiment, and investor attention. Additional data used for this purpose are described in the relevant section. All market-related data come from the Thomson Reuters Eikon database, except the 91-day T-bill yield, which is obtained from the Reserve Bank of India's website.

3. Methodology and estimation procedures

3.1. Estimating MAX factor and its relationship with other risk variables

3.1.1. MAX factor and stock returns

We check for lottery premiums in India by estimating three measures of lottery: MAX, MAX (5), and MAX (L5). We start with a univariate analysis, in which stocks are sorted into deciles based on these measures. We construct monthly rebalanced value-weighted portfolios from P1 to P10, in which P1 and P10 comprise stocks with the lowest and highest values of MAX/MAX (5)/MAX (L5) in the previous month, respectively. As a robustness check, we also estimate MAX-based returns by constructing equally weighted portfolios. As shown in the next section, they provide lower returns than value-weighted portfolios. Consistent with prior research, we next perform further analysis on value-weighted portfolios.

3.1.2. Relationship between MAX factor and other risk variables

After evaluating the profitability of the MAX anomaly, we examine the association between MAX and other risk-based measures. The prominent risk anomalies identified in previous studies are based on beta, IVOL, skewness, and tail risk. Because MAX is also an important kind of risk-seeking behavior that arises out of greater investor attention to high-MAX stocks, we evaluate whether it proxies for other risk-based anomalies.¹

First, we focus on the association between MAX and beta. Betting against beta (BAB) is a prominent risk-based anomaly observed in prior literature (see Bali et al., 2017; Blitz & Vliet, 2007; Frazzini & Pedersen, 2014). As per the BAB effect, low-beta stocks outperform high-beta stocks. According to Bali et al. (2017), lottery demand explains the BAB phenomenon, and the BAB effect is observed in stocks with lower institutional ownership. At the same time, the BAB anomaly can also be explained by the participation of leverage-constrained institutional investors who might prefer high-beta stocks as they offer implicit leverage in the market (see Frazzini & Pedersen, 2014). Because investors pay greater attention to high-beta and high-MAX stocks, we check for a possible association between the two variables. The next risk factor considered is IVOL. Prior work shows that low-IVOL stocks outperform high-IVOL stocks (see Ang et al., 2006; Nartea et al., 2013). A possible reason for this behavior is that investors pay greater attention to stocks with higher IVOL, leading to lower future returns. Thus, we examine whether MAX and IVOL have an overlapping relationship.

Next, we focus on skewness. According to Barberis and Huang (2008), investors might put more weight on low-probability events and prefer stocks with positive skewness. Considerable evidence in prior literature shows that stocks with positive skewness generate lower returns (see Boyer et al., 2010; Conrad et al., 2013; Mitton & Vorkink, 2007). Investors might look at outliers and demand stocks with positive skewness. Thus similar behavioral reasons might drive the anomalies related to skewness and MAX. We analyze the relationship between skewness and MAX and examine whether they overlap.

We also look at the relationship between MAX and tail risk because they are both results of risk-seeking behavior. Whereas the MAX effect is related to risk-seeking behavior on the right tail, the tail-risk puzzle is believed to be an outcome of such behavior on the left tail. According to Atilgan et al. (2020), the left-tail anomaly arises because investors underestimate persistence in left-tail risk, and they overvalue stocks with large recent losses. They expect mean reversion in the short term, which leads to lower future returns on stocks with higher left-tail risk.

We test the association between MAX and other risk-based measures,

estimating the correlation between optimal MAX measure with beta, IVOL, skewness, and tail risk.² Cross-sectional correlations are calculated on a monthly basis, and the average monthly correlation is then estimated.

3.1.3. Cross-sectional tests

We next perform cross-sectional tests on the relationship between MAX and expected returns after controlling for other risk measures and important firm characteristics. To do so, we adopt the methodology proposed by Fama-Mac Beth (1973). Data for all the variables are arranged cross-sectionally. The returns for all stocks in our sample set for month t are regressed on MAX, other risk-based measures, and selected firm characteristics observed in month $t - 1$. Specifically, we use the following regressors: MAX (L5) as the optimal MAX measure; four additional risk measures, namely, firm beta, IVOL, skewness, and tail risk; and three firm characteristics—that is, firm size (market capitalization), value (book-to-market equity ratio) and illiquidity (average trading volume).

Because MAX (L5) is a newly proposed measure, we re-estimate the cross-sectional regressions for India with MAX and MAX (5), which are traditionally used measures.

The cross-sectional regression has two objectives: first, to reconfirm the relationship between MAX and expected returns; and, second, to evaluate that such a relationship is not impacted by the presence of other risk variables.

Our results confirm that MAX is not affected by other risk variables. This motivates us to evaluate the key characteristics of lottery stocks that can be used to construct a comprehensive lottery factor.

3.2. Identifying key lottery characteristics

Traditionally, lottery behavior is defined as investors' risk-seeking behavior due to over-attention to low-probability positive events (Kahneman & Tversky, 1979). MAX is an important characteristic of lottery stocks. However, in this section, we identify other characteristics that represent lottery behavior.

In prior work, price is considered an important characteristic of lottery stocks (Kumar, 2009). Investors seeking cheap bets express their lottery behavior by preferring stocks with low prices. Our results in the following section confirm the opposite relationship between past prices and expected returns. If a low price were a relevant characteristic of lottery stocks, they would have attracted greater investor attention and provided lower returns. To investigate the inverse relationship, we next check whether the price effect is driven in part by the presence of penny stocks in our portfolio. We reconstruct the price-based portfolios after removing penny stocks, where penny stocks are defined as stocks with a price below INR 10. We also check whether the price effect is driven by the small-firm effect, as firm size is measured by market capitalization, which is simply price times the number of shares outstanding. We construct size-based univariate decile portfolios (S1 to S10) based on monthly market capitalization for our sample securities after controlling for penny stocks. We regress the premiums of price-based portfolios on the premiums of size-based portfolios after controlling for penny stocks. It is possible that the price effect may be proxying for the size effect and might not actually be a measure of lottery behavior as shown in previous studies. We also confirm this in the next section. Hence, we do not consider price a lottery characteristic.

Prior work also shows that the beta anomaly is driven primarily by investor demand for lottery-like assets (Bali et al., 2017). However, we ignore beta as a lottery characteristic, as it is a measure of systemic risk. Rather, it is used to evaluate the risk-return relationship of assets based

¹ We confirm that high-MAX stocks have higher risk than low-MAX stocks.

² Our results in the next section show that MAX (L5) is the most appropriate MAX measure for India, as the long-short investment strategy based on it yields highest returns. Hence, we use this MAX measure for further analysis.

on a rational pricing framework. In contrast, lottery behavior is expected to be an outcome of irrational beliefs and preferences, generally held by retail investors, which is also shown by our results.

Next, we evaluate idiosyncratic skewness as a characteristic of lottery stocks. Investors who give excessive weight to low-probability positive events also bet on skewness and chase stocks with high skewness. Hence, like MAX, lottery behavior on the right side of the return distribution can also be measured using skewness. Prior work also identifies skewness as a characteristic of lottery stocks (Brunnermeier et al., 2007; Kumar, 2009; Kumar et al., 2011; Zhu et al., 2021).

In addition to overweighting low-probability positive events, investors might also demonstrate lottery behavior by underweighting negative events. They may chase loss-making stocks due to mean reversion beliefs.³ Such actions are also tantamount to lottery-like behavior. Left-tail risk is a prominent measure used to estimate risk on the left side of the return distribution.

According to Atilgan et al. (2020), the tail risk puzzle is an outcome of risk-seeking behavior on the left-tail side. Hence, we consider tail risk as a characteristic that represents quasi-lottery behavior.

Additionally, we explore IVOL as a characteristic of lottery stocks. We believe that lottery behavior can also be expressed by an over-reaction to any risk variable that attracts attention, as shown in prior work. According to Kumar (2009), in the event of high volatility, investors might believe in a higher probability that extreme return events in the past will be realized again—hence, IVOL is characteristic of lottery stocks. Nartea et al. (2013) show that stocks with greater IVOL imply greater investor attention. Tian et al. (2022) hold that the IVOL effect is enhanced significantly by greater investor attention. However, investors pay more attention to high- or low-IVOL stocks depending on the diversification opportunities in a particular market. Investors in India pay more attention to low-IVOL stocks because fewer diversification opportunities are available (Sehgal et al., 2012; Sehgal & Garg, 2016), and we find this as well, as shown in the next section. Thus, over-attention to IVOL is considered quasi-lottery behavior.

Henceforth, we consider MAX, skewness, tail risk, and IVOL important lottery characteristics. We construct univariate long-short decile portfolios based on these characteristics, which are rebalanced on a monthly basis. These long-short portfolios go long (short) in the lowest (highest) decile. We construct a lottery index based on these characteristics, employing the Z-score methodology (Sehgal & Pandey, 2021). All stocks are ranked in ascending order based on each lottery characteristic.

Specifically, we assign a rank of 1 to stocks with high MAX (5)/MAX (L5), high skewness, low IVOL, and high tail risk. Ranks are assigned in accordance with the results discussed below. We estimate the mean and standard deviation of all the ranks and calculate the standardized Z score for every company based on each measure. Further, the average of the five individual Z scores is used to determine the final Z score for each stock. We call this mean Z score as our lottery index, which is then used as the sorting criteria for constructing univariate decile portfolios Z1 to Z10. Prior research finds a strong preference for lottery-type stocks among retail investors (Cox et al., 2020; Han & Kumar, 2013; Kumar, 2009; Kumar & Lee, 2006). To confirm this, we construct 5×5 bivariate portfolios based on institutional holdings and the Z score. The institutional holdings are used to sort our sample securities into quintiles (I1 to I5), within which we construct quintiles (Z1 to Z5) based on the estimated Z scores, where portfolios I1 (I5) and Z1 (Z5) represent stocks with the lowest (highest) level of institutional holdings and Z scores. To check whether institutional holdings are relevant for determining lottery behavior, we estimate the returns on long-short lottery-based portfolios in groups I1 to I5. If lottery is a retail phenomenon, we expect to see larger premiums in portfolio I1.

³ Mean reversion may be an outcome of disposition bias, which is a tendency to sell winning stocks more aggressively than losing stocks.

3.3. Lottery factor and asset pricing tests

Using the information on the lottery index, we now construct the lottery factor. Specifically, we take the average return for the three portfolios with the least lottery behavior (Z8 to Z10) and label it L3, representing 30 percent of the sample stocks. We employ a similar methodology for the three portfolios (Z1 to Z3) with the most lottery behavior and label it L1. The lottery factor premiums are estimated as the difference in returns between L3 and L1. The lottery factor should proxy for the risk-seeking behavior of investors regarding extreme profit- and loss-making events and hence is expected to play an important role when added to standard asset pricing models, which are based on rational assumptions. Our augmented model is used to explain MAX and other prominent stock market anomalies. We evaluate important market anomalies, fundamentals-based anomalies, and other risk-based anomalies. To examine market anomalies, we construct univariate value-weighted decile portfolios based on size, trading volume, and prior returns. Long-short portfolios are constructed, which go long (short) on stocks that are small (big) in size, have low (high) trading volumes, and high (low) prior returns.⁴

To examine fundamentals-based anomalies, we construct univariate value-weighted decile portfolios based on value and profitability. Long-short portfolios are constructed, which go long (short) on stocks with a high (low) book-to-market equity ratio and high (low) profitability.

Depending on the availability of data, profitability-based portfolios are rebalanced annually, but the other portfolios are rebalanced on a monthly basis.

Finally, we focus on four additional risk-based anomalies. We construct monthly rebalanced univariate value-weighted decile portfolios based on stock beta, IVOL, skewness, and tail risk. Long-short strategies are constructed in which we go long (short) on stocks with low (high) beta, skewness, and tail risk. For IVOL-based portfolios, we take a long (short) position in stocks with high (low) IVOL.

We test for risk-based explanations for these anomalies using standard asset pricing models, namely, capital asset pricing model (CAPM) and Fama-French three-factor (F-F 3) and five-factor (F-F 5) models.

Market capitalization and the ratio of book equity to market equity (B/E) are used to construct size and value factors in the F-F 3 framework. We use 2×3 sorts involving two size-based and three B/E-based portfolios using F-F construction methodology (Fama & French, 1993). We operationalize the F-F five-factor model using $2 \times 2 \times 2 \times 2$ sorts of size, value, profitability, and investment factors. To do so, we construct the profitability and investment factor using the ratio of operating profits to total equity value and change in total assets respectively (Fama & French, 2015). If the returns on any portfolio remain unexplained after employing the F-F 5 framework, we augment it with our lottery factor.

4. Results and discussions

4.1. The performance of MAX-based portfolios and the association of MAX with other risk measures

We document the presence of the lottery effect in the Indian stock market, which is confirmed by all the MAX measures employed in the study. We observe monthly return premiums of 0.5 percent, 0.45 percent, and 1.33 percent for value-weighted portfolios based on low minus high MAX, MAX (5), and MAX (L5) (see Table 1), respectively. For equally weighted portfolios, we observe mean monthly premiums of 0.42 percent, 0.55 percent, and 1.13 percent, respectively.

⁴ In a long-short investment strategy, we try to replicate a zero-cost portfolio, where a short position is treated as a means of financing. Accordingly, we take a long (short) position in high (low)-performing investment. We go long/short on portfolios depending on the direction of their returns.

Table 1
Returns on MAX-based portfolios.

Portfolios	Returns on MAX-based portfolios	Returns on MAX (5)-based portfolios	Returns on MAX (L5)-based portfolios
P1	1.884	1.869	2.267
P2	2.016	2.023	2.001
P3	2.028	1.991	2.380
P4	1.975	2.044	2.173
P5	2.113	2.030	1.981
P6	2.090	2.108	2.005
P7	1.825	2.065	1.916
P8	2.129	2.219	2.115
P9	2.033	1.709	1.701
P10	1.384	1.415	0.939
P1–P10	0.500 (1.117)	0.454 (0.932)	1.327 ^a (3.889)

Notes: We show returns on univariate decile portfolios, P1 to P10, constructed using all 3 MAX measures used in the study. In the construction of these portfolios, stocks are sorted in ascending order of the ranking criterion. The table also highlights the difference in returns of corner portfolios (P1–P10) and their *t*-value (in parentheses).

^a Statistically significant returns at the 5% level.

Directionally, the return patterns of these portfolios are similar. However, premiums based on MAX and MAX (L5) measures are stronger for value-weighted portfolios than equally weighted portfolios.

For all these measures, the MAX effect is believed to arise because of greater investor attention to high-MAX stocks, which also have higher volatility.⁵

An interesting fact highlighted by our work is that Indian investors are myopic in their investment decisions, as the highest and the only statistically significant value of the return premium is observed for MAX (L5). A large difference in the premiums of MAX (L5)-based portfolios than other portfolios suggests the presence of short-term extrapolation bias, in which investors overreact to more recent information. This bias is also confirmed in previous literature (see Cassella & Gulen, 2018). Further, our time-series results are also confirmed by the cross-sectional estimations reported below.

Henceforth, we use MAX (L5) as the optimal MAX measure. Large premiums generated by MAX (L5)-based portfolios offer strong profitable opportunities for global investors.

Given the short-selling constraints in our sample market, investors can also exploit lottery-based strategies only on the long side.⁶ The mean monthly return on the value-weighted low MAX (L5) portfolio is 2.27 percent.

Next, we evaluate the association of MAX with other risk measures. Prior work shows mixed evidence on the relationship between MAX and other variables. Bali et al. (2017) find that lottery demand explains the BAB phenomenon. Zhong and Gray (2016) report a strong correlation between MAX and IVOL. Hai et al. (2020) document that these variables have independent information, and the IVOL effect is persistent regardless of the MAX effect. Further, the MAX effect is found to be robust after controlling for skewness (see Zhong & Gray, 2016). Atilgan et al. (2020) report that stocks with stronger lottery-like features have higher left-tail risk, in which lottery is measured by MAX.

Our findings show that all risk-based measures are virtually uncorrelated or at best mildly associated with MAX, as no correlation value exceeds 0.35 (see Table 2). Thus the MAX effect does not seem to occur at the same time as other risk-based anomalies. The results of Fama-MacBeth regressions reconfirm the significantly negative relationship between MAX (L5) and stock returns (see Table 3). Because MAX (L5) is a newly proposed measure, we re-estimate the cross-sectional regressions for India with MAX and MAX (5), which are traditionally used

Table 2
Correlation between MAX and other risk measures.

MAX and other risk measures	Correlation coefficient
Max (5/L5) & beta	0.082
Max (5/L5) & IVOL	0.277
Max (5/L5) & skewness	0.232
Max (5/L5) & tail risk	0.029

Notes: We show correlation between the most appropriate MAX measure and other risk measures. MAX (L5) is taken as the most appropriate MAX measures because it provides the highest return premium on our long-short portfolio, i. e., P1 (low MAX)–P10 (high MAX). The risk measures considered are stock beta, IVOL, skewness, and tail risk. We calculate the pair-wise cross-sectional correlations each month and then calculate its average monthly value.

Table 3
Cross-sectional tests: Fama-Mac Beth regressions.

Parameters	Value
$\gamma_{0,i}$	2.608 (10.153)
$\gamma_{1,i}$	−0.041 (−3.352)
$\gamma_{2,i}$	−1.740 (−17.210)
$\gamma_{3,i}$	0.535 (13.549)
$\gamma_{4,i}$	−0.178 (−3.969)
$\gamma_{5,i}$	−0.056 (−1.585)
$\gamma_{6,i}$	−0.169 (−6.284)
$\gamma_{7,i}$	0.002 (1.130)
$\gamma_{8,i}$	−0.071 (−3.047)

Notes: We show the results of cross-sectional tests based on Fama-MacBeth regressions. Our estimated cross-sectional model is:

$$R_{i,t} = \gamma_{0,i} + \gamma_{1,i} (\text{MAX}_i(t-1)) + \gamma_{2,i} (\beta_i(t-1)) + \gamma_{3,i} (\text{IVOL}_i(t-1)) + \gamma_{4,i} (\text{SKEW}_i(t-1)) + \gamma_{5,i} (\text{TR}_i(t-1)) + \gamma_{6,i} (\text{M. Cap.}_i(t-1)) + \gamma_{7,i} (\text{B/E}_i(t-1)) + \gamma_{8,i} (\text{VOL}_i(t-1))$$

Where,

$R_{i,t}$ is the return on stock of firm *i* stock at time *t*.

$\gamma_{0,i}$ is the intercept.

$\gamma_{1,i}$, $\gamma_{2,i}$, $\gamma_{3,i}$, $\gamma_{4,i}$, $\gamma_{5,i}$, $\gamma_{6,i}$, $\gamma_{7,i}$, $\gamma_{8,i}$ are the slope coefficients which show sensitivity of returns on stock *i* to the MAX measure, beta, IVOL, skewness, tail risk, market capitalization, book equity-to-market equity, and trading volume.

MAX, β , IVOL, SKEW, TR, M. Cap., B/E, and VOL are the MAX measure, beta, idiosyncratic volatility, skewness, tail risk, market capitalization, and book equity-to-market equity, and trading volume of stock *i* at time *t*−1.

measures. We do not find a significant relationship between MAX/MAX (5) and stock returns.⁷ This reconfirms the results based on the time-series portfolio analysis (see Table 1), showing that MAX (L5) is a more appropriate measure of lottery behavior in the Indian context. We next confirm that the relationship between MAX and returns is not impacted by other risk variables, which is consistent with our correlation results. The MAX effect is also not subsumed by firm characteristics. Thus MAX plays a prominent and unique role in the estimation of stock returns. Because MAX is not related to other risk characteristics, investors can also use other risk measures to demonstrate lottery behavior in stock markets. This motivates us to evaluate the key characteristics of lottery stocks that can be further used to construct a comprehensive lottery factor.

4.2. Lottery characteristics, lottery index and stock returns

As discussed in the previous section, we evaluate whether lottery

⁵ These results are not reported due to space limitations and are available from the authors on request.

⁶ Short-selling positions cannot be held overnight in the Indian market.

⁷ These results are not reported due to space limitations and are available from the authors on request.

behavior can be characterized by measures other than MAX.

First, we focus on price as a characteristic of lottery. Lottery stocks are believed to have low prices, as lottery can be related to placing cheap bets. However, we find a reverse relationship between past prices and expected returns. Low-price stocks outperform high-price stocks in our sample markets. We observe significant monthly price-based premiums of 3.06 percent on long-short portfolios. If a low price is a relevant characteristic of lottery stocks, they should attract greater investor attention and yield lower returns. On further investigation, we find that the price effect is driven in part by the presence of penny stocks in our portfolio. We reconstruct the price-based portfolios after removing penny stocks. We observe a substantial reduction in price-based premiums. The monthly premium declines to 1.36 percent (see Table 4, Panel A). We also check whether the price effect is driven by the small-firm effect. After regressing the premiums of price-based portfolios on the premiums of size-based portfolios after controlling for penny stocks, we find that alpha becomes statistically insignificant (see Table 4, Panel B). Thus we conclude that the price effect is driven predominantly by the size effect in India. Hence, we do not incorporate the last traded price as an important characteristic of lottery stocks.

Next, following prior research, we evaluate other risk-based measures that might represent lottery behavior, that is, skewness, tail risk, and IVOL. Returns on univariate decile portfolios based on these risk measures are reported in Table 5, Panel A. We find that stocks in the lowest decile outperform securities in the highest decile for portfolios based on skewness and tail risk. They yield significant monthly premiums of 0.62 percent and 0.88 percent. Although MAX and skewness are an outcome of risk-seeking behavior on the right-tail side, investors' risk-seeking behavior on the left-tail side explain the tail-risk anomaly. They underweight the probability of loss-making events and expect mean reversion in the short term. These investor actions are also

Table 4

Performance of price-based portfolios before and after controlling for penny stocks.

Panel A: Past price-based portfolio returns	
Portfolios	Returns
LP1	3.986
LP10	0.922
LP1-LP10	3.063** (4.663)
LP1*	2.234
LP10*	0.872
LP1*-LP10*	1.362** (3.056)
Panel B: Regression results	
Regression of price-based portfolios on size-based portfolios (before controlling for penny stocks)	
Parameters	LP1-LP10
Intercept	0.986** (2.989)
β (Size-based portfolios)	0.875 (28.269)
Regression of price-based portfolios on size-based portfolios (after controlling for penny stocks)	
Parameters	LP1*-LP10*
Intercept	0.196 (0.618)
β (Size-based portfolios)	0.491 (16.554)

Notes: This table shows the performance of price-based portfolios before and after controlling for penny stocks. Panel A shows returns on univariate decile corner portfolios. LP1/LP1* (LP10/LP10*) shows the returns on stocks with the lowest (highest) last traded price before/after controlling for penny stocks. It also highlights the returns on long-short portfolios (LP1-LP10)/(LP1*-LP10*) and their *t*-values (in parentheses), which are constructed by going long in LP1/LP1* and short in LP10/LP10*. We specifically show the performance of these portfolios before and after controlling for penny stocks, where penny stocks are defined as stocks below a price of INR 10.

Panel B shows the intercept and beta values (and their *t*-values in parentheses) obtained by regressing the premiums on long-short last traded price-based portfolios on premiums of size-based portfolios, before and after controlling for penny stocks.

^aStatistically significant returns at the 5% level.

Table 5

Returns on portfolios based on key lottery characteristics and lottery index-based portfolios.

Panel A: Returns on portfolios based on key lottery characteristics				
Portfolio numbers	Returns on MAX (L5)-based portfolios	Returns on skewness-based portfolios	Returns on tail risk-based portfolios	Returns on IVOL-based portfolios
1	2.267	2.140	2.931	1.531
2	2.001	2.118	2.375	1.553
3	2.380	2.085	2.425	1.814
4	2.173	2.218	2.350	1.754
5	1.981	2.110	2.128	2.038
6	2.005	2.078	2.292	1.990
7	1.916	1.926	2.108	1.990
8	2.115	1.760	1.984	1.767
9	1.701	1.570	2.176	2.092
10	0.939	1.515	2.052	3.031
1–10	1.327** (3.889)	0.625 ** (2.148)	0.879** (2.462)	–1.500 ** (–2.274)
Panel B: Returns on lottery index-based portfolios				
Portfolios	Returns			
Z1	1.501			
Z2	1.574			
Z3	1.843			
Z4	1.949			
Z5	2.183			
Z6	2.233			
Z7	2.515			
Z8	2.652			
Z9	2.749			
Z10	3.508			
Z10-Z1	2.007** (4.935)			

Notes: This table shows returns on univariate decile portfolios constructed using key lottery characteristics: MAX(L5), skewness, tail risk, and IVOL. Stocks are sorted in ascending order of the ranking criterion. The premiums on long-short portfolios are estimated by going long on the lowest decile and short on the highest decile. The *t*-values are in parentheses.

Panel B shows the returns on our lottery index sorted portfolios based on Z scores, which is calculated using key lottery characteristics. Here, portfolio Z1 (Z10) represents high (low) lottery stocks. The premiums on lottery portfolios (Z10-Z1) and *t*-values are in parentheses.

^aStatistically significant returns at the 5% level.

tantamount to expressing quasi-lottery behavior. In IVOL-based portfolios, we observe a direct relationship in which high-IVOL stocks outperform low-IVOL securities, with a significant monthly premium of 1.5 percent. Investors might bet on low-IVOL stocks because of inadequate diversification opportunities in the Indian market. Our results are confirmed by prior work (see Sehgal et al., 2012; Sehgal & Garg, 2016). This bias toward low-IVOL stocks due to excessive attention is suggestive of irrational investor behavior, as they are paying attention to unsystematic risk, which is not expected to be priced in the rational asset pricing framework. This also indicates an expression of lottery behavior. Thus IVOL is also considered a quasi-lottery characteristic. Henceforth, we consider skewness, tail risk, and IVOL as relevant characteristics of lottery other than MAX. We then construct a lottery index based on these characteristics. Table 5, Panel B, reports the returns on univariate decile portfolios (Z1 to Z10) based on our lottery index (i.e., the mean Z score).

We report significant lottery premiums of 2.01 percent per month, confirming that our lottery index can easily distinguish between stocks with low (Z10) and high (Z1) lottery behavior. These premiums are higher than those for any of the long-short portfolios constructed using a single lottery characteristic.

We further confirm that lottery behavior in our sample market is driven mainly by the actions of retail investors. The results of bivariate portfolios based on institutional holdings and the Z score show that much higher lottery premiums are observed for portfolios with lower institutional holdings. These are also statistically significant at the 5

percent level (see Table 6). Similar premiums for higher institutional holdings are small and statistically insignificant.

4.3. Asset pricing results

The lottery factor constructed using the lottery index has a significantly positive monthly premium of 1.33 percent. This factor proxies for the risk-seeking behavior of investors for extreme profit- and loss-making events, resulting in over-attention bias. Hence, this behavioral factor is expected to play an important role if it is added to standard asset pricing models based on rationality assumptions. Our results show significant returns on the MAX (L5) anomaly in the Indian market, which are not explained by the CAPM, F–F three-factor and F–F five-factor models (see Table 7). When we perform CAPM estimations, we observe significant abnormal returns of 1.13 percent per month, and beta is negative, indicating that low-MAX stocks have a lower beta. When we apply the F–F three-factor model, we still observe abnormal performance, and the premiums become marginally larger, 1.22 percent per month. This is because the coefficient of the book-to-market equity factor is statistically insignificant and therefore does not negate the impact of negative beta for our long-short MAX portfolio.

Abnormal returns on MAX-based portfolios persist even with use of the F–F five-factor model. We find no additional role of profitability and investment factors in explaining the MAX effect. However, abnormal returns are substantially lower and are no longer significant after the F–F five-factor model is augmented by our lottery factor. Given the power of the lottery factor in explaining the MAX effect, we next check its robustness by evaluating its role in describing other prominent equity anomalies.

We evaluate important market, fundamentals-based, and other risk-based anomalies, and the results are in Table 8.

When we apply the CAPM, we obtain statistically significant abnormal monthly returns of, respectively, 1.89 percent, 2.16 percent, 2.10 percent, and 1.07 percent on long-short portfolios based on size, trading volume, beta, and tail risk. The returns of size-based portfolios are explained by employing the F–F three-factor model, and the tail-risk anomaly is explained by the F–F five-factor model. The returns of beta and the illiquidity anomaly remain unexplained even when we use the F–F five-factor model. Our lottery factor again plays an effective role here. These returns are absorbed by the six-factor model, which consists of the Fama-French factors augmented by our lottery factor. We propose this model as the appropriate performance benchmark for the Indian market. The existing standard asset pricing models fail because they assume that investors are rational agents. Thus we recommend that the lottery factor be included in the multifactor asset pricing framework to account for investors' risk-seeking behavior due to the probability of

Table 6

Returns on double-sorted portfolios formed on institutional holdings and lottery index.

Portfolios	Returns
I1(Z5-Z1)	1.916 ^a (4.254)
I2(Z5-Z1)	0.945 ^a (2.977)
I3(Z5-Z1)	1.014 ^a (3.036)
I4(Z5-Z1)	0.902 ^a (2.525)
I5(Z5-Z1)	0.529 (1.866)

Notes: We show the returns on 5×5 bivariate sorted portfolios based on institutional holdings and Z-score. Premiums of lottery-based portfolios (Z5–Z1) within portfolios with lowest (I1) and highest (I5) institutional holdings are shown for both the sample markets. The *t*-values are in parentheses. This exercise confirms whether lottery behavior is predominantly associated with retail participation (proxied by greater non-institutional holdings in a company).

^a Statistically significant returns at the 5% level.

Table 7

Asset pricing results for MAX-based portfolios.

Results based on CAPM	
Intercept	1.133** (3.601)
β (market factor)	−0.193 (−4.308)
Results based on F–F three-factor model	
Intercept	1.222** (3.885)
β (market factor)	−0.192 (−4.109)
β (size factor)	−0.204 (−2.624)
β (value factor)	−0.017 (−0.231)
Results based on F–F five-factor model	
Intercept	0.920** (2.648)
β (market factor)	−0.191 (−4.058)
β (size factor)	−0.150 (−1.780)
β (value factor)	0.115 (1.052)
β (profitability factor)	0.284 (1.636)
β (investment factor)	0.290 (1.672)
Results based on F–F five-factor model augmented with lottery factor	
Intercept	0.443 (1.327)
β (market factor)	−0.126 (−2.787)
β (size factor)	−0.554 (−5.317)
β (value factor)	−0.250 (−2.093)
β (profitability factor)	0.265 (1.638)
β (investment factor)	0.265 (1.634)
β (lottery factor)	0.666 (5.896)

Notes: In this table, we test whether the returns on MAX-based portfolios are explained by standard asset pricing models, i.e., capital asset pricing model (CAPM), Fama-French (F–F) three-factor and F–F five-factor models. Further, we augment the F–F five-factor model with our lottery factor to check whether it absorbs the returns on unexplained portfolios. The *t*-values of intercept and beta coefficients are in parentheses.

^a Statistically significant returns at the 5% level.

incorrectly weighting gain- or loss-making events that leading to over-attention bias. Our behavioral factor lends greater power to existing asset pricing models. However, the proposed model needs to be rigorously tested using data on other global markets in order to evaluate out-of-sample evidence. The efficacy of our lottery factor motivates us to explore the major determinants that result in such irrational investor behavior.

5. Lottery factor: some behavioral explanations

This section analyzes the psychological reasons for lottery behavior in our sample market. Specifically, we check for herd behavior in lottery stocks and examine whether lottery behavior is driven by market- or firm-level sentiment or both. It may also be an outcome of investor attention bias.

Prior work reports herding in lottery stocks (see Gong & Dai, 2017; Kumar et al., 2016).⁸ We look for herding in portfolios comprising lottery (Z1) and nonlottery (Z10) stocks based on our lottery index (see Table 9). Employing the methodology suggested by Chang et al. (2000), we first calculate the equity return dispersion in both portfolios. For this, we use the data on daily stock returns and estimate the cross-sectional absolute deviation (CSAD) using the following equation:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^N |R_{i,t} - R_{m,t}| \quad (1)$$

where

$R_{i,t}$ is the return on stock of firm *i* stock at time *t*

⁸ Herding is believed to arise as an outcome of collective irrational behavior by a group of investors (retail or institutional), and their tendency to invest in the same set of stocks.

Table 8

Asset pricing results for market, fundamentals-based, and other risk-based anomalies.

Results based on CAPM									
Anomaly	Size	Illiquidity	Prior Returns	Value	Profitability	Beta	IVOL	Skewness	Tail Risk
Intercept	1.885 ^a (2.705)	2.162 ^a (5.830)	0.955 (1.762)	1.144 (1.942)	0.749 (1.936)	2.102 ^a (4.678)	0.639 (0.992)	0.146 (0.632)	1.072 ^a (3.082)
β(market factor)	0.192 (1.935)	−0.362 (−6.859)	−0.190 (−2.583)	0.399 (4.765)	−0.217 (−3.958)	−0.762 (−11.908)	0.564 (6.141)	−0.093 (−2.825)	−0.201 (−4.073)
Results based on F-F three-factor model									
Anomaly	Size	Illiquidity	Prior Returns	Value	Profitability	Beta	IVOL	Skewness	Tail Risk
Intercept	0.479 (1.762)	1.725 ^a (6.243)	1.634 (3.558)	−0.095 (−0.384)	1.448 (5.822)	1.879 ^a (4.245)	−0.636 ^a (−2.072)	0.193 (0.828)	0.821 ^a (2.445)
β(market factor)	−0.028 (−0.705)	−0.382 (−9.299)	−0.077 (−1.134)	0.118 (3.212)	−0.062 (−1.689)	−0.787 (−11.983)	0.338 (7.427)	−0.093 (−2.691)	−0.266 (−5.334)
β(size factor)	1.865 (27.733)	0.911 (13.328)	0.139 (1.222)	1.062 (17.394)	−0.602 (−9.752)	0.362 (3.309)	1.527 (20.098)	−0.111 (−1.925)	0.174 (2.102)
β(value factor)	1.203 (19.048)	0.145 (2.257)	−0.734 (−6.886)	1.466 (25.577)	−0.800 (−13.908)	0.145 (1.411)	1.208 (16.939)	−0.006 (−0.110)	0.328 (4.207)
Results based on F-F five-factor model									
Anomaly	Size	Illiquidity	Prior Returns	Value	Profitability	Beta	IVOL	Skewness	Tail Risk
Intercept	0.509 (1.632)	0.960 ^a (3.279)	0.587 (1.195)	0.068 (0.256)	0.579** (2.403)	0.920** (1.970)	−0.559 (−1.578)	0.054 (0.210)	0.648 (1.738)
β(market factor)	−0.053 (−1.254)	−0.369 (−9.327)	−0.040 (−0.605)	0.093 (2.569)	−0.027 (−0.825)	−0.770 (−12.037)	0.320 (6.680)	−0.093 (−2.652)	−0.267 (−5.315)
β(size factor)	1.823 (24.137)	0.973 (13.729)	0.174 (1.460)	1.055 (16.340)	−0.494 (−8.429)	0.458 (4.000)	1.451 (16.932)	−0.105 (−1.671)	0.188 (2.079)
β(value factor)	1.577 (16.072)	0.314 (3.416)	−0.842 (−5.447)	2.001 (23.848)	−0.899 (−11.890)	0.440 (2.959)	1.584 (14.225)	0.063 (0.767)	0.524 (4.471)
β(profitability factor)	−0.542 (−3.474)	0.665 (4.543)	1.380 (5.615)	−0.664 (−4.974)	1.177 (9.776)	0.889 (3.756)	−0.465 (−2.629)	0.160 (1.237)	0.042 (0.225)
β(investment factor)	−0.308 (−1.975)	0.153 (1.045)	0.131 (0.534)	−0.124 (−0.930)	0.578 (4.811)	0.545 (2.304)	−0.428 (−2.421)	0.069 (0.533)	0.245 (1.313)
Results based on F-F five-factor model augmented with lottery factor									
Anomaly	Size	Illiquidity	Prior Returns	Value	Profitability	Beta	IVOL	Skewness	Tail Risk
Intercept	−0.032 (−0.112)	0.412 (1.573)	0.772 (1.528)	−0.223 (−0.844)	0.440 (1.781)	−0.048 (−0.116)	−0.541 (−1.602)	−0.278 (−1.104)	−0.220 (−0.730)
β(market factor)	0.021 (0.532)	−0.295 (−8.322)	−0.065 (−0.956)	0.132 (3.706)	−0.009 (−0.275)	−0.638 (−11.534)	0.370 (7.791)	−0.048 (−1.406)	−0.150 (−3.678)
β(size factor)	1.365 (15.315)	0.509 (6.228)	0.330 (2.097)	0.809 (9.836)	−0.605 (−7.902)	−0.362 (−2.833)	1.138 (10.385)	−0.386 (−4.922)	−0.548 (−5.824)
β(value factor)	1.163 (11.413)	−0.104 (−1.113)	−0.701 (−3.887)	1.779 (18.903)	−1.001 (−11.397)	−0.299 (−2.048)	1.301 (10.380)	−0.191 (−2.130)	−0.139 (−1.293)
β(profitability factor)	−0.563 (−4.065)	0.643 (5.061)	1.387 (5.659)	−0.675 (−5.276)	1.171 (9.812)	0.850 (4.280)	−0.480 (−2.817)	0.147 (1.206)	0.007 (0.052)
β(investment factor)	−0.337 (−2.432)	0.123 (0.971)	0.141 (0.576)	−0.140 (−1.092)	0.572 (4.803)	0.493 (2.482)	−0.448 (−2.631)	0.051 (0.419)	0.198 (1.353)
β(lottery factor)	0.755 (7.818)	0.765 (8.631)	−0.258 (−1.510)	0.406 (4.553)	0.186 (2.226)	1.351 (9.757)	0.517 (4.352)	0.464 (5.449)	1.212 (11.881)

Notes: This table shows the performance of standard asset pricing models in explaining the returns on prominent market anomalies (i.e., size, illiquidity, and prior returns), fundamentals-based anomalies (i.e., value and profitability), and other risk-based anomalies (i.e., beta, IVOL, skewness, and tail risk). The asset pricing framework employed is the same as discussed in Table 7. The *t*-values of intercept and beta coefficients are in parentheses.

^a Statistically significant returns at the 5% level.

Table 9

Herd behavior in lottery stocks.

Portfolios	β ₀	β ₁	β ₂
Z1	1.519 (134.975)	0.253 (22.093)	0.003 (1.683)
Z10	2.051 (114.741)	0.496 (19.996)	−0.016 ^a (−2.689)

Notes: This table shows the herding pattern in portfolios with high (Z1) and low (Z10) lottery behavior.

^a Statistically significant coefficient of the nonlinear term at the 5% level.

$R_{m,t}$ is the cross-sectional average of *N* stock returns in the portfolio at time *t*.

Next, we estimate the following regression:

$$CSAD_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 R_{m,t}^2 + \epsilon_t \quad (2)$$

The presence of herd behavior is confirmed if the coefficient on the

nonlinear term is negative and statistically significant. Our results are contrary to those reported in prior work. We observe herd behavior in nonlottery stocks because lottery is primarily a retail phenomenon. Naive retail investors have varying degrees of risk aversion and construct portfolios based on different lottery characteristics. Hence, their portfolios are likely to be heterogeneous and less related to one another, and they might base their investment decisions on a scattered set of information. However, institutional investors generally have a high degree of risk aversion and develop investment strategies based on common firm characteristics (e.g., size, value, profitability) focusing on a universe of similar large stocks, so they are likely to invest in a similar set of securities. Prior literature also provides evidence of institutional herding (see Choi & Sias, 2009; Sias, 2004; Wang et al., 2020). Sahoo et al. (2023) also confirm the presence in India of herding behavior by institutional investors. Hence, as expected, we observe herding in

nonlottery stocks, which is an outcome of activities by institutional investors.

Next, we check whether lottery behavior is driven by market-level sentiment. We define a market upturn (when the market return is greater than the risk-free return) as a period of positive sentiment and a market downturn (when the market return is less than the risk-free return) as a period of negative sentiment. We evaluate the performance of lottery and nonlottery stocks during market upturns and downturns. To do so, we regress the excess returns of portfolios based on our lottery index (Z1 and Z10) on a dummy variable that takes a value of 1 or 0 in periods of positive or negative sentiment (see Table 10). We find significantly positive beta coefficients for lottery stocks, which implies that Indian investors tend to play the lottery more during a bull market. Thus, market-level sentiment seems to impact lottery behavior in India.

As a robustness check, we employ another measure of market sentiment, suggested by Atigan et al. (2020).⁹ To do so, we define a market upturn (when the market return is greater than the mean market return for the previous 36 months) as a period of positive sentiment and a market downturn (when the market return is less than the mean market return for previous 36 months) as a period of negative sentiment. We observe similar results with this measure.¹⁰

Next, to evaluate the relationship between lottery behavior and firm-level sentiment, we construct a measure of investor sentiment for specific firms. To do so, we build on the methodology proposed by Aboody et al. (2018). Every month, firm-level sentiment is calculated as the average of overnight returns of the prior three trading days. The overnight return is estimated using the following equation:

$$\frac{[(\text{Adjusted opening price on day } t) - (\text{Adjusted closing price on day } t-1)]}{(\text{Adjusted closing price on day } t-1)} \times 100 \quad (3)$$

We construct monthly rebalanced 5×5 bivariate sorted portfolios, in which all sample stocks are first sorted into ascending order quintiles (FS1 to FS5) based on the measure of firm sentiment described above. Within each group, we construct five lottery-based portfolios (Z1 to Z5) based on our lottery index. Our findings indicate that lottery premiums are higher in group FS5 than in FS1 (see Table 11). Thus, firm-level sentiment seems to drive lottery behavior in Indian markets.

Finally, we examine whether investor attention drives lottery premiums. To do so, we construct an index that measures investor eye-catching behavior. This is based on proxies related to stock prices and abnormal trading volumes. Stocks with discrete price movements attract more investor attention than stocks with more continuous price movements. To gauge this, we measure information discreteness (ID) using

Table 10
Lottery behavior and market-level sentiment.

Portfolios	α_i	β_i
Z1	−6.106 (−10.184)	12.283 ^a (15.318)
Z10	2.354 (4.097)	0.265 (0.344)

Notes: We show the performance of lottery (Z1) and nonlottery (Z10) stocks in periods of market upturns and downturns. We regress the returns on portfolios Z1 and Z10 on a dummy variable, which takes a value of 1 or 0 in periods of the positive or negative sentiment using the following equation.

$$R_{i,t} = \alpha_i + \beta_i(d_t) + e_{i,t}$$

Where $R_{p,t}$ is the return on portfolio p at time t , and d_t is the dummy variable at time t . The role of market sentiment is confirmed by the significant slope of the dummy variable in the regression.

^a Statistically significant value of coefficient β at the 5% level.

⁹ Atigan et al. (2020) use a 12-month mean as the benchmark. However, we use a longer window, 36 months, to obtain a better estimate.

¹⁰ These results are not reported due to space limitations and are available from the authors on request.

Table 11
Lottery behavior and firm-level sentiment.

Portfolios	Returns
FS1(Z5-Z1)	1.419 ^a (3.501)
FS2(Z5-Z1)	1.315 ^a (3.504)
FS3(Z5-Z1)	0.908 ^a (2.871)
FS4(Z5-Z1)	1.461 ^a (4.948)
FS5(Z5-Z1)	3.501 ^a (8.538)

Notes: This table shows the returns on 5×5 bivariate sorted portfolios based on firm-level sentiment and lottery index. We report premiums of lottery-based portfolios (Z5–Z1) in portfolios with the lowest (FS1) and highest (FS5) firm sentiment. The t -values are in parentheses.

^a Statistically significant returns at the 5% level.

the following methodology (see Da et al., 2014):

$$ID = \text{PRET} \times (\% \text{ of down days in the past month} - \% \text{ of up days in the past month}) \quad (4)$$

where

PRET is calculated as the absolute value of cumulative daily returns for every month.

Down and up days are defined as days in each month with negative and positive returns, respectively.

Greater investor attention is associated with a higher ID, as it signifies discrete information. We also expect greater investor attention to be related to higher trading activity.

Following Barber and Odean (2008), we construct a measure of abnormal trading volume. It is estimated as the ratio of trading volume at the end of each month to the average over the previous year for each stock.

These characteristics are combined using the Z-score methodology (see Sehgal & Pandey, 2021). We assign rank 1 to stocks with the lowest ID and lowest trading activity and estimate the standardized Z score for each stock. The investor attention index for each stock is constructed by taking the average Z score, which is labeled Z-IA. Low values of Z-IA signify a low degree of investor attention.

We construct monthly rebalanced 5×5 bivariate sorted portfolios, in which the sample stocks are first sorted into quintiles in ascending order (Z-IA1 to Z-IA5) based on our measure of investor attention. We then construct lottery-based quintiles (Z1 to Z5) within each group. Our results show that higher lottery premiums are observed for stocks with high attention (see Table 12). This aligns with our belief that lottery behavior is an outcome of investor overreaction to events that attract attention.

Putting it all together, we conclude that investors demonstrate

Table 12
Lottery behavior and investor attention.

Portfolios	Returns
Z-IA1(Z5-Z1)	1.025 ^a (2.187)
Z-IA 2(Z5-Z1)	1.598 ^a (4.708)
Z-IA 3(Z5-Z1)	1.868 ^a (5.380)
Z-IA 4(Z5-Z1)	1.692 ^a (4.679)
Z-IA 5(Z5-Z1)	2.820 ^a (6.140)

Notes: This table shows the returns on 5×5 bivariate sorted portfolios based on our investor attention index (Z-IA) and lottery index.

Our sample stocks are first sorted into five portfolios (Z-IA1 to Z-IA 5) in ascending order. Within each ID-based group, we further construct five portfolios based on our lottery index. We report the premiums of lottery-based portfolios (Z5–Z1) in portfolios Z-IA1 and Z-IA 5. The t -values are in parentheses.

^a Statistically significant returns at the 5% level.

greater lottery behavior in times of positive market sentiment. Further, in a bull market, stronger lottery behavior is associated with higher firm-level sentiment and overreaction to stocks with greater jumps in prices as well as higher abnormal trading volumes. The lottery phenomenon in India is primarily an outcome of activity by retail investors, who do not show any herd behavior. In contrast, nonlottery stocks demonstrate herd behavior, which may be primarily due to institutional investor activity.

6. Conclusions

This study highlights a few interesting facts about lottery behavior in India. We find that a novel MAX factor that focuses on more recent information is a better measure of lottery behavior than traditional measures suggested by Bali et al. (2011). In addition to MAX, there are other relevant characteristics of lottery stocks, such as skewness, tail risk, and idiosyncratic volatility. We construct a lottery factor that accounts for investors' risk-seeking behavior arising out of mis-weighting of the probability of gain- or loss-making events. This behavior leads to investor overreaction to events that attract attention. We propose a six-factor behavioral asset pricing framework that captures all the major equity anomalies. We observe stronger lottery behavior in bullish markets, which is also associated with higher firm-level sentiment and investor attention bias.

Lottery behavior is mainly an outcome of retail investor activity, and we do not observe any herding in lottery stocks. Our findings offer important insights to global investors who wish to develop profitable trading strategies based on lottery behavior in the Indian securities market. The study also provides an out-of-sample test on the lottery effect in an important emerging market.

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