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Tail risk, beta anomaly, and demand for lottery: what explains cross-sectional variations in equity returns?

Asgar Ali[1] · **K. N. Badhani**[2]

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Abstract
This study investigates the tail-risk and returns relationship in an emerging equity market—India. We observe both the beta and the tail risk anomalies at the univariate portfolio level. However, after controlling for the lottery effects (MAX and idiosyncratic volatility), the relationship between the systematic tail risk measures and the expected returns turns positive for some of the proxies of tail risk, while the relationship between beta and expected returns becomes flat. The lottery effect explains the tail risk anomaly reported in the literate. These results suggest that investors care for probabilities of extreme changes in stock prices but do not care much about moderate variations in stock returns. Emerging markets have a significant presence of individual investors, who consider investing in the stock market as an opportunity to gamble and earn lottery-like payoffs, which results in an overvaluation of lottery stocks. Since these stocks also have high systematic risk and a high probability of extreme negative returns, we observe that the expected returns are negatively correlated with beta and left tail risk measures before controlling for the lottery effects. These results are robust after controlling for other relevant variables such as the size of the firm, book-to-market ratio, momentum, retail ownership, and illiquidity.

Keywords Tail risk · Lower-tail dependence · Behavioural portfolio theory · Beta anomaly · Preference for lottery

JEL Classification G10 · G11 · G12 · G14

✉ Asgar Ali
asgar@dubai.bits-pilani.ac.in

K. N. Badhani
knbadhani@iimkashipur.ac.in

[1] Birla Institute of Technology and Science Pilani, Dubai Campus, Dubai, United Arab Emirates

[2] Indian Institute of Management Kashipur, Udham Singh Nagar, Uttarakhand 244713, India

1 Introduction

The risk-return trade-off is at the heart of finance, but what constitutes the risk is always debatable. The mean–variance framework, which defines the risk in terms of the variance of expected returns, is conceptually elegant and widely used in financial economics. But it is based on unrealistic assumptions and fails to stand empirical validations. The concept of safety-first (Roy 1952) presents a more plausible description of how common people perceive risk. For them, the risk is the probability of the return falling below some threshold or the left tail probability of return distribution. Therefore, tail risk is likely to be a more relevant measure of risk.

Does the market compensate the investors for bearing higher tail risk? Researchers have been addressing this question for some time. One of the challenges in this research is the difficulty in measuring the tail risk due to very few observations available. The researchers have used different approaches to measure tail risk and examined the risk-return relationship.[1] Some studies confirm the positive relationship between tail risk and expected returns (Zhen et al. 2020; Chabi-Yo et al. 2018; Kelly and Jiang 2014; Bali et al. 2014; Bollerslev and Todorov 2011). However, the growing strand of the empirical research presents a negative relationship[2] between the left tail risk and expected stock returns (Bi and Zhu 2020; Atilgan et al. 2020; Long et al. 2018; Gao et al. 2019; and DiTraglia and Gerlach 2013), a phenomenon referred as the 'tail risk anomaly'.

We observe tail risk anomaly in India in portfolio-level analysis. However, once we control for CAPM beta, MAX effect, and idiosyncratic volatility, this anomaly disappears, and in some cases, we obtain a consistent risk-return relationship. MAX effect represents the demand for lottery-like payoffs, which significantly impact the cross-sectional variation in stock returns. Bali et al. (2017) show that the MAX-effect can explain the observed beta anomaly in the US market. We observed a very strong MAX-effect in the Indian stock market and this effect explains the tail risk anomaly and size anomaly together with the beta anomaly. The MAX effect is associated with small stocks and stocks having a high proportion of retail ownership. High idiosyncratic volatility is also associated with speculative assets and is often used as another proxy of demand for lottery-like payoffs (Kumar 2009; Han and Kumar 2013; Bali et al. 2017; Chichernea et al. 2019).

Our results show that the lottery demand and systematic tail risk have a significant relationship with expected returns, but beta does not explain the cross-sectional variation of stock returns. This indicates that the investors care for probabilities of extreme market movements but do not care much about moderate variations in stock returns. Investors prefer stocks with lottery-like characters; therefore, such stocks are overvalued in the market and have low expected (future) returns. Since the lottery stocks also have high beta, the high beta stocks are observed to have low expected returns. Similarly, tail risk and beta are also correlated; therefore, the negative correlation between beta and expected returns produces the inverse relationship between tail

[1] see, for example, Harris et al. (2019), Chabi-Yo et al. (2018), Bollerslev et al. (2015), Kelly and Jiang (2014), Bali et al. (2014), Xiong et al. (2014), Huang et al. (2012).

[2] In some studies, no premium was observed for stocks with higher tail risk (e. g., Van Oordt and Zhou 2016).

risk and expected returns. Once the effects of lottery demand and beta are controlled, we observe that stocks with higher-tail risk have higher expected returns.

We also estimate the impact of conditional value-at-risk (CVaR) on cross-sectional expected returns. After controlling for the systematic tail risk, this estimation captures the marginal effect of idiosyncratic tail risk. Supporting the earlier findings (e.g., Long et al. 2018; Bi and Zhu 2020; Atilgan et al. 2020), we observe an idiosyncratic tail risk anomaly—idiosyncratic tail risk and expected returns are negatively correlated. However, this relationship becomes statistically insignificant when we control for idiosyncratic volatility.

Our results indicate that the investors try to maximize the potential for high returns protecting their investments from extreme losses. The lottery effect (desire for windfall profits) dominates over the protection of wealth motive. Investors appear to show risk-taking rather than risk-averse behaviour. We explain these observations in the light of the 'behavioural portfolio theory' (Shefrin and Statman 2000). According to this theory, investors keep their investments in different mental accounts. They first allocate their investment funds to safer investment portfolios (such as bank deposits, fixed income securities, insurance policies, etc.) to ensure their financial safety. Then they may allocate some money in another mental account that they invest in risky securities (such as equity) to earn speculative profits. While investing in the equity market, they show gambling preference; they take higher risks and invest in stocks with a tiny probability of making skewed high returns, although their mean returns may be low or negative. Therefore, although investors are risk-averse in their overall investment strategy, they show risk-taking behavior while investing in the equity market.

Emerging markets, including India, have significant participation of retail investors in market turnover. These investors are known to show gambling behaviour and lottery preference while investing in the equity market (Kumar 2009; Han and Kumar 2013; Bali et al. 2018). Since retail investors have a higher ownership in small stocks, this behaviour also produces an inverse size-effect; small stocks have lower expected returns than large stocks.

The contribution of our research to the literature is threefold. First, our study considers three different measures of systematic tail risk to ensure that the results are not spurious and sensitive to how the systematic tail risk is defined. Second, the study documents that investors' preference for lottery-like returns distorts the tail risk-return relationship and generates a tail risk anomaly together with the beta and size anomalies. Third, the study's emerging market context presents a research perspective different from research focused on developed markets. Due to the significant presence of individual investors in the market, the emerging markets provide a natural experimental setting to study the impact of their behaviour on asset pricing.

The rest of the study is organized as follows. Section 2 describes the measures of tail risk used in this study. Section 3 describes the data and methodology used. Section 4 presents empirical analysis and results; Sect. 5 discusses the results in the light of the behavioural portfolio theory and concludes the study.

2 Tail risk measures

A major challenge in the study of tail risk behaviour is that the tail risk is difficult to estimate due to a low number of observations that correspond to extremely adverse conditions. Researchers have used different approaches for estimating the tail risk, and these differences in the approach to estimating tail risk may be one of the potential reasons for contradictory results reported in the studies on the relationship between tail risk and expected returns. Therefore, in this study, we are using the following four different measures of tail risk to examine the robustness of results for the choice of the tail risk measures. The first measure (CVaR) captures the total tail risk (sum of systematic and idiosyncratic tail risk), while the remaining three measures capture the systematic tail risk with different assumptions and approaches.

(i) Conditional Value-at-Risk (CVaR)—We calculate the conditional value-at-risk (or expected shortfall) at 0.05 level estimated non-parametrically using empirical quantiles (historical simulation) of daily returns in the sample window. Therefore, it is defined as the average loss at and below the five percent sample quantile of the returns and represents the expected loss in the worst five percent cases.

(ii) Tail Beta (TBETA)—The tail beta was first proposed by Bawa and Lindenberg (1977). This is the lower partial moment-based beta (β_{BL}), defined as the ratio of covariance between excess market returns and excess security returns and variance of excess market returns conditional on market returns being less than a threshold level:

$$\beta_{\mathrm{BL}} = \frac{\mathrm{cov}(r_{\mathrm{i}}, r_{\mathrm{m}} | r_{\mathrm{m}} < h)}{\mathrm{var}(r_{\mathrm{m}} | r_{\mathrm{m}} < h)} \tag{1}$$

where the r_i is the stock excess return, r_m is the market excess return and the h is the pre-specified threshold for market excess return. The observations where the excess market returns are below that threshold will only get considered. Earlier studies estimating downside market risk based on this approach (Jahankhani 1976; Harlow and Rao 1989; Ang et al. 2006a, b) have used different return thresholds, such as the mean of excess market returns, the risk-free rate, and zero rate of return. However, we may use this approach to measure tail-beta by setting threshold h at a sufficiently lower value that a 'safety-first investor' considers relevant to her notion of risk. We estimate tail beta (TB_{BL}) using the left tenth percentile of market excess returns as the threshold.[3] TB_{BL} is calculated for each stock at the end of each month using daily stock returns. As pointed out by Bali et al. (2014), in contrast to the models based on extreme value theory or copula, this model of tail beta does not focus on rear disasters; rather, it considers the more frequent but less extreme tail events that occur regularly.

(iii) Hybrid tail covariance (HTCR)—Bali et al. (2014) proposed hybrid tail covariance (HTCR) as a relevant tail risk measure for investors with a moderately

[3] Earlier studies using this approach for estimating tail-beta include Post and Versijp (2007) and Bali et al (2014).

diversified portfolio[4] with a concentration in some selected stocks. It captures the co-tail risk of the stock and the market portfolio and is defined as the covariance between excess market returns and excess security returns during the individual stock returns' left tail states. We calculate HTCR as follows:

$$\mathrm{HTCR} = \mathrm{cov}(r_i, r_{\mathrm{m}} | r_i < h_i) \tag{2}$$

where r_i is the excess return of an individual stock, r_m is the excess market return, and h_i is the pre-specified threshold level of left tail stock return. In this study, HTCR h_i is set at the tenth percentile of the daily individual stock returns during the sample window.

(iv) Lower-tail Dependence (LTD)—This approach is based on estimating tail dependence using a bi-variate copula as proposed in Chabi-Yo et al. (2018). It captures the crash sensitivity of individual stocks. Chabi-Yo et al. (2018) use the mixed copula approach and search for the best combination from mixtures of different copulas to fit the lower-tail, upper-tail, and main body of joint return distributions. In contrast, we choose the skew-t copula of Azzalini and Capitanio (2003) and estimate it using the procedure suggested in Yoshiba (2018).

Stock returns broadly follow elliptical distributions with heavy tail and moderate skewness. The Student's t-distribution provides a satisfactory approximation of univariate and joint distributions of returns as it can capture the fat tail (McNeil et al. 2015); however, it needs to be modified to accommodate the return skewness. Furthermore, the t-copula has symmetric dependence for the joint upper and lower tails, while stock returns show more dependence in the joint lower tail compared with the joint upper tail. Therefore, the skew-t copula is a better alternative to model the joint distributions and tail behaviour of stock returns. There are different specifications of multivariate skew-t distribution proposed in the literature (see Kotz and Nadarajah 2004, Chapter 5), and different skew-t copulas can be developed based on them. Among them, the skew-t distribution proposed by Azzalini and Capitanio (2003, 2014)[5] and copula implicit in this specification have received considerable attention (Joe 2006, 2015; Kollo and Pettere 2010; Arellano-Valle 2010; Yoshiba 2018).

A copula is the joint distribution function $c(u_1 ... u_n)$ of variables $(i = 1, 2 ... n)$ with uniformly distributed [0,1] marginals, i.e., $u_i \sim \mathrm{uniform}[0, 1]$. Sklar's theorem (Sklar 1959) shows that any d-dimensional joint distribution function can be decomposed into univariate marginal distribution and a copula that completely describes the dependence between d variables. For this, the first one needs to model the univariate marginal distribution and convert the variables into new variables with uniform distribution u_i using probability integral transform and then model the joint distribution

[4] Individual investors generally keep concentrated portfolio of a few stocks, but at the same time they also invest in well diversified portfolios, like mutual funds.

[5] The distribution has four parameters (location parameter ξ, scale parameter ω, degree-of-freedom parameter, ν and skewness parameter α. In multivariate case of d-dimension ξ, ν and ν are vectors of length$d$, while ω is a $d \times d$ positive-definite square matrix. the Azzalini and Capitanio (2014, Chapter 6) give detail description of the distribution and the 'sn package' (maintained by Adelchi Azzalini) provides implementation of this distribution in Yoshiba (2018) provides detailed procedure for estimating skew-t copula and its tail dependence.

using a suitable copula. Each copula gives a unique dependence structure, particularly in terms of tail dependence. Tail dependence measures the probability of two random variables taking extreme values together. Formally it can be defined as follows: Let x and y are two random variables with probability integral transformed variables U_x and U_y, then lower-tail dependence, λ_L and upper-tail dependence λ_U between x and y are defined as—$\lambda_L = \lim_{u \uparrow 0} P\left(U_x < u | U_y < u\right)$, and $\lambda_U = \lim_{u \downarrow 1} P\left(U_x > u | U_y > u\right)$, respectively. Skew-t copula produces asymmetric tail dependence that depends on its skewness and degree-of-freedom parameters. In this study, we use the empirical cumulative density function of individual stock returns and market returns and apply a non-parametric probability integral transformation. Following the maximum likelihood estimation procedure proposed by Yoshiba (2018), the bivariate skew-t copulas are fitted between market returns and returns of each stock at the end of each month using daily stock returns for the previous three years and their lower-tail dependence (LTD) are estimated.

3 Data and methodology

The study is based on the prices of 3085 stocks listed in the Bombay stock exchange (BSE) of India, spanning over twenty-three years from January 1997 to December 2019. Initially, we considered all the 4682 stocks listed in BSE; then excluded stocks with insufficient observations restricting the sample to stocks with observations for a minimum of 72 months. The study mainly uses the daily and monthly adjusted closing prices of stocks along with their trading volume. In addition, data on market capitalization and book-to-market ratio are collected at the end of each month, and the data on the proportion of retail ownership in the firms are collected at a quarterly frequency. The data are obtained from the Prowess database maintained by the Centre for Monitoring Indian Economy (CMIE).

The continuously compounded daily and monthly stock returns are calculated using the first-differences of the natural logarithm of stock prices. The stock excess returns (r_i) are calculated by subtracting the risk-free rate of return from the stock returns. The daily and monthly yields of 91-day Government of India treasury bills are used as the proxy for the risk-free rate of returns.

The tail risk measures discussed in the previous section are calculated using the rolling window estimation. Each risk measure was calculated at the end of each month from January 2000 to December 2019 (a total of 240 months) using daily stock returns of the previous 36 months. The rolling window estimation captures the time-varying nature of risk and several other micro and macro effects (Fama and French 1997, 2005; Lewellen and Nagel 2006). We follow the standard approach of asset pricing studies and analyze the risk-return relationship using the portfolio analysis and the Fama–Macbeth (1973) regressions. First, we evaluate the relationship between the tail risk and expected return at the portfolio level. For this purpose, the equal-weighted and the value-weighted decile portfolios are formed, sorting the stocks on specific tail risk measures. Stocks were arranged in the descending order of the specific tail risk measure at the end of each month starting from January 2000 and divided into ten decile portfolios.[6] The average tail risk of each portfolio at the end of the month t, is compared with the excess return of the portfolio ($r_{p,t+1}$) for the next month t_{+1}. $r_{p,t+1}$ is used as a proxy for expected portfolio return. An additional portfolio is formed, subtracting the expected return of the low-risk decile portfolio from the expected return of the high-risk decile portfolio (H–L Portfolio). This portfolio may be interpreted as a zero-cost spread portfolio that takes the long (buy) position in the high-risk stocks and the short (sell) position in the low-risk stocks and is expected to have a positive return if the market compensates the investors for bearing tail risk.

We obtain a time series of 239 monthly tail risk measures and the expected returns for each of the eleven portfolios. The average tail risk measure and the average excess return are calculated for each portfolio, and the null hypothesis that the average return for the portfolio is different from zero is tested using Newey-West adjusted t-statistics. The calculated average portfolio tail-risk measures, the average excess returns, and their t-statistics are presented in Tables 1, 2, 3 and 4 in the next section.

The expected returns are further regressed to the Carhart (1997) four factors (beta, size, value, and momentum) for each risk-sorted portfolio to control for the well-identified cross-sectional effects. For the construction of size (SMB), value (HML), and momentum (WML) factors, we have followed Fama–French (2015) methodology. The stocks are double sorted—first on size and then on the book-to-market (B/M) ratio and the momentum. The momentum is defined as the previous 11 months' averaged returns of the stock lagged by 1 month. SMB, HML, and WML factors were constructed, following the procedure suggested by Fama–French (2015), using equal-weighted and value-weighted average returns of relevant double-sorted portfolios over the last 12 months.

The intercept (α_{pt}) obtained from the following Fama–French-Carhart model for each risk sorted portfolio is used as its return adjusted for common factors or alpha:

$$r_{\mathrm{p,t}} = \alpha_{\mathrm{p,t}} + \beta_{1,\mathrm{p,\,t}}\left(r_{\mathrm{m,t}} - r_{\mathrm{f,t}}\right) + \beta_{2,\mathrm{p,t}}\mathrm{SMB_t} + \beta_{3,\mathrm{p,t}}\mathrm{HML_t} + \beta_{4,\mathrm{p,t}}\mathrm{WML_t} + u_{\mathrm{p,t+1}} \tag{3}$$

Thus, the estimated regression model provides us with the alpha (α_{pt}) for each portfolio p. The α_{pt} values are then compared across the risk-sorted portfolios.

If the four-factor model is able to explain the returns, the expected value of α_p should be indistinguishable from zero. If the risk proxy under consideration has some additional explanatory power and the risk-return trade-off is held, the value of alpha (α_p) is expected to increase with increasing decile of tail risk. The H–L Portfolio is expected to have a positive alpha for the risk-return trade-off. The results of this analysis are presented in the last two rows of Tables 1, 2, 3 and 4.

Although the portfolio analysis clearly shows how returns vary with changing levels of risk with respect to a particular risk proxy, it is not flexible enough to control the impact of other risk measures and common factors affecting cross-sectional variations

[6] We are using an unbalanced panel data as many stocks were listed after year 2000 and many other stocks were delisted during the sample period. The actual number of total sample stocks vary each month depending on availability of data. Each decile portfolio for the month contains nearest integer number of stocks dividing the number of available sample stocks by ten. Any excess or shortfall in number of stocks is adjusted in last portfolio.

Table 1 Expected returns on CVaR sorted decile portfolios

Portfolios	High	9	8	7	6	5	4	3	2	Low	High-Low
Panel A- Equal weighted portfolio excess returns											
CVAR	17.87	14.28	12.56	10.95	9.41	8.11	7.09	6.47	5.94	4.73	13.14
Exret	− 0.58	−0.73	−0.75	−0.90	−0.72	−0.61	−0.40	− 0.36	−0.18	0.26	− 0.84
t-stat	*−0.78*	*− 0.93*	*− 0.97*	*− 1.20*	*− 1.00*	*− 0.85*	*− 0.63*	*− 0.58*	*− 0.31*	*0.56*	*− 1.79*
Intercepts	−1.91	−2.11	−1.98	−2.03	−1.59	−1.39	−1.24	− 1.03	−1.05	−0.40	−1.51
t-stat	*− 7.58*	*− 8.05*	*− 7.47*	*− 7.70*	*− 5.95*	*− 5.26*	*− 4.92*	*− 4.14*	*− 4.24*	*− 1.95*	*− 5.88*
Panel: B- Value weighted portfolio excess returns											
Exret	2.02	2.12	1.55	1.20	1.00	0.08	1.06	0.93	0.51	0.89	1.13
t-stat	*1.89*	*2.12*	*1.77*	*1.44*	*1.18*	*0.10*	*1.55*	*1.54*	*0.85*	*2.41*	*1.29*
Intercepts	0.22	0.06	−0.24	−0.71	−0.35	−0.84	−0.06	0.03	−0.39	0.28	−0.07
t-stat	*0.41*	*0.13*	*− 0.64*	*− 2.06*	*− 0.91*	*− 2.58*	*− 0.22*	*0.12*	*− 2.16*	*2.11*	*− 0.12*

Table 2 Expected returns on TBETA sorted decile portfolios

Portfolios	High	9	8	7	6	5	4	3	2	Low	High-Low
Panel: A- Equal weighted portfolio excess returns											
TBETA	2.37	1.65	1.37	1.16	0.98	0.81	0.63	0.42	0.13	−0.68	3.05
Exret	−0.88	−0.70	−0.61	−0.49	−0.36	−0.40	−0.31	−0.45	−0.61	−0.56	−0.32
t-stat	*[− 1.12]*	*[− 0.97]*	*[− 0.90]*	*[− 0.73]*	*[− 0.54]*	*[− 0.61]*	*[− 0.48]*	*[− 0.69]*	*[− 0.94]*	*[− 0.84]*	*[− 1.11]*
Intercepts	−1.95	−1.74	−1.64	−1.38	−1.36	−1.31	−1.21	−1.36	−1.60	−1.49	−0.46
t-stat	*[− 6.69]*	*[− 6.47]*	*[− 5.96]*	*[− 5.17]*	*[− 4.96]*	*[− 5.10]*	*[− 4.76]*	*[− 5.41]*	*[− 6.39]*	*[− 5.69]*	*[− 1.79]*
Panel: B- Value weighted portfolio excess returns											
Exret	−0.37	0.62	0.53	0.46	1.02	0.82	0.76	0.92	0.98	1.44	−1.81
t-stat	*[− 0.52]*	*[0.98]*	*[0.94]*	*[0.79]*	*[1.90]*	*[1.59]*	*[1.59]*	*[1.89]*	*[1.96]*	*[2.24]*	*[− 2.96]*
Intercepts	−1.27	−0.36	−0.18	−0.20	0.35	0.15	0.17	0.32	0.18	0.30	−1.58
t-stat	*[− 3.33]*	*[− 1.58]*	*[− 0.83]*	*[− 0.96]*	*[1.55]*	*[0.67]*	*[0.84]*	*[1.52]*	*[0.65]*	*[0.76]*	*[− 2.73]*

Table 3 Expected returns on HTCR sorted decile portfolios

Portfolios	High	9	8	7	6	5	4	3	2	Low	High-Low
Panel: A- Equal weighted portfolio excess returns											
HTCR	2.54	1.68	1.29	0.99	0.72	0.48	0.25	0.03	−0.24	−1.01	3.55
Exret	−0.86	−0.46	−0.51	−0.49	−0.38	−0.23	−0.44	−0.60	−0.34	− 1.06	0.19
t-stat	*[−1.24]*	*[− 0.68]*	*[− 0.77]*	*[− 0.76]*	*[− 0.57]*	*[− 0.34]*	*[− 0.64]*	*[− 0.86]*	*[− 0.50]*	*[− 1.43]*	*[0.63]*
Intercepts	−1.78	−1.45	−1.51	− 1.51	−1.41	−1.21	−1.43	−1.57	−1.24	−1.89	0.11
t-stat	*[− −6.24]*	*[−5.40]*	*[− 5.56]*	*[−5.99]*	*[-5.30]*	*[− 4.50]*	*[− 5.23]*	*[− 6.03]*	*[− 4.90]*	*[− 7.01]*	*[0.48]*
Panel: B-Value weighted portfolio excess returns											
Exret	0.70	0.32	0.44	0.95	0.72	0.74	1.31	0.90	1.26	0.91	−0.21
t-stat	*[1.16]*	*[0.60]*	*[0.73]*	*[1.91]*	*[1.49]*	*[1.30]*	*[2.33]*	*[1.46]*	*[1.74]*	*[1.25]*	*[− 0.42]*
Intercepts	− 0.11	−0.33	−0.40	0.21	0.11	−0.12	0.52	−0.01	0.02	−0.36	0.25
t-stat	*[− 0.43]*	*[− 1.78]*	*[− 1.95]*	*[1.35]*	*[0.58]*	*[− 0.50]*	*[1.55]*	*[− 0.03]*	*[0.05]*	*[− 0.98]*	*[0.49]*

Table 4 Expected returns on LTD sorted decile portfolios

Portfolios	High	9	8	7	6	5	4	3	2	Low	High-Low
Panel: A- Equal weighted portfolio excess returns											
LTD	0.33	0.21	0.16	0.12	0.08	0.06	0.03	0.02	0.01	0.00	0.32
Exret	−0.80	−330.26	−0.45	−0.29	−0.25	−0.10	−0.50	−0.60	−0.55	−0.52	−0.28
t-stat	*[−1.14]*	*[− 0.39]*	*[− 0.68]*	*[− 0.44]*	*[− 0.36]*	*[− 0.15]*	*[− 0.71]*	*[− 0.83]*	*[− 0.76]*	*[− 0.76]*	*[− 0.60]*
Intercepts	− 1.88	−1.34	−1.31	−1.24	−1.14	−1.00	−1.47	−1.46	−1.46	−1.60	−0.28
t-stat	*[−6.43]*	*[− 4.85]*	*[− 4.65]*	*[− 4.50]*	*[− 3.83]*	*[− 3.44]*	*[− 5.38]*	*[− 4.99]*	*[− 5.02]*	*[− 5.20]*	*[− 0.90]*
Panel: B- Value weighted portfolio excess returns											
Exret	0.52	0.81	0.82	0.75	0.80	1.19	1.13	1.10	1.39	1.77	−1.25
t-stat	*[1.02]*	*[1.74]*	*[1.72]*	*[1.57]*	*[1.47]*	*[2.35]*	*[1.95]*	*[1.76]*	*[1.73]*	*[2.54]*	*[− 1.97]*
Intercepts	−0.15	0.19	0.19	0.11	0.14	0.46	0.27	0.09	0.26	0.39	−0.54
t-stat	*[− 0.69]*	*[0.97]*	*[0.84]*	*[0.38]*	*[0.50]*	*[1.78]*	*[1.02]*	*[0.26]*	*[0.70]*	*[0.78]*	*[− 0.95]*

in stock returns. Therefore, in the next step, we use the following Fama Macbeth (1973) cross-sectional regression to analyze the impact of tail risk on expected returns and the mediating role of other factors:

$$r_{i,t+1} = \alpha_t + \gamma_{jt}\sigma_{jit} + \sum_{k=1}^{K} \lambda_{kt} f_{kit} + v_{it} \quad (4)$$

The σ_{jpt} is the specific j tail risk measure for stock i and period t included in the analysis and f_{kit} is the kth specific control variable. With different combinations of control variables, this equation is estimated every month using a rolling window. The control variables include the stock's CAPM beta (BETA), size of the firm (SIZE) proxied by the logarithm of market capitalization, book to market ratio of stock (BMR), an average of the previous 11-month realized returns to capture momentum effect (MOM), the proportion of individual ownership (INDOWN), illiquidity of individual stocks (ILLIQ) obtained following Amihud (2002), idiosyncratic volatility (IVOL) and the MAX (average of the four highest daily returns in a given month) which proxies the lottery-like effect. Idiosyncratic volatility (IVOL) is calculated using the standard deviation of residuals from the Fama–French-Carhart regression (Eq. 3). This procedure produces a monthly time series of estimated parameters γ_j and λ_k. The average value of estimated parameters and their Newey-West adjusted t-statistics are used for making inferences following Fama Macbeth (1973). The analysis is done separately for each of the three systematic tail-risk measures used in the study. The results are presented in Table 5, 6, and 7 in the next section.

4 Analysis and results

Table 8 summarizes the descriptive statistics for the variables used in the study. The presented statistics are calculated using the cross-sectional average values of 3085 stocks. The equal-weighted mean of excess returns is negative[7] (−0.67% per month). This, together with a negatively skewed (−0.89) distribution of excess returns, indicates that the majority of stocks earn negative or below average excess returns, while only a few successful stocks contribute to positive equity premium.

The mean of traditional market beta is 0.77, while the mean of tail-beta (TBETA) is 0.87. This indicates that the stock returns are more sensitive to market returns during the market downturn. In comparison to traditional market beta, tail-beta has higher dispersion, negative skewness (−0.64), and higher kurtosis (2.78). The hybrid tail covariance (HTCR) and lower-tail dependence (LTD) also show high dispersion (in terms of coefficient of variation), indicating stocks have higher variations in terms of the tail risk in comparison to the traditional market beta. Notably, LTD can only take the value between zero and one, and the maximum estimated value of average LTD

[7] The value weighted average excess return is 9.98 percent per annum. The market indices (Nifty and Sensex) have also earned positive risk premium of around 3.12 percent per annum. While, the equal weighted average excess returns of the sample stocks is negative. This implies that majority of stocks have given returns lower than the risk-free rate and positive market risk premium is attributed to a small number of better performing large stocks.

Table 5 Fama–Macbeth cross-sectional test for TBETA

Model	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
Intercept	−0.42	0.38	-2.81^{***}	-2.39^{***}	−1.90	− 1.54	0.97	1.02	3.06^{***}	3.98^{***}	4.00^{***}
	[-0.67]	*[0.71]*	*[− 3.46]*	*[− 3.24]*	*[− 1.84]*	*[− 1.59]*	*[0.98]*	*[1.05]*	*[3.27]*	*[4.54]*	*[4.57]*
BETA		-1.26^{***}		-1.37^{***}		-1.24^{***}		−0.66	−0.26	−0.40	−0.43
		[−2.85]		*[−3.80]*		*[−3.02]*		*[−1.70]*	*[−0.69]*	*[−1.14]*	*[− 1.04]*
TBETA	−0.12	0.13^{**}	−0.11	0.17^{***}	−0.05	0.23^{**}	0.04	0.18**	0.21^{**}	0.15^{**}	0.14^{**}
	[−1.11]	*[2.23]*	*[− 1.45]*	*[3.06]*	*[− 0.54]*	*[2.53]*	*[0.45]*	*[2.11]*	*[2.27]*	*[2.05]*	*[2.03]*
CVaR									-0.25^{***}		−0.11
									[−5.27]		*[− 1.33]*
SIZE			0.14^{**}	0.19^{***}	0.11	0.15^{**}	−0.02	0.01	−0.10	-0.17^{**}	-0.16^{**}
			[2.02]	*[2.83]*	*[1.54]*	*[1.96]*	*[−0.34]*	*[−0.03]*	*[−1.43]*	*[−2.41]*	*[−2.37]*
BMR			1.67^{***}	1.74^{***}	1.17^{***}	1.24^{***}	1.04^{***}	1.07^{***}	1.09^{***}	0.98^{***}	0.99^{***}
			[7.31]	*[8.19]*	*[4.75]*	*[5.62]*	*[4.19]*	*[4.85]*	*[4.94]*	*[4.36]*	*[4.40]*
MOM			0.13^{***}	0.12^{***}	0.17^{***}	0.16^{***}	0.17^{***}	0.16^{***}	0.16^{***}	0.18^{***}	0.17^{***}
			[5.05]	*[5.39]*	*[6.90]*	*[7.38]*	*[6.89]*	*[7.27]*	*[7.15]*	*[7.59]*	*[7.48]*
INDOWN					-0.02^{***}	0.01^{***}	-0.02^{***}	-0.02^{***}	−0.02	-0.02^{***}	-0.02^{***}
					[− 4.01]	*[− 3.24]*	*[− 3.85]*	*[− 3.51]*	*[− 4.11]*	*[− 4.17]*	*[− 4.18]*
ILLIQ					0.01^{**}	0.01*	0.01^{***}	0.01^{***}	0.01^{***}	0.02^{***}	0.02^{***}
					[2.35]	*[1.85]*	*[3.51]*	*[3.15]*	*[4.03]*	*[3.97]*	*[3.99]*
MAX							-0.42^{***}	-0.40^{***}	-0.37^{***}	-0.36^{***}	-0.36^{***}
							[−11.93]	*[−13.21]*	*[− 11.63]*	*[− 11.39]*	*[− 11.55]*
IVOL										-0.59^{***}	-0.38^{***}
										[−5.15]	*[−2.87]*
R.Square	0.60%	2.60%	5.20%	6.60%	6.90%	8.40%	7.90%	9.30%	9.74%	9.84%	10.13%

The figures in the brackets [.] are t-statistics adjusted for the Newey West (1987) robust standard errors
**, and *** show the statistical significance at 5% and 1% levels, respectively

Table 6 Fama–Macbeth cross-sectional test for HTCR

Model	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
Intercept	− 0.53	0.43	−2.86***	−2.27***	−1.95	−1.36	0.98	1.12	3.16***	3.96***	3.98***
	[−0.78]	[0.83]	[−3.55]	[−3.21]	[−1.88]	[−1.45]	[0.98]	[1.18]	[3.40]	[4.47]	[4.49]
BETA		−1.35***		−1.40***		− 1.30***		− 0.69	−0.28	−0.41	−0.42
		[−2.83]		[−3.67]		[− 3.14]		[− 1.74]	[− 0.70]	[− 1.12]	[− 0.99]
HTCR	0.06	0.24***	0.01	0.22***	0.09	0.28***	0.11	0.21**	0.15	0.10	0.11
	[0.66]	[2.52]	[0.17]	[3.44]	[1.15]	[3.38]	[1.36]	[2.49]	[1.89]	[1.34]	[1.43]
CVaR									−0.25***		−0.11
									[− 5.27]		[−1.40]
SIZE			0.13**	0.18***	0.10	0.14	−0.03	−0.00	−0.11	−0.16**	−0.16**
			[2.01]	[2.84]	[1.45]	[1.86]	[− 0.38]	[− 0.01]	[− 1.54]	[− 2.39]	[− 2.35]
BMR			1.66***	1.71***	1.14***	1.22***	1.02***	1.05***	1.07***	0.97***	0.98***
			[7.24]	[8.17]	[4.56]	[5.56]	[4.04]	[4.78]	[4.88]	[4.34]	[4.40]
MOM			0.13***	0.12***	0.17***	0.16***	0.17***	0.16***	0.16***	0.18***	0.17***
			[5.17]	[5.59]	[6.69]	[7.35]	[6.78]	[7.23]	[7.22]	[7.62]	[7.56]
INDOWN					− 0.02***	−0.01***	− 0.02***	− 0.02***	−0.02***	−0.02***	−0.02***
					[− 3.91]	[−3.09]	[−3.72]	[−3.33]	[−4.00]	[−4.07]	[− 4.09]
ILLIQ					0.01***	0.01**	0.01***	0.01***	0.01***	0.02***	0.02***
					[2.58]	[1.96]	[3.60]	[3.10]	[4.00]	[3.93]	[3.96]
MAX							−0.42***	−0.40***	−0.37***	−0.36***	−0.36***
							[−11.82]	[−13.37]	[−11.63]	[−11.36]	[−11.52]
IVOL										−0.57***	−0.36***
										[−5.09]	[− 2.81]
R.square	0.70%	3.00%	5.10%	6.70%	6.80%	8.50%	7.80%	9.30%	9.78%	9.86%	10.13%

The figures in the brackets [.] are t-statistics adjusted for the Newey West (1987) robust standard errors
, and * show the statistical significance at 5% and 1% levels, respectively.

Table 7 Fama–MacBeth cross-sectional test for LTD

Model	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
Intercept	−0.48	0.43	−2.99***	−2.03***	−2.06	−1.10	0.87	1.19	3.11***	4.03***	4.08***
	[−0.71]	*[0.82]*	*[−3.56]*	*[−2.89]*	*[−1.94]*	*[−1.20]*	*[0.85]*	*[1.28]*	*[3.35]*	*[4.67]*	*[4.70]*
BETA		−1.44***		−1.45***		−1.36***		−0.66	−0.21	−0.28	−0.36
		[−3.03]		*[−3.95]*		*[−3.41]*		*[−1.76]*	*[−0.55]*	*[−0.85]*	*[−0.87]*
LTD	−0.95	1.39	−1.42**	1.45***	−0.73	1.82***	−0.54	0.73**	0.35	−0.12	−0.02
	[−0.79]	*[1.11]*	*[−2.06]*	*[2.61]*	*[−1.09]*	*[3.34]*	*[−0.79]*	*[1.97]*	*[0.69]*	*[−0.25]*	*[−0.05]*
CVaR									−0.24***		−0.10
									[−5.12]		*[−1.20]*
SIZE			0.17***	0.15**	0.13	0.10	0.00	−0.01	1.04***	0.94***	0.94***
			[2.59]	*[2.41]*	*[1.74]*	*[1.44]*	*[−0.04]*	*[−0.17]*	*[4.77]*	*[4.24]*	*[4.27]*
BMR			1.65***	1.65***	1.14***	1.17***	1.02***	1.01***	0.17***	0.18***	0.17***
			[7.41]	*[7.91]*	*[4.76]*	*[5.32]*	*[4.23]*	*[4.60]*	*[7.14]*	*[7.55]*	*[7.47]*
MOM			0.13***	0.13***	0.17***	0.16***	0.16***	0.16***	−0.02***	−0.02***	−0.02***
			[5.24]	*[5.64]*	*[6.88]*	*[7.41]*	*[6.87]*	*[7.19]*	*[−4.15]*	*[−4.17]*	*[−4.17]*
INDOWN					−0.02***	−0.02***	−0.02***	−0.02***	0.02***	0.02***	0.02***
					[−3.86]	*[−3.47]*	*[−3.72]*	*[−3.60]*	*[4.03]*	*[3.94]*	*[3.94]*
ILLIQ					0.01**	0.01	0.01***	0.01***	−0.36***	−0.35***	−0.35***
					[2.31]	*[1.94]*	*[3.58]*	*[3.27]*	*[−11.86]*	*[−11.70]*	*[−11.88]*
MAX							−0.42***	−0.39***	1.04***	0.94***	0.94***
							[−9.79]	*[−10.13]*	*[4.77]*	*[4.24]*	*[4.27]*
IVOL										−0.59***	−0.40***

Table 7 (continued)

Model	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
										[−5.07]	*[−2.93]*
R.Square	1.50%	3.50%	5.50%	6.80%	7.10%	8.40%	8.10%	9.20%	9.68%	9.79%	10.09%

Italic values highlight the obtained t statistical values of estimated coefficients
The figures in the brackets [.] are t-statistics adjusted for the Newey West (1987) robust standard errors
, and * show the statistical significance at 5% and 1% levels, respectively.

Table 8 Descriptive statistics

Descriptive	EX-RET	BETA	CVaR	TBETA	HTCR	LTD	SIZE	BMR	MOM	IND_OWN	ILLIQ	MAX	IVOL
MEAN	− 0.67	0.76	9.16	0.86	0.58	0.08	6.30	0.82	0.20	30.27	16.49	5.02	7.87
STD	1.54	0.35	3.22	0.51	0.57	0.08	2.28	0.41	1.56	16.16	20.90	1.27	2.63
SKEW	− 0.90	0.12	1.02	− 0.71	0.20	1.19	0.71	0.94	− 1.18	0.63	6.77	0.72	1.47
KURT	2.01	0.06	1.60	2.83	0.50	1.36	0.11	2.17	2.88	0.07	99.40	2.79	5.30
MIN	− 9.42	− 0.21	0.71	− 2.43	− 2.99	0.00	1.64	0.01	− 8.98	0.30	0.00	0.74	1.74
Q1	− 1.41	0.52	6.85	0.59	0.13	0.02	4.56	0.53	− 0.57	18.11	5.16	4.20	5.97
MED	− 0.42	0.77	8.39	0.90	0.53	0.07	5.94	0.79	0.48	28.39	12.39	4.95	7.50
Q3	0.39	0.99	11.08	1.18	0.98	0.13	7.72	1.05	1.21	40.02	20.69	5.74	9.23
MAX	7.27	2.39	31.26	3.39	2.64	0.48	14.63	3.26	6.49	85.98	477.63	13.82	30.93

Italic values highlight the obtained t statistical values of estimated coefficients for a stock is 0.48. In contrast to the other tail risk measures, the mean value for LTD is smaller (0.09) and has positive skewness. The Table presents the descriptive for the other cross-sectional characteristics of sample stocks.

Table 9 reports the Pearson's coefficients of correlation for the cross-sectional averages of different tail risk measures, expected stock returns, and other cross-sectional characteristics of stocks. The CAPM beta has significant positive correlations with systematic tail risk measures. Three systematic tail risk measures are also positively correlated with each other, but CVaR is negatively correlated to them. The excess returns show positive but low correlations with beta and systematic tail risk measures. Max and idiosyncratic volatility (IVOL) are used as a proxy of the lottery effect in the literature; therefore, as expected, these two variables are highly correlated (corr = + 0.90). Notably, the Max and idiosyncratic volatility (IVOL) are also highly correlated with CVaR, implying that the stocks with lottery-like characteristics also have high overall and idiosyncratic tail risk.[8]

4.1 Portfolio-level analysis

To examine the impact of tail risk sensitivity on stock returns, we first evaluate the tail risk-return relationship at the portfolio level. The equal and the value-weighted portfolios sorted on a particular tail risk measure are formed every month. Then, the excess returns and returns adjusted for common factors (alphas) of the portfolios are calculated for the next month. The following tables present the averages of the monthly excess returns and alpha values for tail risk sorted portfolios together with their Newey-West t-statistics.

4.1.1 CVaR (expected shortfall) and stock returns

Table 1 presents the average excess returns and alphas for CVaR sorted portfolios. The decile sorted equal-weighted portfolios show a − 0.58% monthly average excess return for the highest decile portfolio and a 0.26% return for the lowest decile portfolio; however, the excess return does not show any monotonous trend with changing deciles of CVaR. The return of an arbitrage portfolio with a short position in the lowest decile stocks and a long position in the highest decile stocks is negative (− 0.84 percent per month, though this return is not statistically different from zero (t = 1.79). However, the four-factor adjusted excess return of the arbitrage portfolio is also negative (− 1.51, t = − 5.88) and statistically significant. This observation is inconsistent with the notion of risk-return trade-off.

The value-weighted portfolio returns also do not present significant spreads between the high and low decile sorted stocks (Panel B). The high-low return spread is 1.13% (t = 1.29); while after adjusting for Fama–French-Carhart factors, the spread becomes − 0.07 (t = 0.12). In both cases, the spread is indistinguishable from zero. These mixed

[8] Max and IVOL are more correlated with overall measure of tail risk (i.e., CVaR), rather than the measures of systematic tail risk. It implies that the high correlation between CVaR and measures of lottery effect is due to idiosyncratic part of tail risk and stocks with lottery like features also have high idiosyncratic tail risk.

Table 9 Correlations among tail risk measures and other variables

Correlation	EX-RET	BETA	CVaR	TBETA	HTCR	LTD	SIZE	BMR	MOM	IND_OWN	ILLIQ	MAX	IVOL
EX-RET	1												
BETA	0.02	1											
CVaR	− 0.10	− 0.22	1										
TBETA	0.06	0.65	− 0.16	1									
HTCR	0.14	0.61	− 0.32	0.52	1								
LTD	0.11	0.76	− 0.41	0.53	0.71	1							
SIZE	0.25	0.55	− 0.63	0.38	0.53	0.71	1						
BMR	− 0.32	− 0.11	0.40	− 0.09	− 0.16	− 0.23	− 0.51	1					
MOM	0.89	0.07	0.01	0.10	0.14	0.11	0.20	− 0.26	1				
IND_OWN	− 0.26	− 0.34	0.41	− 0.26	− 0.32	− 0.39	− 0.66	0.38	− 0.22	1			
ILLIQ	− 0.22	− 0.24	0.29	− 0.21	− 0.25	− 0.34	− 0.43	0.3	− 0.14	0.19	1		
MAX	− 0.18	− 0.09	0.75	− 0.11	− 0.28	− 0.40	− 0.70	0.47	− 0.06	0.42	0.42	1	
IVOL	− 0.22	− 0.21	0.73	− 0.19	− 0.37	− 0.49	− 0.69	0.42	− 0.12	0.43	0.41	0.90	1

Italic values highlight the obtained t statistical values of estimated coefficients results do not provide any clear direction for the relationship between the CVaR and stock returns.

4.1.2 TBETA and stock returns

Table 2 presents the average excess returns and alphas for the tail-beta (TBETA) sorted portfolios. Interestingly, these results demonstrate a decreasing pattern of portfolio excess returns for the increasing deciles tail-beta. The average tail beta of the stocks in the highest tail beta decile is 2.37, while that of the stocks in the lowest tail beta decile is − 0.68. Panel A of the Table shows that the excess returns and alphas for equal-weighted portfolios decrease (though not monotonously) with increasing deciles of tail risk. The high-low spread of excess returns (− 0.32 percent per month, t-stat = 1.11) and alpha (− 0.46 percent per month, t-stat = 1.79) are also negative though not distinguishable from zero.

A similar pattern is observed in the returns of value-weighted portfolios (Panel-B); however, in this case, the high-low spreads are negative and statistically significant. An investor taking a long position in high tail beta stocks and a short position in low tail beta stocks has a return of -1.81 percent per month (t-stat = 2.96). After adjusting for Fama–French-Carhart's four factors, the returns (alpha) of her portfolio are − 1.58 percent per month (t-stat = 2.73). These results are also anomalous from the point of view of risk-return trade-off.

4.1.3 HTCR and stock returns

Table 3 presents the average excess returns and alphas for the hybrid tail covariance (HTCR) sorted portfolios. The average HTCR of the stocks in the highest HTCR decile is 2.54, while that of the stocks in the lowest tail beta decile is − 1.01. We do not observe any monotonous change in excess returns and alphas as we move from the low HTCR decile to high decile portfolios. In the case of equal-weighted portfolios, the high-low return spread is 0.19 percent per month (t-stat = 0.63), and the alpha spread is 0.11 percent per month (t-stat = 0.48). Although the high-low spreads are positive, these are not distinguishable from zero. In the case of value-weighted portfolios, the return spread is negative (− 0.21 percent, t-stat = 0.42) while alpha spread is positive (0.25 percent, t-stat = 0.49). However, the spreads are not distinguishable from zero again.

4.1.4 LTD and stock returns

The decile portfolios formed by sorting the stocks on lower-tail dependence (LTD) also present similar results. The average LTD of portfolios varies from 0.00 to 0.33. Table 4 shows that the excess returns and the Carhart alphas do not change monotonously with the change in LTD in both the equal- and the value-weighted portfolios. The high-low returns and alpha spreads are negative and statistically non-distinguishable from zero for equal-weighted portfolios. For value-weighted portfolios also, returns and alpha spreads are negative, and the return spread in this case (− 1.25 percent, t-stat = 1.97) is statistically significant.

The portfolio level analysis suggests the presence of the tail risk anomaly in the Indian stock market. The portfolios with higher tail risk have lower returns than those with lower-tail risk, although the statistical significance of return spread is not clearly established. In the next section, we attempt to explain this anomaly after controlling the impact of other risk measures and common factors affecting cross-sectional variations in returns.

4.2 Fama–Macbeth cross-sectional regression

The major advantage that portfolio-level analysis is that it does not impose a functional form on the relationship between variables of interest. However, this methodology suffers from two potential disadvantages. First, it throws a significant amount of cross-sectional information due to cross-sectional aggregation at the portfolio level. Second, it becomes difficult to control several relevant factors in such settings simultaneously (Bali et al. 2011). Fama–Macbeth (1973) cross-sectional regressions estimated at individual stock level provide a very flexible strategy to deal with these issues. The following section analyses the relationship between tail risk and expected stock returns using the Fama–Macbeth methodology with different combinations of control variables. This analysis helps us to understand the apparently anomalous results observed in the previous section.

The Fama–Macbeth cross-sectional regressions (Eq. 4) are estimated with eleven different specifications following the methodology described in the earlier section and using the data from February 2000 to December 2019. This procedure produces a monthly time series of estimated parameters $\gamma_j \text{and} \lambda_k (k = 1 \ldots m, \text{m} = \text{numberofcontrolvariables})$ for 239 months. The time-series averages of the estimated parameters are obtained, and the null hypothesis that the individual estimated parameter is non-distinguishable from zero is tested using t-statistic adjusted for the Newey-West (1987) robust standard error.

4.2.1 TBETA and expected returns

Table 5 presents the results of the Fama–Macbeth cross-sectional regression of 1 month ahead excess stock returns on tail-beta (TBETA), controlling different common factors. In Model I, no control variable is included, and excess returns are regressed to TBETA. The average estimated slope coefficient (γ_j) is negative, albeit non-distinguishable from zero. In Model II, the traditional CAPM beta is also included in the regression, and the slope coefficient of TBETA turns positive (0.13, t-stat = 2.23). However, the slope coefficient of CAPM beta (known as the slope of the Security Market Line, SML) is negative (− 1.26, t = 2.85). This shows a strong beta anomaly in the market; the high beta stocks give lower returns than the low beta stocks.

In Model III, three control variables—size, book-to-market value ratio (BMR), and momentum (MOM) are added to Model I. The slope coefficient of TBETA again turns negative and non-distinguishable from zero (− 0.11, t-stat = 1.45). Consistent with existing literature, expected returns are positively correlated to BMR and momentum. However, the returns are also positively correlated with size; large stocks give higher returns than small stocks. This observation is anomalous considering the small stock premium (size premium) documented in the literature[9] (Fama and French 1993). In Model IV, we augment Model III by including CAPM beta in the regressors. This model shows an improvement in R-square, and the slope coefficient of TBETA again turns positive and statistically significant (0.17, t-state = 3.06).

The contemporary literature (Long et al. 2018; Atilgan et al. 2020) documents a significant relationship between individual ownership and the tail risk anomaly. We include the proportion of individual (retail) ownership (INDOWN) together with illiquidity (ILLIQ) in our regression models, once in the absence of CAPM beta and then in its presence (Model V and VI). Both of these variables have a significant impact on expected returns. INDOWN has a negative relationship with expected returns, while ILLIQ impacts expected returns positively. These two factors also explain the inverse size premium, which now turns insignificant.[10] However, including these control variables does not change the nature of the relationship between TBETA and expected returns. The slope coefficient of TBETA is insignificant without controlling for CAPM beta, which turns positive and significant when CAPM beta is included in the regression. This observation confirms the significant confounding role of CAPM beta in explaining the relationship between TBETA and expected returns. It appears that investors like high beta stocks as these stocks are likely to generate more speculative profits; therefore, high beta stocks are overpriced and have lower expected returns. Table 9 shows that the CAPM beta and tail-beta are significantly correlated (corr = + 0.65). Due to this, the positive correlation of tail-beta and expected returns is annihilated by the negative correlation of CAPM beta and expected returns, and TBETA shows a negatively tilted slope coefficient unless the impact of CAPM beta is controlled in the regression.

If the above hypothesis is true, the demand for lottery-like payoffs should explain the observed beta anomaly. We include lottery demand (Bali et al. 2011), represented by MAX, as a control variable to test this hypothesis and estimate the regression equation with and without including CAPM beta (Model VII and VIII). MAX shows a very strong negative relationship with expected returns. The speculative investors prefer the stocks with lottery-like payoffs, making these stocks overvalued. Consistent with our hypothesis, the negative relationship between CAPM beta and expected return turns insignificant in the presence of the MAX factor. Therefore, the MAX factor seems to explain the observed beta anomaly.

Models IX to XI shows the interaction of CVaR and idiosyncratic volatility (IVOL). Controlling for the effect of systematic tail risk measures, TBETA, when we introduce CVaR in the regression model, it is expected to capture the marginal impact of idiosyncratic tail risk. Similar to previous studies (such as Long et al. 2018; Bi and Zhu 2020), we observe a strong negative relationship between CVaR and expected returns (− 0.25, t = 5.27). However, as Table 9 shows, CVaR is highly correlated

[9] However, the insignificant or the negative size premiums have been observed in different markets across the world in recent empirical studies and existence of size premium is being debated (see Van Dijk 2011; Astakhov et al. 2019, for a survey).

[10] Ownership percentage of retail investors explains the inverted size premium more consistently. Retail investors have higher ownership in small stocks and speculative trading activities of these investors are likely to cause overvaluation of these stocks. We will elaborate on this in the next section.

with one of the measures of lottery effect—IVOL (see Bali et al. 2017); we introduce IVOL in the model (Model X). In conformity with the 'idiosyncratic volatility puzzle' documented in the literature (Ang et al. 2006b), we observe a negative relationship between IVOL and expected returns (− 0.59, $t = 5.51$). When CVaR is included in the model, after controlling for the effect of IVOL, the effect of CVaR on expected returns becomes indistinguishable from zero (− 0.11, $t = 1.33$). Notably, after controlling for MAX and IVOL, the inverted size effect disappears, and consistent with established literature (Fama and French 1993), the relationship between firm size and stock returns becomes negative (− 0.16, $t = 2.37$).

Both MAX and IVOL, are found to be associated with the lottery effect. A high correlation is also observed between these two factors. The literature shows that the MAX effect subsumes the IVOL anomaly in the US and European stock markets (Bali et al. 2011; Annaert et al. 2013). But in our study, the IVOL effect persists even after controlling for the MAX effect, suggesting that some other factors may also be causing the IVOL effect.[11] However, these two factors have a significant role in explaining cross-sectional variation in stock returns as evident from the the comparison of Model VI and Model X.

This analysis shows that the three effects – tail risk, CAPM beta, and MAX effect, interact with one another. We get anomalous results if we fail to control any one of these effects. Investors seem to care for the probability of extreme losses (tail risk) and chances to earn lottery-like payoffs (MAX effect), but they do not care much about moderate variations in stock prices. Since the lottery effect is quite strong and is positively related to high beta stocks, it makes these stocks overvalued (Bali et al. 2017) and is responsible for the observed beta anomaly. The lottery effect explains both the beta anomaly and the inverted size premium puzzle in the Indian stock market. To check the robustness of our results, we perform the same analysis with other tail risk measures.

4.2.2 HTCR and expected returns

The HTCR presents another dimension of systematic tail risk that emphasizes the individual stock level tail dispersion. Since the investors looking for lottery-like returns intentionally do not diversify their portfolios completely; rather, they optimally choose to overweight some selective stocks in their portfolio to maximize the probability of a large gain. Bali et al. (2014) have proposed their hybrid tail covariance (HTCR) measure as a relevant tail risk measure for such an under-diversified portfolio. HTCR encompasses both the idiosyncratic and systematic components of tail risk.

Table 6 presents the results of the Fama–Macbeth cross-sectional regression of 1 month ahead excess stock returns on HTCR controlling different common factors.

[11] Similar results were observed from Chinese market (Hai et al. 2020; Wan 2018). The literature suggest that the IVOL effect may also be caused by factors like heterogeneous belief, short sale constraints, information asymmetry, short-run return reversal and asymmetric limits to arbitrage (see Hou and Loh 2016, Footnote 1). He and Xue (2022) classify these factors in two groups—The first group focuses on some proxies for the lottery preferences of investors, including skewness and expected idiosyncratic skewness coskewness beta and idiosyncratic coskewness beta, and maximum daily return. The second group focuses on various forms of market frictions, such as order imbalances, return reversals, illiquidity and the effect of arbitrage costs.

Various regression models in the Table are formed in the same manner as formulated in the case of TBETA (Table 5). Model I shows that HTCR has no significant impact on expected returns as the slope coefficient (0.06, t-stat = 0.66) is not distinguishable from zero. As we include the market beta in the regression (Model II), the slope coefficient of HTCR (0.24, t-sata = 2.52) changes tremendously and turns positive and statistically significant. However, we observe a considerable beta anomaly as the slope coefficient of beta in the regression (− 1.35, t-state = 2.83) is negative and statistically significant. We obtain similar results in Models III, IV, V, and VI, which include SIZE, BMR, MOM, INDOWN, and ILLIQ as control variables. However, when we also include MAX as a control variable (Models VII and VIII), the slope coefficient of CAPM beta turns insignificant.

However, when CVaR is introduced in the regression, the coefficient of HTCR turns insignificant (Model IX). Including IVOL in the regression also has a similar effect (Model X and XI). This also subsumes the anomalous negative relationship between CVaR and expected returns observed in Model IX. These results indicate that the idiosyncratic volatility effect subsumed the positive HTCR—expected return relationship.

4.2.3 LTD and expected returns

The association between the market movements and the individual stock returns can also follow the non-linear relationship. Copula-based lower-tail dependence (LTD) may capture the tail risk beyond the risk captured by the linear association implied in other tail risk measures. Chabi-Yo et al. (2018), who proposed the copula-based lower-tail dependence measure, report a positive relationship between the expected stock returns and LTD in the US equity market.

Table 7 presents the results of cross-sectional regressions using LTD as the tail risk measure. The results are very similar to the results observed using HTCR as a tail-risk measure. Before using any control variable (Model I), the slope coefficient of the regression of the expected return on LTD (− 0.95, t-stat = 0.79) is negative and non-distinguishable from zero. This coefficient turns positive when we include CAPM beta and other control variables in the regression. We observe a significant negative relationship between CAPM beta and expected return (beta anomaly) which becomes insignificant (-0.66, t-stat = 0.76) when we control for the MAX effect. However, similar to the case of HTCR, the effect of LTD on expected returns disappears as the IVOL is included in the regression model (Model X and XI). Similar to the previous two cases, after controlling for LTD as a measure of systematic tail risk and lottery effect (using Max and IVOL), CVaR does not appear to have any impact on expected returns.

5 Discussion and conclusion

Our results show investors care about extreme outcomes—tail risk and lottery-like payoffs. However, the motive to earn speculative profits overweights the safety of wealth motive, while investing in stock market. The analysis using alternative measures of tail risk suggests that the tail risk and returns do not have anomolus negative relataionship after controlling for other relevant factors. At least for one of the measure (tail beta), the positive risk-return relationship is observed, suggesting that the investors try to minimize the possibility of extreme loss. On the other hand, investors in the equity market chase lottery-like payoffs; therefore, stocks having such payoffs are overvalued and provide low expected returns. The lottery effect (MAX and IVOL factors) seems to be the strongest factor in explaining the cross-sectional variations in stock returns. This section tries to explain these results in the light of the behavioural portfolio theory (Shefrin and Statman 2000). This theory focuses on the twin desires of investors for security (S) and potential (P).

Mental accounting is the most important underlying feature of behavioural portfolio theory. According to this theory, household investors hold their financial assets in multiple layered portfolios (mental accounts) rather than in a single portfolio, as assumed in Markowitz-Sharpe modern portfolio theory. In each layer of investment, they may have different financial goals and risk preferences,[12] and they are hardly willing to transfer wealth from one portfolio layer to another (Shefrin and Thaler 1988). This makes it possible to act in a risk-seeking manner in one layer (e.g., buying lottery tickets) while simultaneously acting in a risk-averse manner in another layer (e.g., buying insurance).[13] For example, in Oehler and Horn (2020) model, a household investor has three hierarchical layers of investment needs and products (forming an investment pyramid)—basic financial needs and products, additional financial needs and products, and a high aspirational layer. In the first two layers at the bottom, the investor focuses on her financial security and stability and invests in insurance, residential property, and financial products with low to moderate risk and returns. On the other hand, the investor wants to make her fortune in the high aspirational layer. She invests in financial assets with high risk and looks for lottery-like payoffs. The equity investments, in most cases, are included in this layer. Since she has already protected her financial stability in the first two layers of investment, she could bear a total loss of the funds in the third layer and treat this fund as a speculative investment.

It is important to note that retail (individual) investors play an important role in the Indian stock market. As per National Stock Exchange data (NSE Market Pulse, June 2021), the retail investors hold 18 percent ownership of the free-float market capitalization of NSE-listed companies at the end of March 2021. Retail ownership is more concentrated in small firms. The ownership of retail investors drops to 8.1 percent of free-float market capitalization if only constituent companies of the Nifty 50 index are considered. As expected, the share of retail investors in corporate ownership has come down, and the share of domestic and foreign institutional investors has increased

[12] Recent literature has focused on how individuals allocate their funds among and within the several investment layers. See for example, Das et al. (2010), Baptista (2012), Parker (2021).

[13] Simultaneous investment in lottery and insurance is known as Friedman-Savage Puzzle in the literature.

over the years. However, retail investors emerge as the biggest player in terms of the trading volume. They contributed 45 percent of the turnover in the cash segment during the Financial Year 2020–21. Their participation in the turnover of derivative markets is also equally high. Notably, the share of retail investors in trading volume has increased during the last five years, though their share in corporate ownership has come down. This data reflect the speculative trading activities of retail investors in the market. The middle class in the country is starting to use risky financial markets for the first time, and equity investing is gaining popularity in smaller cities and towns (Security and Exchange Board of India, Handbook of Statistics 2021). For these new investors, equity markets are not the place where they invest money for the long term. Rather they make direct investments[14] in the equity market on concentrated portfolios with speculative motives (Badarinza et al. 2017; Campbell et al. 2019).

A large body of empirical research indicates that retail investors trade more actively and speculatively with asymmetric information and hold underdiversified portfolios. Individual investors enjoy trading in the stock market, treating it like a form of fun and exciting gambling activity (Grinblatt and Keloharju 2009; Gao and Lin 2015), and expect to earn a big fortune in the market. Since they have already protected themselves in other safer investments,[15] they are willing to take more risk in the market and behave like 'risk takers' rather than 'risk averse' investors. They prefer investing in lottery stocks, which have a tiny probability of earning high returns,[16] though their expected returns are low. Therefore, lottery stocks with high volatility and positively skewed returns become overvalued and earn low future returns. Studies have documented the gambling motive and speculation of individual investors and their preference for lottery stocks (Kumar 2009; Han and Kumar 2013; Bali et al. 2018). The lottery effect is stronger for stocks with high retail ownership[17] (Han and Kumar 2013; Bali et al. 2017; Lin and Liu 2018).

With the limited amount of attention that individual investors can devote to investing, they tend to invest in glamorous stocks that have performed better in the recent past, leading to the overvaluation of such stocks. This is reflected in the strong role of the MAX-factor in determining expected returns (Bali et al. 2018). High idiosyncratic volatility is another feature of the gambling stocks preferred by individual investors (Han and Kumar 2013), which emerge as another strong factor explaining cross-sectional variations in stock returns.

Since lottery stocks are high beta stocks, the lottery effect pulls expected returns of high beta stocks downwards and produces the beta anomaly. Bali et al. (2017) argue

[14] This trend is also observed in other emerging markets Badarinza. (2016). In developed market on the other hand, most of the investment is channelized through financial intermediaries (institutional investors) and household investors are shifting towards passive investing Anadu et al.(2020).

[15] According to RBI data only 4 percent of household financial investments are in stocks and bonds in 2018–19, while 37 percent is in the form of bank deposits, 19 percent in provident funds and other retirement saving schemes and 10 percent in government sponsored saving schemes. (Reserve Bank of India, Handbook of Statistics on Indian Economy, Table 12).

[16] Barberis and Huang (2008) argue that the investors with cumulative prospect theory utility overweight tiny probabilities of large gains.

[17] While individual investors are mainly considered responsible for lottery-effect but studies shows that the institutional investors also invest in lottery stocks for example Akbas and Genc (2020) and Agarwal et al. (2021) document preference of mutual funds for lottery stocks.

that the beta anomaly no longer exists when beta-sorted portfolios are neutralized to lottery demand. Our results are consistent with this line of argument. Since the retail investors' participation is quite high in the market, we observe a very strong MAX and IVOL effects. These effects produce an equally strong beta anomaly. The nature of the beta anomaly observed in India is different from the US market. In the US, the relationship between stock beta and expected return is observed to be flatter compared to what is implied under CAPM; hence low beta stocks produce high risk-adjusted returns or alpha (Black et al. 1972; Frazzini and Pedersen 2014). On the other hand, in this study, we observe a significantly downward sloping security market line (SML) that becomes flat when the lottery effect is considered. This implies that the strong lottery effect produces a strong beta anomaly.

This argument is consistent with other observations in the study. We observe that the proportion of retail investors' share in corporate ownership is negatively related to expected returns. Since their ownership is more concentrated on small stocks, these stocks have lower expected returns. This produces an inverted size effect in the Indian market—the small stocks have lower returns than the large stocks. This inverted size effect disappears when we control for individual ownership, MAX-effect, and IVOL, and we get the expected negative relationship between size and returns.

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Data availability We have all the data related to our study and we are ready to provide all the data and the research codes used in the study whenever will be asked by the journal for the verification of our results produced in the manuscript.

Declarations

Conflicts of interest The authors have no conflicts of interest to declare that are relevant to the content of this article.

Ethics approval This manuscript complies with all the ethical standards.

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