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Research Article

Evidence of the Preference for Skewness from the Indian Stock Market

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Abstract: *The portfolio of least risky stocks outperforms the market returns and its counterparts in the Indian equity market. These results are robust for the study period from January 2000 to September 2022. The low-risk phenomenon is not a substitute for any established factor. A portfolio-level cross-sectional regression analysis reveals that the highest return during the previous month, the MAX factor, and projected stock returns have a negative and substantial relationship. The difference in excess returns and risk-adjusted returns between the stocks in the lowest and highest MAX deciles is more than 1.5%. These outcomes hold up well against the three Fama and French (1993) factor asset pricing models. The low-risk phenomenon is not driven by a preference for skewness in the Indian equity market.*

Keywords: *Lottery-Like Payoffs, Skewness Preference, Idiosyncratic Volatility, Cross-Sectional Return Predictability.*

I. INTRODUCTION

After Sharpe (1964) and Lintner (1965) published their groundbreaking work, the Capital Asset Pricing Model (CAPM) has been tested for its practicality and capability of estimating the returns from an investment. The covariance between a stock's return and the market portfolio determines the expected return on an individual stock in the CAPM setup. The model assumes that investors are rational individuals and are willing to take higher risks only if they anticipate higher returns. Thus, CAPM predicts a linear positive relationship between systematic risk and return as the model assumes that idiosyncratic risk is diversified. Thus, diversification is crucial in this model. However, academic and industry research throws empirical evidence of a negative risk-return relationship and provides economic and behavioural biases that cause this phenomenon. They call it the low-risk volatility or the low-risk effect. Black (1972, 1993), Frazzini and Pedersen (2014) attribute the low-risk effect to the constraints on leverage available for investment. Others attribute it to behavioural aspects such as overconfidence, representativeness bias, attention-grabbing bias, relative performance process of investors, and call option-like compensation structure of institutional investors. Bali, Cakici and Whitelaw (2011) attribute the low-risk effect to investors' preference for skewness or lottery-like payoffs. Investors are ready to take riskier bets with an expectation of huge upsides and limited downside by investing in penny stocks, though the probability of positive returns is bleak (Kumar, 2009). Bali et al. (2011) negate the empirical evidence presented by Ang, Hodrick, Xing and Zhang (2006, 2009) of an inverse idiosyncratic risk and return relationship. They design the MAX to capture investors' inclination for lottery-like payoff investments. They show that the inverse relation between idiosyncratic volatility and stock returns disappears when MAX is included as a control variable. MAX is the average of five days of highest returns delivered by the stock in a period.

There are no studies on MAX variable returns in the Indian equity market. The present study is an attempt to fill this research gap. Following are the research questions that this paper will attempt to answer:

1) Does the Indian stock market deliver positive risk-adjusted returns for the low-risk / low-volatility / low-risk effect?
2) Is the low-risk effect a representation of any other established factors like size or value factor?
3) Does the MAX factor deliver positive statistically significant returns in the stock market of India?
4) Does an investor's inclination for lottery demand stocks determine the low-risk effect in the stock market of India?

The study shows that the risk and return relationship is inverse for portfolios constructed with volatility and idiosyncratic volatility as risk metrics. Over the course of the study period, the excess returns from the least risky portfolios outperformed the market returns. It notes that none of the established components can be replaced by the low-risk effect; rather, it is an exclusive factor. The low-MAX stock portfolio beats the returns of the market. More specifically, the study examines the monthly returns on the resulting portfolios from January 2000 to September 2022 and ranks stocks according to their five highest daily return from the previous month. For value-weighted decile portfolios rebalanced monthly, the difference in returns between the portfolios with the highest and lowest maximum daily returns is 1.85%. The three-factor Fama-French alpha is 1.81%. There is a statistically significant difference between the two returns. By design, the MAX is a result of two ingredients – skewness and volatility. The study further decomposes the MAX returns into returns from skewness represented by Scaled MAX (S-MAX) and total volatility (T-VOL) following Asness, Frazzini, Gormsen and Pedersen (2020). In the Indian equity market, though the L-MAX factor that goes long-short MAX deliver positive returns, returns to S-MAX are insignificant, which indicates that preference for skewness does not drive the low-risk effect in the Indian stock market. This finding is different than found in the developed markets.

The rest of the paper is organized in the following manner – Part II presents the review of the literature, and Part III presents the Data, methodology, results, and discussion. Part IV lays forth the conclusion, followed by References.

II. LITERATURE REVIEW

Though many academic and industry studies report a negative risk-return relationship called the low-risk effect, it received recognition only after the path-breaking research of Frazzini and Pedersen (2014). Blitz and Vliet (2007), Ang, Hodrick, Xing and Zhang (2006, 2009), Clarke, de Silva and Thorley (2010), Baker, Bradley and Wurgler (2011), Baker and Haugen (2012), Walkshäusl (2014), Blitz, Pang and Vliet (2013), Carvalho, Zakaria, Lu and Moulin (2014), Chow, Hsu, Kuo and Li (2014) report the existence of the low-risk effect in United States, other developed markets and emerging markets. Frazzini and Pedersen (2014) also show that the Betting Against Beta (BAB) created to capture the low-risk effect delivers positive alpha in the equity, treasury bond, corporate bond and derivative markets of developed nations.

Common risk measures used to study the low-risk effect are the volatility of stock returns, beta, and idiosyncratic volatility. Various studies use a variety of portfolio weighing schemes - equal-weighted, market capitalization-weighted (value-weighted), inverse-beta weighted, inverse-volatility weighted or rank-weighted stocks in the portfolio. They also use various methods of computing portfolio returns - simple or compounded returns. They even differ in the number of divisions in which the stocks are distributed - decile, quintile or tercile portfolios. Despite all these permutations and combinations, the low-risk effect prevails. After a lot of discussion on the characteristics of the low-risk effect portfolios, investigations began on what has driven it for decades.

Some studies refuse the prevalence of the low-risk effect. Bali and Cakici (2008) argue that the high returns from investing in low idiosyncratic volatility stocks, as reported by Ang et al. (2006), are because the low-risk portfolios consist of small and illiquid stocks. They claim that the low-risk effect is due to investors' preference for skewed returns that overprice small stocks and later diminish their returns. The inverse risk-return relationship becomes insignificant upon eliminating these stocks from the sample data. Even Boyer, Mitton, and Vorkink (2010) support the same argument. Bali, Cakici and Whitelaw (2011) prove the case further by developing the MAX. According to them, MAX captures the returns to skewness. They show that MAX is an autonomous variable and not a representation of idiosyncratic volatility. Scherer (2011) and Shah (2011) argue that the low-risk effect is merely a proxy for the value effect and has considerable industry tilt.

Li, Sullivan, and Garcia-Feijóo (2014) highlight that the low-risk investment return is unavailable to investors because of its investment in illiquid stocks and high transaction cost, and the long-short strategy is impractical. Novy-Marx (2014) and Fama and French (2016) demonstrate that the profitability factor explains the performance of the risk-sorted portfolios in time-series regressions. Novy-Marx and Velikov (2018) show that shorting highly illiquid micro-cap stocks and active hedging drive the BAB premium. Stambaugh, Yu and Yuan (2015) show that the negative risk-return relation exists among over-priced stocks and not among underpriced stocks. The inverse unsystematic risk-return relation in over-priced equity stocks exists in both cross-section and time series, and it grows stronger because of high investor sentiment and the elimination of small stocks.

Similarly, Li, Sullivan and Garcia-Feijóo (2016) explain that the excess return to the low-risk stock portfolio is more likely driven by market mispricing connected with volatility, while Bali, Brown, Murray and Tang (2017) find that not beta but idiosyncratic volatility determines the low-risk effect demonstrate how the beta anomaly is significantly influenced by investors' desire for lottery-style equities. When lottery demand is eliminated from beta-sorted portfolios or when a lottery demand component is included in the factor model, the beta anomaly vanishes. The beta anomaly only appears when the price impact of lottery demand is concentrated in the high-beta equities and it is concentrated in stocks with low institutional ownership levels. The alpha of portfolios double sorted on mispricing and beta is examined by Asness et al. (2020). They demonstrate how some but not all of the low-risk effect can be explained by stock mispricing and how specific alpha and beta metrics mitigate the effect.

A literature review of the low-risk effect reveals a good amount of academic and practitioner research in the developed markets but very little research in the emerging markets and only a few research papers in India. The MAX factor's performance in the Indian equity market has not been studied. Driven by these academic works, this study investigates how extraordinary positive returns factor into stock cross-sectional pricing using the MAX factor.

This paper thus lays forth the following research objectives:

1) To examine the returns to the low-risk effect in the stock market of India
2) To examine the returns to the MAX factor
3) To decompose the MAX returns into returns from a preference for skewness and returns to low volatility.

The sample data is from stocks listed on the largest stock exchange of India – the National Stock Exchange of India (NSE). The data was collected from the Centre for Monitoring the Indian Economy's Prowess IQ database from December 1998 to September 2022. The excess returns are returns over the T-bill rate. Nifty 500 index returns are a proxy for benchmark equity market returns. The sample consists of all stocks listed on the. It varies between 700 to 1400 across the study period. The stocks that do not have returns for the past 12 months consistently are removed from the sample. The study constructs portfolios from January 2000 to September 2022. The portfolio returns are rebalanced every calendar month. Volatility is calculated on the stock's daily returns for the previous 12 months. MAX is calculated following Bali, Cakici and Whitelaw (2011). The average of a stock's five highest daily returns over the previous month is MAX, and the average of a stock's twenty highest daily returns over the past 12 months is MAX 1y.

A stock can have a high MAX return either because of its positive skewness or its volatile returns. To isolate the skewness effect that represents demand for lottery like payoffs of investors, Asness et al. (2020) devised the Scaled MAX (S-MAX) variable. S-MAX detaches a stock's return distribution that represents a preference for skewness. An investor without constraints who desires to earn lottery-like returns can raise money through leverage and build a portfolio of stocks with low volatility and high skewness. The L-MAX factor captures the returns to long low MAX and short high MAX portfolios.

The study also computes the size (SML) and value (VMG) factors, as in Fama and French (1993) and uses the three-factor model to test the robustness of the results.

The study presents the portfolios' excess returns and alphas as a monthly percentage. Sharpe ratios and portfolio return volatility are annualized. It reports t-values below the estimated regression coefficient. Ex-post beta is the realized coefficient on the market returns.

III. RESULTS AND DISCUSSION

A) Performance of Volatility based value weighted decile portfolios

Table 1 reports the value-weighted returns of the volatility-sorted decile (D) portfolios. Volatility increases from D1 to D10, but D1 earns a higher return than D10. Thus, the risk-return relationship is inverse. The CAPM alpha and three-factor alpha of D1 are statistically significant at 5%. D1 has the highest Sharpe ratio. The ex-post beta increases from D1 to D10. This shows that the low-risk effect using volatility as a risk measure provides positive and statistically significant alphas in the Indian equity market and also beats the benchmark.

Table 1: Volatility based decile portfolios

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Market index
Excess Returns	0.64	0.23	0.46	0.20	0.34	0.13	-0.21	-0.52	-0.51	-0.07	0.39
CAPM alpha	**0.27**	-0.15	0.05	-0.09	0.05	-0.24	-0.52	-0.80	-0.54	0.16	
t-statistics	2.03	-0.21	0.62	-0.31	0.18	-0.80	-1.44	-2.13	-1.03	0.21	
Alpha Three factor	**0.29**	-0.15	0.01	-0.27	-0.08	-0.41	-0.73	-0.96	-0.62	0.12	
t-statistics	2.08	-0.66	0.12	-1.13	-0.36	-1.61	-2.39	-3.03	-1.22	0.15	
Beta ex-post	0.69	0.85	1.06	1.07	1.17	1.26	1.34	1.48	1.69	1.32	
Volatility	19.50	25.02	29.76	30.23	33.34	35.71	39.08	41.57	52.04	52.80	25.71
Sharpe ratio	0.36	0.12	0.19	0.08	0.12	0.01	-0.09	-0.17	-0.12	-0.01	0.17

Bold figures indicate 5% statistical significance *Author's calculations.*

B) Performance of Idiosyncratic Volatility based value weighted decile portfolios

Just like the results of the low-volatility effect shown in Table 1, Table 2 reports the value-weighted returns of the idiosyncratic volatility-sorted decile portfolios. Portfolio D1 has the highest returns while D10 earns the lowest, but the alphas are not statistically significant. D1 has the highest Sharpe ratio. The ex-post beta and volatility of these portfolios monotonically increase from D1 to D10. These results also prove show that in the Indian equity market idiosyncratic volatility-based portfolios deliver positive returns. The long-short strategy will deliver a monthly return of 2.02% on average.

Table 2: Idiosyncratic Volatility-Based Decile Portfolios

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Market index
Excess returns	0.63	0.33	0.43	0.46	0.09	0.10	0.16	0.21	-0.39	-1.39	0.36
CAPM alpha	0.36	0.04	0.13	0.14	-0.20	-0.18	-0.06	0.02	-0.51	**-1.33**	
t-statistics	1.76	0.19	0.53	0.68	-0.73	-0.61	-0.18	0.05	-1.22	-2.17	
Alpha three-factor	0.33	0.01	0.05	0.06	-0.26	-0.29	-0.16	-0.12	-0.63	**-1.65**	
t-statistics	1.66	0.07	0.22	0.31	-1.02	-1.13	-0.50	-0.34	-1.72	-3.35	
Beta ex-post	0.72	0.83	0.93	1.02	1.04	1.23	1.33	1.41	1.44	1.20	
Volatility	21.37	23.68	26.96	28.29	30.06	34.80	38.56	41.12	42.82	44.09	25.71
Sharpe ratio	0.37	0.17	0.19	0.20	0.04	0.03	0.05	0.06	-0.11	-0.35	0.17

Bold figures indicate 5% statistical significance *Author's calculations.*

C) Performance of MAX based value weighted decile portfolios

The properties of the ten MAX-sorted portfolios are produced in Table 3. It provides information on excess returns, ex-post beta, three-factor alpha, return volatility, and Sharpe ratio. Stocks with low MAX are included in portfolio D1, and stocks with the highest MAX are included in portfolio D10. The lowest MAX portfolios have an excess return of 0.80% on a monthly average. Both the three-factor alpha and the CAPM alpha are statistically significant. From D1 to D10, the ex-post beta and the portfolio returns volatility to rise. Whereas D10 has the lowest Sharpe ratio, D1 has the greatest. These results show that MAX in the Indian equities market yields positive returns.

Table 3: MAX-based decile portfolios

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Excess returns	0.80	0.37	0.15	-0.19	0.22	0.43	0.40	-0.15	0.16	-1.05
CAPM alpha	**0.55**	0.18	-0.14	-0.45	-0.07	0.13	0.16	-0.24	-0.13	-1.04
t-statistics	2.23	0.40	-0.53	-1.78	-0.30	0.43	0.52	-0.88	-0.17	-1.96
3F alpha	**0.50**	0.03	-0.17	-0.51	-0.20	0.12	0.09	-0.45	-0.15	**-1.34**
t-statistics	2.04	0.17	-0.71	-2.00	-0.87	0.09	0.28	-1.45	-0.42	-3.01
Ex-post beta	0.70	0.78	0.86	0.91	0.97	1.19	1.22	1.26	1.40	1.39
Volatility	22.19	22.82	25.81	27.15	28.17	31.29	35.77	37.16	42.14	43.84
Sharpe ratio	0.45	0.19	0.07	-0.08	0.09	0.17	0.15	-0.03	0.05	-0.27

Bold figures indicate 5% statistical significance *Author's calculations.*

D) Decomposing L-MAX into S-MAX and T-VOL

Table 1 demonstrates that in the Indian stock market, MAX provides a positive and significant alpha. The study creates the L-MAX factor in order to investigate MAX's robustness in more detail. The long-short MAX-based portfolios designed in accordance with Asness et al. (2020) are called L-MAX. It goes long low-MAX stocks and shorts high-MAX stocks. The study divides the L-MAX factor into S-MAX and T-VOL in order to determine whether volatility or return skewness accounts for the return to the L-MAX factor. MAX divided by volatility equals scaled MAX. The S-MAX factor shorts stocks with a high-scaled MAX and goes long on stocks with a low-scaled-MAX. The TVOL factor trades low-volatility equities long and high-volatility stocks short.

$$L - MAX_t = a_1 + a_2 S - MAX_t + a_3 T - VOL_t + \varepsilon_t \tag{1}$$

Table 4: Regression of L-MAX on S-MAX and T-VOL

		L-MAX
Intercept		0.00
		-1.90
S-MAX		**0.35**
		11.83
T-VOL		**0.74**
		47.21
R^2		0.93

Bold figures indicate 5% statistical significance. Author's calculations

The regression of L-MAX on S-MAX and T-VOL explains 93% of the relation, which turns the intercept zero. Both T-VOL and S-MAX combine to explain the L-MAX, but T-VOL explains most of its variation. The intercept of the regression is zero, which shows that the right-hand side factors fully explain the left-hand side factors. Both S-MAX and T-VOL explain the L-MAX factor in its entirety.

E) Comparative performance of L-MAX, S-MAX and Idiosyncratic volatility (I-VOL) factors

Table 5 shows the alphas and regression coefficients of S-MAX, L-MAX and I-VOL factors on the control variables - MKT, SML and VMG. Alpha is a monthly percent. The Sharpe ratio is annualized. The study observes the performance of unsystematic risk related factors - L-MAX, S-MAX and I-VOL factors. S-MAX delivers negative alpha. The performance of L-MAX and I-VOL is similar. L-MAX factor's Sharpe ratio is lower than that of the I-VOL factor. L-MAX and I-VOL factors load negatively on size and positively on factor. This shows that their portfolios consist of more large-value stocks. However it is obvious that the Sharpe ratios of all these factors are low. Thus, S-MAX earns non-positive alpha, but L-MAX and I-VOL factors carry positive and significant alphas.

Additionally, S-MAX 1y and L-MAX 1y are calculated to change the time span during which the idiosyncratic risk variables' features are evaluated. L-MAX 1y and SMAX 1y use the one-year characteristics of MAX as opposed to the one-month features. Nevertheless, the study notes that altering the properties of the MAX variable has no effect on the alpha of these variables.

Table 5: Performance and factor exposure of all idiosyncratic volatility-related factors

	S-MAX	S-MAX	L-MAX	L-MAX	I-VOL	I-VOL	S-MAX1Y	L-MAX1Y
One factor alpha	-0.26	-0.26	**0.54**	**0.54**	**0.72**	**0.75**	**-0.92**	**0.61**
t-statistics	-1.16	-1.21	2.04	2.12	2.82	3.14	-3.63	2.28
Market	**0.11**	**0.09**	**- 0.44**	**-0.45**	**-0.48**	**-0.45**	**0.26**	**-0.59**
t-statistics	3.37	2.84	-12.78	-11.94	-13.84	-12.40	7.18	-15.07
SML		0.04		**-0.22**		**-0.27**	-0.06	**-0.39**

t-statistics		0.91		-3.37		-4.66	-0.83	-6.10
VMG		0.00		**0.15**		0.08	-0.08	0.06
t-statistics		-0.03		2.39		1.45	-1.16	0.98
Sharpe ratio	-0.25	-0.25	0.08	0.08	0.19	0.19	-0.71	-0.06
R^2	0.05	0.05	0.42	0.45	0.46	0.51	0.19	0.63

Bold figures indicate 5% statistical significance *Author's calculations.*

IV. CONCLUSION

The analysis of the study comes to the conclusion that alphas are statistically significant and low risk effect returns outperform market returns. In the Indian stock market, the low-risk effect is an independent factor that does not take the place of any well-established factors. Positive and statistically significant returns are produced by the lottery element. But volatility, not return skewness, explains a large portion of this element. The returns remain unchanged even if the characteristics of this factor specifically designed to capture lottery-like demand are altered. The analysis comes to the conclusion that the low-risk effect in the Indian stock market is not primarily driven by a preference for lottery stocks. It will be easier to quantify the cause of the low-risk impact on the Indian stock market with more research in this area.

Interest Conflicts
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