Are Idiosyncratic Risk and Extreme Positive Return Priced in the Indian Equity Market?

Abstract:

In this paper, we examine whether the IVOL (Idiosyncratic Volatility) and MAX (Extreme Positive Return) can predict future returns in the Indian stock market where a short sale is restricted with no naked short sale allowed. We find that both IVOL and MAX have significantly positive and persistent effects on expected returns in this market. In subsamples, we document that small firms have positive IVOL and MAX effects. However, more interestingly, after including all the controls, in contrast to the finding of Bali et al. (2011), the IVOL and MAX effects are significantly negative for the large firms in this market implying the investors' response to IVOL and MAX with the perception of low growth prospects of large firms. We use both portfolio level and firm level Fama-Macbeth cross-sectional analysis to show the effects.

Keywords: MAX effet, IVOL effect, Indian Stock Market

1. Introduction :

Idiosyncratic risk comes as a surprising puzzle in the asset-pricing literature when Ang et al. (2006) find that the portfolios containing the highest level of idiosyncratic risk yield significantly lower returns than do their counterparts with the lowest level of such risk. The inability of either the existing asset pricing models or exposure to aggregate volatility risk to explain this return differential is the fundamental part of the puzzle. The finding is the exact opposite of the results of Merton (1987), who shows that in a market with frictions (limited access to information by the investors), since unsystematic risk cannot be fully diversified away by the investors, there is a positive relationship between idiosyncratic risk and expected returns of stocks. This puzzle continues to surprise when Ang et al. (2009), as before, show that the market return volatility is a priced cross-sectional risk factor in each of the G7 countries and therefore, demand thorough research on the issue. Though in inial response, e.g., Bali and Cakici (2008), and Fu (2009) contest this observation, several studies, e.g., Pukthuanthong-Le and Visaltanachoti (2009), and Nartea et al. (2011) corroborate the seminal work of Ang et al. (2006, 2009) and revealed that the information content of idiosyncratic risk has become an important issue in asset pricing (Malagon et al. 2015a).

There are two factions of literature in the discussion of idiosyncratic risk. The first strand of studies doubts the underlying risk measure and its construction. This faction of research shows that, due to diverse methodologies and data used for analyses, the estimation of idiosyncratic risk may vary and, conclude that the much established empirical evidence of a negative relationship between idiosyncratic risk and return is not robust. In addition to those discussed earlier in this paper, Huang et al. (2010) connect the puzzling relation to microstructure issues, e.g., return reversals or trading nonsynchronicity. Moreover, Han and Lesmond (2011) and Malagon et al.

(2015b) conclude that as the investment time horizon increases, the relationship between risk and return tends to be positive. The second faction of studies in idiosyncratic risk confirms the support towards the soundness of the measures involved in the controversial empirical evidence of a negative relationship between idiosyncratic risks and returns of portfolios. This faction explains that the evidence is largely driven by familiar factors, such as market microstructure or investor preferences. For instance, Kapadia (2006) links the puzzling observation to investors' preference for skewness by showing a high correlation between idiosyncratic risk and cross-sectional skewness. Similarly, Boyer et al. (2010) also explain the anomaly as investors' preference for high idiosyncratic skewness. Bali et al. (2011) also find the investors' preference as an explanation for the anomaly and show the tilt of investors towards stocks with lottery-like payouts. In contrast, Gao et al. (2010) account investor sentiment as a cause for the negative relationship between idiosyncratic risk and expected return while George and Hwang (2011) concluded that difference of opinion is the main reason for the anomaly. However, Jiang et al. (2009) refute the investor preference hypothesis for explaining the anomaly, and Chen et al. (2012) refute the argument of market microstructure. Going back to the estimation of idiosyncratic risk, investors' preference for skewness and stocks with lottery-like payout cannot confirm the robustness of the measure of such risk, and vice versa.

Another but related part of the story is the MAX effect introduced by Bali et al. (2011). They show portfolios with high maximum daily returns (high MAX stocks) significantly underperform next month in comparison to their counterparts with low maximum daily returns (low MAX stocks) over the prior month. Later, Nartea et al. (2014), Walkshäusl (2014), Zhong and Gray (2016), Chan and Chui (2016), Wan (2018), and Ali et al. (2019b) study South Korean, European, Australian, Hong Kong, Chinese, and Turkish markets respectively to confirm the robustness of the MAX effect. Moreover, Chee (2012) finds a MAX effect in the Japanese market with bivariate sorts only after controlling for firm characteristics but not with sorts of a single portfolio. Similarly, Annaert et al. (2013) find evidence of a MAX effect in 13 European countries after controlling for potential confounding influences using cross-sectional regressions and two-stage portfolio sorts while finding a weak effect with univariate portfolio sorts. This series of mixed findings motivate us to look for the MAX effect at an individual level for other countries. Moreover, Aboulamer and Kryzanowski (2016) find exactly the opposite result in the Canadian stock market, i.e., a positive relationship between maximum returns in the previous month and returns in the next month. This anomalous result introduces a controversy on much established negative MAX effect and therefore also demands further research on this issue in other individual markets.

The asset pricing literature is also investigating other factors and their interactions with the MAX effect for cross-sectional returns in the US. Chen and Petkova (2012) find that high MAX stocks have high R&D expenditures implying that MAX is the signal of high growth opportunities adjusted in the price. Han and Kumar (2013) document that speculative retail investors exhibit a strong gambling preference and therefore trade lottery-like stocks. Fong and Toh (2014) find that institutional ownership and investor sentiment influence the significance of the negative MAX effect. The negative MAX effect follows only high-state sentiment, and the strongest negative MAX effect is observed in stocks with low institutional ownership. Frazzini and Pedersen (2014) document that one can earn an abnormal return with a ‘betting against beta’ strategy by taking a long (short) position in stocks with the low (high) beta. However, Bali et al. (2014), later, show that such abnormal return does not exist after controlling for MAX. Such continuous development of the idiosyncratic risk and MAX effect gives rise to scope for further research at the micro level for individual countries and for this paper we choose India as a growing economy.

Each country has its own unique market settings and they influence investors in different ways. Hence, countrywise research is important in many aspects. In this paper, we consider Indian market as a sample of our research because India is a unique market where short selling was banned by the Securities and Exchange Board of India (SEBI) in March 2001 due to a crash in stock prices and the allegations on the-then president of Bombay Stock Exchange (BSE) of using confidential information from the BSE's surveillance department for making gains and contributing to volatility. Only retail investors were allowed to short-sell shortly after the ban. While SEBI absolved the president of any wrongdoing later, not until 2005 it recommended for short-selling by institutional investors like mutual funds while issued guidelines of short-selling for such investors in July 2007 allowing to start short-selling the following year. However, naked short-selling is always prohibited in Indian market requiring investors to fulfill their contractual obligation and deliver the securities during the time of settlement. This unique feature of the Indian market makes it important to study further the puzzle of a negative relationship between idiosyncratic risk and expected return in a much-restricted market.

In this paper, the findings in the Indian market are remarkably different from the evidence in USA, Europe, China, Africa, Australia, Hong Kong, Brazil, Turkey, Finland, and South Korea. Ang et al. (2006) show evidence of a negative relationship between IVOL and cross-sectional returns in the US equity market. Bali et al. (2011) also show a significant negative relationship between extreme positive return (MAX) and the next month's return. They claim that after including IVOL and MIN as controls, the MAX coefficient remains significantly negative. While IVOL coefficient is no longer statistically significant i.e., MAX is the true effect in the US market rather than the IVOL. Nartea et al. (2013), Berggrun et al. (2017), Nartea and Wu (2013), Nartea et al. (2014), Zhong (2018), Ali et al.(2019a), Ali et al (2019b), Walkshäusl (2014), and Wu et al. (2019) show the significantly negative relationship of both MAX and IVOL with future return in the Chinese, the Brazilian, the Hong Kong, the South Korean, the Australian, the Finnish, the Turkish, the European, and the African markets, respectively**.** In contrast, India, Canada (Aboulamer et al. 2016) and some Southeast Asian countries (Nartea et al. 2011) are the few exceptions where the relationship between IVOL-MAX and future returns is significantly positive. Therefore, these markets, where investors underprice the stocks with high IVOL and high MAX, demand comprehensive research. Table 1 summarizes the finding of authors in various markets.

[Insert table 1 here]

Though Aziz and Ansari (2017) show a positive relationship between IVOL and future return in the Indian market, our research is unique, extensive, and more informative in the following aspects. First, we use a much larger sample in terms of both time and the number of stocks. Aziz and Ansari (2017) use data for the sample period between 1999 and 2014, whereas our sample data ranges from 1990 to 2018. Moreover, Aziz and Ansari (2017) use S&P BSE-500 firms but we use data of all available active and delisted stocks (4616 firms) throughout the tenure. Since we include all delisted (dead) stocks in our sample, our data is free from survivorship bias. Second, in addition to the IVOL effect, we show a complete analysis of the MAX effect in this paper. We also provide the full study of IVOL_CAPM and IVOL_FF separately. Third, we provide an interesting finding that large firms have negative and significant IVOL and MAX effects in the Indian market. Furthermore, our paper contains month to month transition matrix which shows persistence of MAX stocks over time.

This paper contains four main contributions. First, our goal is to see if the anomalous relationship between idiosyncratic risk and expected return holds in growing but a restricted market like India. Not surprisingly, we found a positive relationship between idiosyncratic risk and expected return, as opposed to Ang et al. (2006, 2009), in Indian stock market by using both portfolio level and firm level Fama-MacBeth (1973) regression analysis. The second contribution of this paper is finding out the relationship between extreme positive returns and future returns. We show that a strategy involving a long (short) position on the stocks with past month's high (low) daily extreme positive returns generate significantly positive succeeding returns. This positive MAX effect is consistent with the Canadian Market where extreme positive return yielding stocks show better performance in the subsequent month (Aboulamer and Kryzanowski, 2016). Third, we check the persistence of the MAX effect, i.e., we report a month to month stock transition matrix to see what proportion of stocks remain in the same portfolio in the subsequent month, and we find that MAX stocks are persistent in the extreme portfolios.

Our fourth, and perhaps the most interesting, contribution is the relationship between idiosyncratic volatility (IVOL) and MAX effect. Bali et al. (2011), using MAX as a control in the US market, show that negative IVOL and return relationship gets reversed. Annaert et al. (2013) and Walkshäusl (2014) also indicate that negative IVOL coefficient is also absorbed by MAX in the European market. On the other hand, Nartea et al. (2014) show that IVOL and MAX are independent with each other in the South Korean market. Wan (2018) demonstrate that the IVOL absorbs the MAX, and the IVOL coefficient reverses the extreme negative returns (MIN) coefficient in the Chinese stock market. In the Indian market, we also find a positive relationship between IVOL and MAX effect in the whole sample. Then we divide all stocks into two categories by the median value of their size and run Fama-Macbeth regression on those subsamples. The results are somewhat interesting in case of large sized-firms subsample where we find significantly negative IVOL and MAX coefficients after putting all the controls in the model. This result is surprising because, in the US market, Bali at el. (2011) demonstrate that generally small stocks have higher negative MAX and IVOL effects. Aboulamer and Kryzanowski (2016) also confirm similar negative effects in the Canadian Market. In the Indian market, we show large firms produce significantly negative IVOL coefficient whereas small firms IVOL effect is somewhat positive. The large firms with high idiosyncratic risk and MAX effect in one month experience negative returns in the succeeding month. This finding implies that investors perceive the idiosyncratic risk of small firms as growth prospects while seeing such risk of large firms as a negative signal due to lower growth opportunities.

The remainder of the paper advances as follows. Section 2 explains the sources and characteristics of data in 2.1 and methodology in 2.2. Section 3 presents the results with subsections 3.1 for the IVOL effect, 3.2 for the MAX effect, 3.3 for MAX and the idiosyncratic volatility puzzle, and 3.4 for the subsample test of the results. Section 4 concludes the paper.

2. Data:

We use the daily data for all firms available on the Indian stock exchange from January 1990 to July 2018. We obtained the data comprising 4616 firms from the Compustat database and the monthly Fama-French (1993) factor from the Dartmouth webpage (http://mba.tuck.dartmouth.edu).

Using the daily stock return, we calculate the following variables:

stock return ($return_{i,t}$), maximum daily return over the previous month ($MAX_{i,t}$), minimum daily return over the previous month ($MIN_{i,t}$), momentum ($MOM_{i,t}$), short-term reversal ($Ra\ EV_{i,t}$), skewnewss ($SKEW_{i,t}$), market beta ($BETA_{i,t}$), idiosyncratic volatility ($IVOL_{i,t}$), illiquidity(

$ILLIQ_{i,t}$). We calculate the daily stock return as the logarithmic difference of daily stock prices. $MAX_{i,t}$ is the maximum daily return in the month $t-1$ for the firm i. $return_{i,t}$ is the average of daily stock returns for firm i during the month of t. We calculate $MAX(n)_{i,t}$ as the average of n maximum daily returns for firm i during the month $t-1$ when $n = 2, \ldots, 5$.

Following Jegadeesh and Titman (2001), we calculate the momentum variable $MOM_{i,t}$ as the cumulative return of stock i for 11 months over the period from $t-2$ to $t-12$. The short-term reversal variable $REV_{i,t}$ is the daily average return of stock i in month $t-1$ (Jegadeesh (1990), Lehmann (1990)). $SKEW_{i,t}$ is calculated as the skewness of daily stock return of firm i during the month $t-1$. $SIZE_{i,t}$ is calculated by the natural logarithm of the market value of the equity of stock i in month $t-1$. Illiquidity($ILLIQ_{i,t}$) is the absolute daily average stock return over a month divided by its trading volume of stock i in month $t-1$.

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i (R_{m,d} - r_{f,d}) + e_{i,d} \quad (1)$$

where $R_{i,d}$ is the return on stock i on day d, $R_{m,d}$ is the market return on day d. $r_{f,d}$ is the risk-free rate on day d, and $e_{i,d}$ is the idiosyncratic return on day d. We use the daily stock returns of month $t-1$ to estimate the equation and then calculate the market BETA of stock i in month t ($\widehat{\beta_i}$) and the idiosyncratic volatility of stock i in month t is $ivol = \sqrt{var(e_{id})}$. To calculate three factors alpha, we use:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1i}(R_{m,d} - r_{f,d}) + \beta_{2i} SMB + \beta_{3i} HML + e_{i,d} \quad (2)$$

IVOL_CAPM is calculated from the error term of equation 1 (CAPM model) and IVOL_FF is calculated by using the error terms of equation 2 (Fama-French three-factor model)

[Insert table 2 here]

[Insert table 3 here]

Table 2 shows the summary statistics of relevant variables. The mean of average monthly return for equal weighted return is 0.011 and the standard deviation is 0.142. The mean of the average value weighted return portfolio is 0.014 with a standard deviation of 0.143. The average of the MAX return is 0.065 and the standard deviation is 0.047. Table 3 indicates the correlation coefficient matrix of the same variables. We find that there is a positive relationship between MAX and IVOL variables.

3. Methodology and Results

In this paper, both portfolio level analysis and firm-level Fama-MacBeth (1973) cross-sectional regression analysis are used. The portfolio-level analysis does not impose any functional form on the relation between MAX and future returns. Hence it has the advantage of being non-parametric (Bali et al 2011).

On the other hand, the firm-level cross-sectional analysis helps to capture information that is eliminated in portfolio level analysis through aggregation. In the Fama–MacBeth framework we first estimate the average coefficients by using time series regression and then apply cross-sectional regression with those estimated betas. There are several advantages (see Amit Goyal 2012) of the Fama–MacBeth approach. First, it can easily handle panel data which are not balanced. In addition, the distribution of the risk premium estimates does not depend on the number of stocks, which may vary from time to time. Second, even though we use constant betas, this framework is flexible to allow for time-varying betas. Third, it may be a possibility that autocorrelation in returns leads to autocorrelation problems in risk premium estimates. This is recognized by Newey–West corrections to variance formulas.

3.1 The IVOL effect:

First, we find a positive relationship between stock returns and past month's IVOL by using both portfolio level and firm level Fama-MacBeth (1973) regression analysis in the Indian stock market. This result is consistent with the findings of Merton (1987) where he argues that the relationship between stock return and idiosyncratic volatility may be positive since investors hold undiversified portfolios and seek higher return for the firm-specific risk. The same positive IVOL-return relationship is demonstrated by Malkiel & Xu (2002). They argue that IVOL could be priced to compensate investors who failed to hold the market portfolio. At first, we report the result of univariate portfolio level analysis in table 4.

[Insert table 4 here]

Panel A of Table 4 shows 10 portfolios sorted by IVOL_CAPM. The equal-weighted return for the lowest IVOL_CAPM portfolio is 0.976 and the highest IVOL_CAPM portfolio is 4.976. The return difference between these two extreme portfolios is 3.999 with a t-statistic of 3.651. The Fama-French three-factor alpha difference is 3.772 while the associated a t-statistic of this difference is 4.598. Similarly, the value-weighted return for the lowest IVOL_CAPM portfolio is 3.074 and the highest IVOL_CAPM portfolio is 6.511. The return difference of the highest and the lowest IVOL_CAPM portfolios is 3.436 when the related t value is 2.177. The Fama-French three-factor alpha difference for value weighted return is 3.151 and it produces a significant t value of 2.527 related to this difference. The high value of t-stat for return and Fama-French three-factor alpha differences indicate the relationship between lag firm-level volatility and return is positive in the Indian stock market. Panel B of Table 3 shows the same portfolio level analysis by using IVOL_FF. The equal-weighted return for the lowest IVOL_FF portfolio is 1.087 and the highest IVOL_FF portfolio is 5.380. The return difference between these two extreme portfolios is 4.293 with a statistically significant t-statistic of 3.484. The Fama-French three-factor alpha difference is 4.309 with a similar strong t value of 4.671. Likewise, the value-weighted return for the lowest IVOL_FF portfolio is 3.808 and the highest IVOL_FF portfolio is 6.271. The return difference of the highest and the lowest IVOL_FF portfolios is 2.464 and its corresponding t value is 1.209. The Fama-French three-factor alpha difference for value weighted return is 1.913 with a relatively weak t value of 1.018. From both IVOL_CAPM and IVOL_FF sorted portfolios, we observe that the IVOL effect is positive.

Though many recent imperial findings reveal the puzzling negative relationship between lag idiosyncratic volatility and return in many counties such as the US and China, the Indian evidence is somewhat opposite. In the US market, Ang et al., (2006) show that the portfolios with the highest firm-level volatility generate significantly lower returns which are portrayed as a puzzling negative relationship between idiosyncratic volatility and return. Wan (2018) also show the same negative IVOL return relation in the Chinese market. The speculative investor's possible demand for lottery-like stocks are responsible for this kind of puzzling negative IVOL-return relation, demonstrated by many researchers. On the other hand, the positive IVOL- return relation is caused by undiversified investors who like to pursue higher returns for bearing firm-specific risk. In the Indian market, this positive relationship between firm-specific risk and return exists even after using several variables as controls. However, the magnitude of this positive relationship is lesser in case of double-sorted portfolios. In tables 5 and 6, we report double-sorted portfolios where we show the relationship between IVOL_CAPM and IVOL_FF with future stock returns after controlling for the beta, momentum, short term reversals, a book to market value and liquidity. In tables 4 and 5, first, we sort 10 portfolios based on each character variable and then again within each portfolio, we sort stocks based on IVOL.

[Insert table 5 here]

[Insert table 6 here]

In table 5, we see that the extreme portfolio differences for IVOL_CAPM sorted portfolios are positive even after controlling for the beta, momentum, short term reversals, a book to market value, and illiquidity. However, the magnitude is lesser and not significant in many cases. The bivariate sorted extreme portfolio differences are significant in case of momentum and illiquidity but for other characters, it is not significant. We observe similar results in the case of value weighted return portfolios in panel B of Table 5. Table 6 also reports similar bivariate sort by IVO_FF after controlling beta, momentum, short term reversals, a book to market value, and illiquidity. Panel A of Table 6 shows the equal-weighted return portfolios and panel B reports value weighted return portfolios.

To show the relationship between IVOL and return, we use the Fama-MacBeth (1973) regression approach in this section. In Fama-Macbeth approach, we can use many control variables simultaneously. In this paper, we use related control variables like market beta (BETA), a book to market (BM), size (SIZE), momentum (MOM), reversal (REV), illiquidity (ILLIQ) and skewness (SKEW). We also include the maximum daily return of the previous month (MAX) as a control in the certain model to check whether the sign of MAX or IVOL changes after inclusion of both variables together. To find the magnitude of the IVOL effect (for IVOL_CAPM) in the Indian stock market, we use the following economic specifications:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{t,1} IVOL\_CAPM_{i,t} + \gamma_{t,2} BETA_{i,t} + \gamma_{t,3} SIZE_{i,t} + \gamma_{t,4} MOM_{i,t} + \gamma_{t,5} ILLIQ_{i,t} + \gamma_{t,6} REV_{i,t} + \gamma_{t,7} SKEW_{i,t} + \gamma_{t,8}\, MAX + \varepsilon_{i,t+1} \quad (3)$$

[Insert table 7 here]

Panel A of Table 7 presents 10 different model's regression coefficients and its associated t-statistics with the equal weighted return. In the first model, the IVOL_CAPM coefficient is significantly positive where there is no control with the main independent variable. We see that the results are in line with other models' results where we gradually include all the related controls with the IVOL_CAPM. In the last model, IVOL_CAPM appears with all the controls as well as MAX. We observe that the positive coefficient of IVOL_CAPM also exists even after putting MAX as a control. However, the sign of MAX coefficient is significantly negative. In the later part of this paper, we will see what is the MAX coefficient without IVOL as a control. The IVOL return relation changes in the US stock market after putting MAX as a control, shown by Bali et al. (2011). In the European market, IVOL effect is also subsumed by MAX, demonstrated by Walkshäusl (2014). In the Chinese stock market, Wan (2018) indicates that IVOL is proxied by MAX and MIN. It is not surprising that highly volatile stocks have high MAX and MIN returns.

We again run similar regressions with IVOL_FF as a main explanatory variable in this section. To find the magnitude of the IVOL effect (for IVOL_FF) in the Indian stock market, we use the following economic specifications:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{t,1} IVOL\_FF_{i,t} + \gamma_{t,2} BETA_{i,t} + \gamma_{t,3} SIZE_{i,t} + \gamma_{t,4} MOM_{i,t} + \gamma_{t,5} ILLIQ_{i,t} + \gamma_{t,6} REV_{i,t} + \gamma_{t,7} SKEW_{i,t} + \gamma_{t,8}\, MAX + \varepsilon_{i,t+1} \quad (4)$$

[Insert table 8 here]

Just like IVOL_CAPM coefficients in table 8, IVOL_FF coefficients are significantly positive. The positive coefficients exist even after inclusion of other control variables. However, the sign of IVOL_FF has changed after including MAX with other control. The correlation between both IVOL and MAX is positive, and it gives an intuition of why MAX subsumes the predictive power of IVOL.

Indian stock market is dominated by individual investors and it is not surprising that those investors are not properly diversified. Hence mispricing may exist in the Indian Market on a small scale. The mispricing (due to market inefficiency) may happen through two forms. One form is overpricing, and the other form is underpricing. The possible reason for overpricing (especially lottery-like stocks) is the speculative investors' tendency to chasing stocks which have high past payoffs. On the other hand, undiversified investors cannot diversify firm-specific risks fully and demand premium for having those risks. In the Indian stock market, evidence shows that this kind of risk premium exists, i.e., investors underprice those stocks which have high idiosyncratic volatility in the past month.

3.2 The MAX effect:

The second contribution of this paper is to find out the relationship between extreme positive returns and future returns. Bali et al. (2011) show that the stocks with high positive return show a lower performance in the subsequent month in the US stock market. The same negative MAX effect prevails in European market confirmed by Walkshäusl (2014). He finds a highly significant MAX anomaly in 11 developed markets: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain. This paper also claims that MAX effect is stronger among those firms which have high cash flow volatility, and weaker for firms having high profitability. Wan (2018) also shows a similar negative MAX effect with high IVOL anomaly in the Chinese stock market. He argues that this anomalous negative relationship is the result of typical investor behavioral biases in this market. In contrast, we show that a strategy involving a long (short) position on the stocks with past month's high (low) daily extreme positive returns generate significantly positive succeeding returns. This positive MAX effect is consistent with the

Canadian Market where extreme positive return yielding stocks show better performance in the subsequent month (Aboulamer and Kryzanowski, 2016).

In this section, we report the result of univariate portfolio level analysis in table 8 which shows that in most of the cases the MAX effect is significantly positive.

[Insert table 9 here]

Table 8 shows 10 portfolios sorted by MAX. The equal-weighted return for the lowest MAX portfolio is -0.726 and the highest MAX portfolio is 2.010. The return difference between these two extreme portfolios is 2.736 while the associated t value is 1.648. The Fama-French three-factor alpha difference is 2.473 and it produces a t-statistic of 3.828 meaning that the return difference is highly significant. Similarly, the value-weighted return for the lowest MAX portfolio is -0.368 and the highest MAX portfolio is 2.520. The return difference of the highest and the lowest MAX portfolios is 2.888 with a t-statistic of 3.484. The Fama-French three-factor alpha difference for value weighted return is 2.618 and its corresponding t value is 4.011. The high value of t-stat for value weighted return and Fama-French three factor alpha differences indicate the relationship between the lag maximum return of the previous month and the return in succeeding month is positive in Indian stock market.

Now we report double-sorted portfolios in table 9 where we show the relationship between MAX with future stock returns after controlling for the beta, momentum, short term reversals, the book to market value and liquidity. In table 10, first, we sort 10 portfolios based on each character variable and then again within each portfolio, we sort stocks based on MAX.

[Insert table 10 here]

In table 10, we see that the extreme portfolio differences for MAX sorted portfolios are positive even after controlling for beta, momentum, short term reversals, book to market value, and illiquidity. However, the magnitude is lesser and not significant in many cases. The bivariate sorted extreme portfolio differences are significant in case of momentum and illiquidity but for other variables, those are not significant. The results of the bivariate sort with MAX is fairly consistent with IVOL bivariate sort. Hence, MAX can be used as a proxy for IVOL. We also report single sort portfolios.

[Insert table 11 here]

Table 11 reports univariate sort portfolio based on MAX (n) where MAX2 is the average of the maximum two daily returns of previous month, MAX3 is the average of the maximum three daily returns of previous month, MAX4 is the average of the maximum four daily returns of previous month, MAX5 is the average of the maximum five daily returns of the previous month. The return difference is significant among two extreme portfolios in both equal weighted and value weighted return case.

To show the relationship between the maximum daily return of a month (MAX) and future return, we again use Fama-MacBeth (1973) regression approach. This time we use related control variables such as market beta (BETA), book to market (BM), size (SIZE), momentum (MOM), reversal (REV), illiquidity (ILLIQ) and skewness (SKEW). The model for detecting MAX effect is as follows:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{t,1}MAX_{i,t} + \gamma_{t,2}BETA_{i,t} + \gamma_{t,3}SIZE_{i,t} + \gamma_{t,4}MOM_{i,t} + \gamma_{t,5}ILLIQ_{i,t} + \gamma_{t,6}REV_{i,t} + \gamma_{t,7}SKEW_{i,t} + \varepsilon_{i,t+1} \qquad (5)$$

[Insert table 12 here]

Panel A of Table 12 presents 10 different models' regression coefficients and its associated t-statistics with an equal-weighted return. In the first model, the MAX coefficient is significantly positive where there is no control with the main independent variable. However, it is evident that after including other controls, the magnitude of the MAX coefficient becomes lower. In the last model, MAX appears with all the controls and it shows a negative MAX coefficient. That indicates MAX coefficient is changed with the inclusion of other controls. We see comparable results in table 11 where MAX coefficient is significantly negative in the last model.

3.3 Persistence in Extreme Returns

To check the persistence of MAX, we report a month to month stock transition matrix in table 12. It indicates what proportion of stocks shifted from one portfolio to the other in next month. The diagonal elements of the matrix represent the proportions of stocks remaining in the same portfolio in the subsequent month. If this shifting is completely random than it would be around 10 percent. But the diagonal element of two extreme portfolios is more than 25 percent implying that MAX stocks are persistent in the extreme portfolios.

[Insert table 13 here]

3.4 Is the IVOL anomaly driven by the MAX effect?

In this section, we run Fama-MacBeth (1973) regression by keeping only two regressors-(IVOL and MAX) together. Hence the model is

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{t,1} IVOL_{i,t} + \gamma_{t,2} MAX_{i,t} + \varepsilon_{i,t+1} \qquad (6)$$

[Insert table 14 here]

Panel A of Table 13 shows that positive IVOL_CAPM coefficient is not absorbed by MAX but MAX subsume IVOL_FF in the Indian stock market. The value-weighted return regression results are almost similar to the equal weighted regression results.

3.5 Large and small size subsamples:

After getting the positive IVOL and MAX effect on the whole sample in the Indian stock market, we create large and small size subsamples. We divide all stocks into two categories by the median value of their size and run Fama-MacBeth regression on those subsamples. The results are somewhat interesting in case of large size sample firms. In the large sample, we see significantly negative IVOL and MAX coefficients in the Indian market after putting all the controls in the model.

[Insert table 16 here]

[Insert table 17 here]

[Insert table 18 here]

Panel A and B of table 15 show the Fama-MacBeth regression coefficients with its associated t-statistics for small firms of Indian stock market where IVOL_CAPM is the main regressor. Panel A represents equal-weighted return regression and panel B denotes the same value weighted return regression. Both Panel A and B of table 15 have significantly positive IVOL_CAPM coefficients without any control. But after putting all relevant controls, the coefficients are insignificant. On the other hand, in panel C and D in table 15, we see that the IVOL_CAPM coefficient is negative and after putting other controls in the model, the IVOL_CAPM coefficient is significantly negative. This result is surprising because in the US market Bali at el. (2011) demonstrate that generally small stocks have high negative MAX and IVOL effects, which is not consistent with the results of the Indian market. In fact, in the Indian stock market, large firms produce significantly negative IVOL coefficient and small firms IVOL effect is somewhat positive.

Panel A and B of Table 16 also show similar Fama-MacBeth regression coefficients with its associated t-statistics for small firms in the Indian stock market where IVOL_FF is the main regressor. Panel A represents equal-weighted return regression and panel B denotes the same value weighted return regression. Both Panel A and B of table 15 have significantly positive IVOL_FF coefficients without any control. But after putting all relevant controls, the coefficients are insignificant. On the other hand, in panel C and D in table 16, we see that the IVOL_FF coefficient is significantly negative and after putting other controls in the model, the IVOL_FF coefficient is significantly negative. Panel A and B of Table 17 also show FamaMacbeth regression coefficients with its associated t-statistics for small firms in the Indian stock market where MAX is the main regressor. Panel A represents equal-weighted return regression and panel B denotes the same value weighted return regression. Both Panel A and B of table 16 have significantly positive MAX coefficients without any control. But after putting all relevant controls, the coefficients are significantly negative. On the other hand, in panel C and D in table 16, we see that the MAX coefficient is negative and after putting other controls in the model, the MAX coefficient is significantly negative.

4. Conclusion:

Asset pricing literature, addressing the anomaly of idiosyncratic volatility, suggests that the investors are related to this anomaly. Investor preferences or pricing inability are two major reasons in many studies for the negative risk-return relationship. There are also studies on the estimation methods of idiosyncratic risk, and factions of supporters and opponents of these measurement methods. However, there are very few works on individual markets, especially those where trading is restricted in some way. Not surprisingly, we find a positive relation between idiosyncratic volatility and expected return in the Indian market where a short sale is allowed only for institutional and retail investors and the naked short sale is completely prohibited. This implies that investors tend to underprice stocks with idiosyncratic volatility in this market. Moreover, we find that there is a positive MAX effect consistent with Canadian Market where extreme positive return yielding stocks show persistently better performance in the subsequent month.

The fundamental concept of risk-return relationship is positive. Hence, investors should logically underprice stocks with high idiosyncratic volatility. However, most papers in recent time period demonstrate a negative MAX-IVOL relationship with the future returns. In contrast, Aboulamer and Kryzanowski (2016) corroborate and show the positive relationship between idiosyncratic volatility and future returns in the Canadian market. Nartea et al. (2011) also demonstrate similar finding using data of Malaysia, Singapore, Thailand, and Indonesia. In line to these papers, our research also validates a positive risk-return relationship in an important emerging market- India. This result is also consistent with the theory of under-diversification (e.g., Levy, 1978; and Merton, 1987) where investors like to have compensation for bearing risk. This study establishes another anomalous finding in contrast to the empirical results in developed economies and demonstrates the fact that generalizing all market characters with the same risk-return relationship could be misleading.

In the Indian market, we find a positive relationship between IVOL and MAX effect in the whole sample. However, with two subsamples of large and small firms, we find that in case of a subsample of large firms, both coefficients of IVOL and MAX are significantly negative while for small firms IVOL coefficient is positive. This is an anomalous result since Bali et al. (2011), and later, Aboulamer and Kryzanowski (2016) document that in general, there are negative coefficients for IVOL and MAX effects for small stocks. However, this feature of a market is the reflection of investors' varying responses to IVOL and MAX depending on the growth prospects of firms. Investors perceive high idiosyncratic risk as a positive signal for small firms since such firms also possess high growth prospects whereas see such risk of large firms as a negative signal due to low growth opportunities. In this paper, we only examine the IVOL and MAX effect on the Indian equity market, leaving two questions for future research. First, is the persistence of returns for MAX portfolios in the succeeding month related to investor ignorance or lack of arbitrage opportunities in the Indian equity market? Second, is the negative IVOL effect for large firms a common feature in markets with trade restrictions?

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Table 1: List of Recent (After 2010) significant papers related to IVOL and MAX effect

Authors	**Year**	**Market**	**IVOL effect**	**MAX effect**	**IVOL MAX together as control**
Aboulamer et al.	2016	Canada	Positive	Positive	IVOL is the true effect and MAX is vanished
Ali et al.	2019	Turkey	Negative	Negative	NA
Ali et al.	2019	Finland	Negative	Negative	Both IVOL and MAX effect exist together
Bali et al.	2011	US	Negative	Negative	IVOL vanished and MAX is the true effect
Berggrun et al.	2019	Brazil	Negative	Negative	IVOL vanished and MAX is the true effect
Nartea et al.	2011	Southeast Asia	Positive	NA	NA
Nartea et al.	2013	Hong Kong	Negative	NA	NA
Walkshäusl	2014	Europe	Negative	Negative	IVOL vanished and MAX is the true effect
Wu et al.	2019	Africa	Negative	Negative	IVOL vanished and MAX is the true effect
Zhong et al.	2016	Australia	Negative	Negative	NA

Table 2: Summary Statistics

	mean	median	std.dev	min	max	range
Return	0.011	0.000	0.142	-0.257	0.315	0.572
VWreturn	0.014	0.000	0.143	-0.250	0.325	0.575
MAX	0.065	0.050	0.047	0.000	0.190	0.190
IVOL_CAPM	0.031	0.026	0.111	0.000	48.089	48.089
IVO_FF	0.026	0.024	0.014	0.005	0.060	0.055
ILLIQ	4.535	1.481	6.787	0.002	25.441	25.439
REV	0.011	0.000	0.143	-0.257	0.317	0.575
MOM	0.153	0.114	0.545	-0.854	1.251	2.105
BETA	0.683	0.628	0.860	-0.878	2.437	3.315
SIZE	23.804	23.694	2.285	20.079	28.138	8.058
SKEW	0.278	0.215	0.771	-1.236	1.902	3.138
BM	1.145	0.182	2.390	-0.022	9.723	9.745
MAX2	0.054	0.049	0.035	0.000	0.142	0.142
MAX3	0.047	0.045	0.030	0.000	0.118	0.118
MAX4	0.041	0.039	0.026	0.000	0.102	0.102
MAX5	0.037	0.035	0.024	0.000	0.090	0.090

Note: This table shows summary statistics for the 4616 firms included in India in the sample period from January 1990 to July 2018. MAX is the maximum daily stock return over the previous month. Size (SIZE) is the natural logarithm of market equity (stock price multiplied by the number of shares outstanding) at the end of the month. $MOM_{i,t}$ as the cumulative return of stock i for 11 months over the period from $t-2$ to $t-12$. Illiquidity (ILLIQ) is the absolute monthly stock return divided by its trading volume. Short-term reversal (REV) is the monthly stock return over a month. Skewness (SKEW) is total skewness using daily stock returns over a month. Idiosyncratic volatility (IVOL_CAPM) is the idiosyncratic volatility relative to the CAPM model, Idiosyncratic volatility (IVOL_FF) is the idiosyncratic volatility relative to the Fama-French three factor model. MAX2 is the average of the maximum two daily returns of the previous month, MAX3 is the average of the maximum three daily returns of the previous month, MAX4 is the average of the maximum four daily returns of the previous month, MAX5 is the average of the maximum five daily returns of the previous month.

Table 3: Correlation coefficient matrix of variables

	MAX	IVOL_CAPM	IVOL_FF	ILLIQ	REV	MOM	BETA	SIZE	SKEW	BM
MAX	1.000	0.151	0.686	0.134	0.043	0.172	0.282	-0.008	0.497	0.034
IVOL_CAPM		1.000	0.167	0.070	0.010	0.052	0.028	-0.041	0.031	0.017
IVOL_FF			1.000	0.220	0.034	0.095	0.119	-0.193	0.119	0.051
ILLIQ				1.000	0.033	0.088	-0.099	-0.381	-0.065	-0.118
REV					1.000	0.305	0.047	0.052	0.017	-0.048
MOM						1.000	0.112	0.109	0.099	-0.122
BETA							1.000	0.288	0.111	0.012
SIZE								1.000	0.109	-0.077
SKEW									1.000	-0.013
BM										1.000

Note: Correlation coefficient matrix table for relevant variables. Blue and red shades indicate the intensity of positive and negative correlation among variables

Table 4: IVOL_CAPM and IVOL_FF sorted Portfolio return

Panel A: Portfolio return based on IVOL_CAPM

Portfolios	EW	VW
	Avg. Return	Avg. Return
Low IVOL_CAPM	0.976	3.074
2	1.544	4.261
3	2.019	3.007
4	1.895	2.626
5	2.018	3.097
6	2.109	3.022
7	2.414	3.291
8	2.123	2.923
9	3.258	3.750
High IVOL_CAPM	4.976	6.511
Diff 10-1	3.999***	3.436**
t value	(3.651)	(2.177)
Three factor alpha Diff 10-1	3.772***	3.151**
t value	(4.598)	(2.527)

Panel B: Portfolio return based on IVOL_FF

Portfolios	EW	VW
	Avg. Return	Avg. Return
Low IVOL_FF	1.087	3.808
2	1.429	2.463
3	1.921	2.752
4	2.109	3.635
5	1.898	2.810
6	2.172	3.367
7	2.439	3.610
8	2.274	3.409
9	2.626	3.437
High IVOL_FF	5.380	6.271
Diff 10-1	4.293***	2.464
t value	(3.484)	(1.209)
Three factor alpha Diff 10-1	4.309***	1.913
t value	(4.671)	(1.018)

Note: The results present the average return of the 10 portfolios of each month formed from January 1990 to July 2018 of 4616 Indian firms based on idiosyncratic volatility calculated from CAPM model (IVOL_CAPM) and idiosyncratic volatility calculated from FF model (IVOL_FF). The IVOL portfolios are shaped each month by assigning all stocks to ten equal portfolios. The last two row represents the return and three-factor alpha difference between two extreme portfolios. Returns are the average monthly return

Table 5: Double sorted Portfolios return based on IVOL_CAPM and other characters

Panel A: Equal Weighted Portfolios

Portfolios	BETA	MOM	REV	ILLIQ	BM
Low IVOL_CAPM	1.621	0.078	1.070	0.477	0.908
2	0.981	1.320	1.583	1.468	1.230
3	0.798	1.360	1.565	1.365	1.586
4	0.781	1.457	1.387	1.497	1.645
5	1.422	1.554	1.453	1.419	1.559
6	1.595	1.775	1.409	1.399	1.623
7	1.767	1.723	1.398	1.701	1.682
8	1.768	1.693	1.661	1.595	1.465
9	1.799	1.580	1.544	1.877	1.457
High IVOL_CAPM	1.989	1.981	1.452	1.725	1.367
Diff 10-1	0.368	1.903**	0.382	1.248*	0.459
t values	(0.432)	(2.367)	(0.471)	(2.022)	(0.606)

Panel B: Value Weighted Portfolios

Portfolios	BETA	MOM	REV	ILLIQ	BM
Low IVOL_CAPM	2.086	0.479	1.528	0.767	1.433
2	1.508	1.660	1.997	1.880	1.799
3	1.377	1.700	1.959	1.844	2.124
4	1.200	1.788	1.766	1.935	2.111
5	1.886	1.919	1.859	1.861	1.995
6	2.105	2.156	1.812	1.864	2.043
7	2.210	2.196	1.837	2.183	2.076
8	2.175	2.329	2.148	2.091	1.888
9	2.173	2.307	2.104	2.411	1.865
High IVOL_CAPM	2.390	2.575	2.099	2.273	1.776
Diff 10-1	0.304	2.096**	0.571	1.506**	0.343
t value	(0.350)	(2.577)	(0.704)	(2.435)	(0.452)

Note: The results present the average return of the 10 portfolios of each month formed from January 1990 to July 2018 of 4616 Indian firms based on idiosyncratic volatility calculated from CAPM model (IVOL_CAPM) after controlling beta (BETA), momentum (MOM), a reversal (REV), market illiquidity (ILLIQ) and book to market ratio (BM). The IVOL_CAPM portfolios are shaped each month by assigning all stocks to three equal portfolios based on each character variable and then again sort all stocks within each portfolio based on IVOL_CAPM. The last row represents the return difference between two extreme portfolios. Returns are the average monthly return

Table 6: Double sorted Portfolios return based on IVOL_FF and other characters

Panel A: Equal Weighted Portfolios

Portfolios	BETA	MOM	REV	ILLIQ	BM
Low IVOL_FF	1.480	0.137	1.078	0.502	0.908
2	1.011	1.327	1.563	1.443	1.230
3	0.917	1.349	1.562	1.365	1.586
4	0.840	1.440	1.364	1.496	1.645
5	1.463	1.526	1.460	1.420	1.559
6	1.618	1.720	1.441	1.399	1.623
7	1.756	1.708	1.396	1.701	1.682
8	1.726	1.683	1.678	1.595	1.465
9	1.699	1.627	1.666	1.877	1.457
High IVOL_FF	2.011	2.006	1.313	1.725	1.367
Diff 10-1	0.531	1.869**	0.235	1.223*	0.459
t values	(0.613)	(2.336)	(0.290)	(1.981)	(0.606)

Panel B: Value Weighted Portfolios

Portfolios	BETA	MOM	REV	ILLIQ	BM
Low IVOL_FF	1.946	0.478	1.531	0.767	1.433
2	1.438	1.659	1.995	1.880	1.799
3	1.323	1.698	1.959	1.844	2.124
4	1.247	1.793	1.764	1.935	2.111
5	1.901	1.910	1.859	1.861	1.995
6	2.093	2.163	1.816	1.864	2.043
7	2.219	2.194	1.841	2.184	2.076
8	2.205	2.336	2.148	2.089	1.888
9	2.192	2.295	2.108	2.412	1.865
High IVOL_FF	2.547	2.583	2.089	2.272	1.776
Diff 10-1	0.601	2.105**	0.558	1.505**	0.343
t value	(0.692)	(2.588)	(0.689)	(2.434)	(0.343)

Note: The results present the average return of the 10 portfolios of each month formed from January 1990 to July 2018 of 4616 Indian firms based on idiosyncratic volatility calculated from Fama-French thre factor model (IVOL_FF) after controlling beta (BETA), momentum (MOM), a reversal (REV), market illiquidity (ILLIQ) and book to market ratio (BM). The IVOL_FF portfolios are shaped each month by assigning all stocks to three equal portfolios based on each character variable and then again sort all stocks within each portfolio based on IVOL_FF. The last row represents the return difference between two extreme portfolios. Returns are the average monthly return

Table 7: Fama-Macbeth Regression with IVOL_CAPM and other controls

Panel A: Equal Weighted return

INTERCEPT	IVOL_CAPM	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW	MAX
011**	0.072**								
(2.868)	(2.704)								
0.011**	0.067**	0.000							
(3.104)	(2.610)	(0.625)							
0.011**	0.054*		0.005						
(2.904)	(2.079)		(1.529)						
0.034*	0.047*			-0.000					
(2.398)	(1.958)			(-1.619)					
0.010**	0.065**				0.002				
(2.677)	(2.311)				(1.012)				
0.010**	0.071**					0.005			
(2.706)	(2.636)					(0.852)			
0.011**	0.068**						0.685		
(2.786)	(2.376)						(0.812)		
0.012**	0.056*							-0.001	
(3.055)	(2.101)							(-0.883)	
0.013***	0.058*								-0.004
(3.558)	(2.085)								(-0.206)
0.049***	0.056*	0.000	0.006*	-0.001*	0.004**	0.003	-0.624	0.001	-0.068***
(2.823)	(2.078)	(0.555)	(1.808)	(-2.179)	(2.565)	(0.668)	(-0.635)	(1.079)	(-3.274)

Panel B: Value Weighted return

INTERCEPT	IVOL_CAPM	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW	MAX
0.016***	0.069**								
(4.097)	(2.522)								
0.016***	0.064**	0.000							
(4.470)	(2.403)	0.443							
0.016***	0.054*		0.006						
(4.141)	(2.018)		(1.531)						
0.037**	0.048*			-0.001					
(2.576)	(1.971)			(-1.453)					
0.014***	0.058*				0.005**				
(3.786)	(2.000)				(2.297)				
0.015***	0.068**					0.007			
(4.104)	(2.477)					(1.193)			
0.016***	0.061*						1.473		
(3.955)	(2.086)						(1.710)		
0.017***	0.053*							0.000	
(4.285)	(1.934)							(-0.640)	
0.018***	0.058*								-0.002
(4.842)	(2.045)								(-0.107)
0.050**	0.054*	0.000	0.004	-0.001*	0.007***	0.003	0.272	0.001	-0.077***
(2.841)	(2.005)	(0.047)	(1.244)	(-1.913)	(4.034)	(0.511)	(0.276)	(1.297)	(-3.773)

Note: This table reports the monthly Fama-Macbeth cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics for the equation (3) of 4616 Indian firms for the period from Jan-1990 to Jan-2018. We regress the monthly stock return on a set of lag explanatory variable that includes idiosyncratic volatility calculated from CAPM model (IVOL_CAPM), market beta (BETA), book to market ratio (BM), firm Size (SIZE) momentum (MOM), illiquidity (ILLQ), short-term reversal (REV), skewness (SKEW) and maximum daily return over a month (MAX)

Table 8: Fama-Macbeth Regression with IVOL_FF and other controls

Panel A: Equal Weighted return

INTERCEPT	IVOL_FF	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW	MAX
0.010**	0.127*								
(2.680)	(2.233)								
0.010	0.120*	0.000							
(2.879)	(2.184)	(0.532)							
0.010**	0.104*		0.006*						
(2.704)	(1.866)		(1.797)						
0.043**	0.052			-0.001*					
(3.052)	(1.025)			(-2.195)					
0.010**	0.073				0.003				
(2.652)	(1.217)				(1.601)				
0.009**	0.121*					0.007			
(2.479)	(2.174)					(1.119)			
0.010**	0.114*						1.371		
(2.587)	(1.903)						(1.607)		
0.012**	0.084							0.000	
(2.972)	(1.507)							(-0.564)	
0.012***	0.041								0.023
(3.140)	(0.696)								(1.155)
0.055***	-0.092*	0.000	0.007*	-0.002*	0.005**	0.004	-0.235	0.000	-0.013
(3.183)	(-1.717)	(-0.175)	(2.064)	(-2.507)	(2.914)	(0.849)	(-0.241)	(-0.033)	(-0.600)

Panel B: Value Weighted return

INTERCEPT	IVOL_FF	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW	MAX
0.014***	0.139**								
(3.825)	(2.427)								
0.015***	0.132**'	0.000							
(4.125)	(2.401)	(0.349)							
0.015***	0.121*		0.007						
(3.820)	(2.167)		(1.676)						
0.045***	0.073			-0.001					
(3.201)	(1.438)			(-2.034)					
0.014***	0.085				0.006**				
(3.627)	(1.434)				(2.994)				
0.014***	0.132**					0.009			
(3.777)	(2.350)					(1.529)			
0.014***	0.115*						2.212**		
(3.714)	(1.911)						(2.550)		
0.016***	0.099*							0.000	
(4.080)	(1.781)							(-0.430)	
0.016***	0.051								0.025
(4.304)	(0.867)								(1.261)
0.054***	-0.059	-0.001	0.005	-0.001*	0.008*	0.004	0.736	0.000	-0.025
(3.105)	(-1.111)	(-0.614)	(1.495)	(-2.189)	(4.452)	(0.714)	(0.750)	(0.114)	(-1.190)

Note: This table reports the monthly Fama-Macbeth cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics for the equation (4) of 4616 Indian firms for the period from January 1990 to July-2018. We regress the monthly stock return on a set of lag explanatory variable that includes idiosyncratic volatility calculated from Fama-French three factor model (IVOL_FF), market beta (BETA), book to market ratio (BM), firm Size (SIZE) momentum (MOM), illiquidity (ILLIQ), short-term reversal (REV), skewness (SKEW) and maximum daily return over a month (MAX)

Table 9: MAX sorted Portfolio return

Panel A: Portfolio return based on MAX

Portfolios	EW	VW
	Avg. Return	Avg. Return
Low MAX	-0.726	-0.368
2	0.772	1.231
3	1.713	2.200
4	1.587	2.097
5	1.677	2.190
6	2.070	2.589
7	2.255	2.761
8	2.322	2.874
9	1.994	2.531
High MAX	2.010	2.520
Diff 10-1	2.736	2.888***
t value	(1.648)	(3.484)
Three factor alpha Diff 10-1	2.473***	2.618***
t value	(3.828)	(4.011)

Note: The results present the average return of the 10 portfolios of each month formed from January 1990 to July 2018 of 4616 Indian firms based on maximum returns in previous months (MAX). The MAX portfolios are shaped each month by assigning all stocks to ten equal portfolios based on the MAX variable. The last two row represents the return and three-factor alpha difference between two extreme portfolios. Returns are the average monthly return

Table 10: Double sorted Portfolios return based on MAX and other characters

Panel A: Equal Weighted Portfolios

Portfolios	BETA	MOM	REV	ILLIQ	BM
Low MAX	1.627	0.114	1.096	0.549	0.907
2	1.076	1.335	1.579	1.397	1.231
3	0.955	1.359	1.574	1.365	1.586
4	0.772	1.456	1.373	1.498	1.645
5	1.436	1.522	1.443	1.417	1.559
6	1.633	1.705	1.430	1.398	1.623
7	1.751	1.710	1.403	1.699	1.682
8	1.713	1.733	1.675	1.594	1.465
9	1.703	1.623	1.527	1.865	1.458
High MAX	1.857	1.965	1.423	1.740	1.366
Diff 10-1	0.230	1.851**	0.327	1.191*	0.460
t values	(0.266)	(2.320)	(0.404)	(1.928)	(0.606)

Panel B: Value Weighted Portfolios

Portfolios	BETA	MOM	REV	ILLIQ	BM
Low MAX	2.086	0.479	1.528	0.767	1.433
2	1.508	1.660	1.997	1.880	1.799
3	1.377	1.700	1.959	1.844	2.124
4	1.200	1.788	1.766	1.935	2.111
5	1.886	1.919	1.859	1.861	1.995
6	2.105	2.156	1.812	1.864	2.043
7	2.210	2.196	1.837	2.183	2.076
8	2.175	2.329	2.148	2.091	1.888
9	2.173	2.307	2.104	2.411	1.865
High MAX	2.390	2.575	2.099	2.273	1.776
Diff 10-1	0.304	2.096**	0.571	1.506**	0.343
t value	(0.350)	(2.576)	(0.704)	(2.435)	(0.452)

Note: The results present the average return of the 10 portfolios of each month formed from January 1990 to July 2018 of 4616 Indian firms based on maximum returns in previous months (MAX) after controlling beta (BETA), momentum (MOM), a reversal (REV), market illiquidity (ILLIQ) and book to market ratio (BM). The MAX portfolios are shaped each month by assigning all stocks to three equal portfolios based on each character variable and then again sort all stocks within each portfolio based on MAX. The last row represents the return difference between two extreme portfolios. Returns are the average monthly return

Table 11: Portfolios return based on MAX (n)

Panel A: Equal Weighted Portfolios

Portfolios	Avg. Return (MAX2 sorted)	Avg. Return (MAX3 sorted)	Avg. Return (MAX4 sorted)	Avg. Return (MAX5 sorted)
Low MAX	-0.788	-0.875	-0.887	-0.919
2	0.691	0.713	0.643	0.605
3	1.630	1.677	1.666	1.786
4	1.886	1.891	2.080	2.106
5	1.767	2.038	2.129	2.180
6	2.057	1.901	1.958	2.082
7	2.056	2.154	2.164	2.187
8	2.350	2.185	1.942	1.802
9	2.084	2.068	2.035	1.966
High MAX	1.941	1.922	1.944	1.879
Diff 10-1	2.729***	2.797***	2.831***	-2.798***
t values	(3.302)	(3.400)	(3.446)	(3.404)
FF alpha	2.485***	2.555***	2.583***	2.553***
t values	(3.829)	(3.907)	(3.947)	(3.901)

Panel B: Value Weighted Portfolios

Portfolios	Avg. Return (MAX2 sorted)	Avg. Return (MAX3 sorted)	Avg. Return (MAX4 sorted)	Avg. Return (MAX5 sorted)
Low MAX	-0.368	-0.535	-0.546	-0.571
2	1.231	1.161	1.076	1.021
3	2.200	2.115	2.132	2.258
4	2.097	2.430	2.596	2.604
5	2.190	2.516	2.617	2.682
6	2.589	2.440	2.489	2.600
7	2.761	2.731	2.705	2.740
8	2.874	2.692	2.486	2.356
9	2.531	2.605	2.573	2.506
High MAX	2.520	2.468	2.495	2.426
Diff 10-1	2.888***	3.003***	3.040***	2.998***
t value	(3.484)	(3.649)	(3.695)	(3.645)
FF alpha	2.618***	2.754***	2.787***	2.748***
t values	(4.011)	(4.167)	(4.216)	(4.160)

Note: The results present the average return of the 10 portfolios of each month formed from January 1990 to July 2018 of 4616 Indian firms based on maximum returns in previous months (MAX (n)). The MAX (n) portfolios are shaped each month by assigning all stocks to ten equal portfolios based on the MAX variable. The last two row represents the return difference between two extreme portfolios. Returns are the average monthly return

Table12: Fama-Macbeth Regression with MAX and other controls

Panel A: Equal Weighted return

INTERCEPT	MAX	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW
0.012***	0.038*							
(3.349)	(1.895)							
0.012***	0.036*	0.000						
(3.546)	(1.891)	(0.373)						
0.012***	0.029		0.006					
(3.408)	(1.486)		(1.751)					
0.047***	0.012			-0.001**				
(3.294)	(0.648)			(-2.391)				
0.012***	0.015				0.004			
(3.269)	(0.783)				(1.830)			
0.011***	0.040*					0.008		
(3.038)	(2.065)					(1.268)		
0.012***	0.031						1.822**	
(3.124)	(1.562)						(2.215)	
0.013***	0.030							-0.001
(3.382)	(1.325)							(-1.326)
0.052**	-0.034*	0.000	0.006*	-0.002**	0.005**	0.005	-0.300	0.000
(2.972)	(-1.833)	(0.529)	(1.935)	(-2.376)	(2.749)	(0.878)	(-0.309)	(0.417)

Panel B: Value Weighted return

INTERCEPT	MAX	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW
0.017***	0.041*							
(4.589)	(2.123)							
0.017***	0.039*	0.000						
(4.882)	(2.109)	(0.210)						
0.017***	0.032*		0.007					
(4.667)	(1.707)		(1.657)					
0.050***	0.015			-0.001**				
(3.502)	(0.868)			(-2.266)				
0.016***	0.009				0.006**			
(4.444)	(0.467)				(3.230)			
0.016***	0.045*					0.010		
(4.439)	(2.303)					(1.647)		
0.016***	0.033*						2.658**	
(4.270)	(1.654)						(3.152)	
0.018***	0.032							-0.001
(4.595)	(1.458)							(-1.129)
0.053**	-0.042**	0.000	0.004	-0.001*	0.008***	0.004	0.695	0.000
(2.988)	(-2.272)	(0.052)	(1.333)	(-2.118)	(4.247)	(0.770)	(0.715)	(0.545)

Note: This table reports the monthly Fama-Macbeth cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics for the equation (5) of 4616 Indian firms for the period from January 1990 to July 2018. We regress the monthly stock return on a set explanatory variable that includes maximum daily return over a month (MAX), market beta (BETA), book to market reatio (BM), firm Size (SIZE) momentum (MOM), illiquidity (ILLQ), short-term reversal (REV), and skewness (SKEW)

Table 13: Month to Month Stock Transition Matrix

	1	2	3	4	5	6	7	8	9	10
1	0.357	0.127	0.094	0.075	0.067	0.062	0.055	0.048	0.048	0.067
2	0.126	0.209	0.133	0.106	0.091	0.085	0.085	0.066	0.053	0.048
3	0.090	0.135	0.148	0.132	0.101	0.096	0.090	0.086	0.067	0.055
4	0.076	0.108	0.130	0.134	0.129	0.109	0.094	0.090	0.071	0.060
5	0.065	0.085	0.106	0.135	0.155	0.138	0.099	0.079	0.076	0.063
6	0.068	0.076	0.089	0.107	0.143	0.156	0.119	0.087	0.080	0.072
7	0.059	0.082	0.090	0.092	0.101	0.127	0.145	0.116	0.100	0.087
8	0.044	0.067	0.085	0.088	0.077	0.087	0.124	0.154	0.143	0.117
9	0.047	0.052	0.068	0.068	0.076	0.081	0.100	0.141	0.188	0.151
10	0.064	0.053	0.053	0.059	0.056	0.055	0.086	0.132	0.168	0.273

Table 14: Fama-Macbeth Regression with IVOL and MAX together

Panel A: Equal Weighted return regression

INTERCEPT	IVOL_CAPM	IVOL_FF	MAX
0.013***	0.058*		-0.004
(3.558)	(2.085)		(-0.206)
0.012***		0.041	0.023
(3.140)		(0.696)	(1.155)

Panel B: Value Weighted return regression

INTERCEPT	IVOL_CAPM	IVOL_FF	MAX
0.018***	0.058*		-0.002
(4.842)	(2.045)		(-0.107)
0.016***		0.051	0.025
(4.304)		(0.867)	(1.261)

Note: This table reports the monthly Fama-Macbeth cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics in equation (6) of 4616 Indian firms for the period from Jan-1990 to Jan-2018. We regress the monthly stock return on a set of lag explanatory variable that includes idiosyncratic volatility from CAPM model (IVOL_CAPM), idiosyncratic volatility from Fama-French three factor model (IVOL_FF), the maximum daily return in a month (MAX)

Table 15: Fama-Macbeth Regression with IVOL_CAPM and other controls for Small and Large Firms

Panel A: Equal Weighted return regression for Small firms

INTERCEPT	IVOL_CAPM	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW
0.011**	0.110***							
(2.537)	(2.935)							
0.134***	0.032	0.000	0.012*	-0.005***	0.002	-0.007	-1.206	0.000
(4.300)	(0.773)	(-0.421)	(2.117)	(-3.964)	(0.582)	(-0.890)	(-0.906)	(0.314)

Panel B: Value Weighted return regression for Small firms

INTERCEPT	IVOL_CAPM	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW
0.015***	0.102**							
(3.727)	(2.687)							
0.135***	0.008	-0.001	0.008	-0.005***	0.002	-0.012	-0.530	-0.001
(4.131)	(0.170)	(-0.640)	(1.393)	(-3.622)	(0.814)	(-1.698)	(-0.362)	(-0.515)

Panel C: Equal Weighted return regression for Large firms

INTERCEPT	IVOL_CAPM	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW
0.014***	-0.052							
(3.613)	(-1.523)							
0.007	-0.167***	0.002	-0.009	0.000	0.007***	0.012	-0.705	-0.001
(0.292)	(-5.130)	(1.311)	(-0.393)	(0.222)	(3.099)	(1.710)	(-0.546)	(-1.107)

Panel D: Value Weighted return regression for Large Firms

INTERCEPT	IVOL_CAPM	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW
0.019***	-0.050							
(4.856)	(-1.465)							
0.009	-0.169***	0.000	-0.008	0.000	0.010***	0.018**	1.062	-0.001
(0.347)	(-5.500)	(0.373)	(-0.336)	(0.279)	(4.377)	(2.462)	(0.791)	(-0.719)

Note: This table reports the monthly Fama-Macbeth cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics for the equation (3) of large and small Indian firms separately for the period from Jan-1990 to Jan-2018. We regress the monthly stock return on a set of lag explanatory variable that includes idiosyncratic volatility calculated from CAPM model (IVOL_CAPM), market beta (BETA), book to market (BM), momentum (MOM), illiquidity (ILLQ), short-term reversal (REV), firm Size (SIZE) and skewness (SKEW),

Table 16: Fama-Macbeth Regression with IVOL_FF and other controls for Small and Large Firms

Panel A: Equal Weighted return regression for Small firms

INTERCEPT	IVOL_FF	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW
0.007	0.232***							
(1.855)	(3.570)							
0.147***	0.006	-0.001	0.012*	-0.006***	0.002	-0.007	-1.431	0.001
(4.355)	(0.097)	(-0.770)	(2.143)	(-4.016)	(0.574)	(-0.932)	(-1.023)	(0.901)

Panel B: Value Weighted return regression for Small firms

INTERCEPT	IVOL_FF	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW
0.012**	0.239***							
(2.935)	(3.526)							
0.173***	0.013	-0.001	0.014**	-0.007	0.004	-0.013	0.224	0.000
(5.450)	(0.190)	(-0.749)	(2.557)	(-5.063)	(1.668)	(-1.728)	(0.173)	(-0.386)

Panel C: Equal Weighted return regression for Large firms

INTERCEPT	IVOL_FF	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW
0.016***	-0.136**							
(4.113)	(-2.740)							
0.013	-0.278***	0.001	-0.011	0.000	0.007***	0.013	-0.247	0.000
(0.550)	(-6.251)	(1.152)	(-0.515)	(0.049)	(3.237)	(1.857)	(-0.191)	(-0.365)

Panel D: Value Weighted return regression for Large Firms

INTERCEPT	IVOL_FF	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW
0.020***	-0.116**							
(5.188)	(-2.338)							
0.016	-0.253***	0.000	-0.009	0.000	0.010	0.020	1.392	0.000
(0.607)	(-5.839)	(0.260)	(-0.381)	(0.068)	(4.586)	(2.634)	(1.042)	(0.025)

Note: This table reports the monthly Fama-Macbeth cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics for the equation (4) of large and small Indian firms separately for the period from Jan-1990 to Jan-2018. We regress the monthly stock return on a set of lag explanatory variable that includes idiosyncratic volatility calculated from Fama-French three factor model (IVOL_FF), market beta (BETA), book to market (BM), momentum (MOM), illiquidity (ILLQ), short-term reversal (REV), firm Size (SIZE) and skewness (SKEW),

Table 17: Fama-Macbeth Regression with MAX and other controls for Small and Large Firms

Panel A: Equal Weighted return regression for Small firms

INTERCEPT	MAX	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW
0.013***	0.050*							
(3.436)	(2.255)							
0.168***	-0.033	-0.001	0.014*	-0.007***	0.004	-0.009	-0.636	0.002
(5.044)	(-1.280)	(-0.615)	(1.876)	(-4.608)	(1.156)	(-1.019)	(-0.417)	(1.789)

Panel B: Value Weighted return regression for Small firms

INTERCEPT	MAX	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW
0.017***	0.056**							
(4.554)	(2.439)							
0.194***	-0.038	0.000	0.016*	-0.008***	0.007*	-0.014	0.819	0.001
(5.735)	(-1.450)	(-0.283)	(2.292)	(-5.280)	(2.166)	(-1.701)	(0.575)	(0.797)

Panel C: Equal Weighted return regression for Large firms

INTERCEPT	MAX	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW
0.015***	-0.021							
(3.949)	(-0.968)							
0.005	-0.080***	0.003	-0.018	0.000	0.007***	0.012	-0.481	0.001
(0.223)	(-3.379)	(2.190)	(-0.796)	(0.284)	(3.256)	(1.645)	(-0.365)	(0.855)

Panel D: Value Weighted return regression for Large Firms

INTERCEPT	MAX	BETA	BM	SIZE	MOM	REV	ILLIQ	SKEW
0.019***	-0.027							
(5.198)	(-1.120)							
0.013**	-0.099***	0.002	-0.011	0.000	0.010***	0.018**	1.489	0.002*
(0.475)	(-4.278)	(1.257)	(-0.451)	(0.155)	(4.483)	(2.424)	(1.103)	(1.868)

Note: This table reports the monthly Fama-Macbeth cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics for the equation (5) of large and small Indian firms separately for the period from Jan-1990 to Jan-2018. We regress the monthly stock return on a set of lag explanatory variable that includes maximum daily return of previous month (MAX), market beta (BETA), book to market (BM), momentum (MOM), illiquidity (ILLQ), short-term reversal (REV), firm size (SIZE) and skewness (SKEW),