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Idiosyncratic volatility and stock returns: Indian evidence

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Abstract: This paper examines the idiosyncratic volatility (IV) puzzle in the Indian stock market for the period 1999–2014. Univariate and bivariate sorting, as well as cross-section regressions, suggest a positive relation between idiosyncratic volatility and future stock returns. However, this relation is sensitive to the choices of portfolio weighting schemes, types of stocks (small, medium, and large), model specifications, and sample periods. Additionally, this study also contests the assumption that the relation between stock returns and predictor variables (including IV) remains same across different points of the conditional distribution and argues that an insignificant relation at the mean level may be significant at the extreme quantiles of the conditional distribution.

Subjects: Mathematical Economics; Investment & Securities; Risk Management

Keywords: idiosyncratic volatility; asset pricing; emerging markets; quantile regression

JEL classifications: G12; C21

1. Introduction

The question of whether idiosyncratic volatility is a priced factor is important. In the framework of classical asset pricing model of Sharpe (1964) and Lintner (1965), idiosyncratic volatility is irrelevant. On the other hand, the theories of incomplete markets and under-diversification (Constantinides &

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PUBLIC INTEREST STATEMENT

Risk has bemused both academicians and investors. The general understanding is that a higher risk is compensated by a higher return in the market. Moreover, if a person is following the conventional wisdom of “not putting all eggs in one basket” and keeps his holdings diversified, he must not care about the firm-specific or idiosyncratic risk, since a diversified portfolio drives out the idiosyncratic risk. However, some recent studies showed that a higher firm-specific risk is followed by a puzzlingly low return in the subsequent month. This finding goes both against the theory and intuition. In this study, we explored the relationship between firm-specific or idiosyncratic risk and stock returns in the Indian stock market. We find that the idiosyncratic risk is associated with the return but this relation is fragile and sensitive to many factors. An investment strategy based on idiosyncratic volatility has to keep many factors under consideration to make it profitable.

Duffie, 1996; Levy, 1978; Merton, 1987) predict a positive relationship between idiosyncratic volatility (IV hereafter) and expected stock returns. Additionally, theories inspired from the prospect theory of Kahneman and Tversky (1979) (such as Barberis & Huang, 2008; Bhootra & Hur, 2015) suggest a negative relation between IV and stock returns. Apart from the theoretical contradictions, empirical studies also provide diverging results.

The empirical literature yields three kinds of results on the relation between stock returns and idiosyncratic risk; No relation (Fama & MacBeth, 1973), Positive relation (Bali & Cakici, 2008; Brockman, Schutte, & Wu, 2009; Friend, Westerfield, & Granito, 1978; Fu, 2009; Huang, Liu, Rhee, & Zhang, 2010; Lehmann, 1990b; Malkiel & Xu, 1997, 2002; Tinic & West, 1986), and negative relation (Ang, Hodrick, Xing, & Zhang, 2006, 2009; Chabi-Yo, 2011; Chen, Chollete, & Ray, 2010; Guo & Savickas, 2010).

The most widely cited paper is Ang et al. (2009) which finds a strong negative relation between idiosyncratic volatility and future stock returns. Subsequent papers have proposed explanations of the idiosyncratic volatility puzzle. Bali and Cakici (2008) demonstrate that the relation between idiosyncratic volatility and future stock returns is sensitive to the choices of data frequency, portfolio weighting schemes, breakpoint calculations and choice of screens in sample selection. Fu (2009) finds that a measure of expected idiosyncratic volatility based on an exponential GARCH model has a positive relationship with the future stock returns. Huang et al. (2010) show that the idiosyncratic volatility puzzle is driven by the short-term reversal. Bali, Cakici, and Whitelaw (2011) demonstrate that the idiosyncratic volatility effect disappears after controlling for the “lottery stocks”. Han and Lesmond (2011) find that the liquidity shocks and market microstructure effects are responsible for the idiosyncratic volatility effect.

In the Indian context, the pricing of idiosyncratic volatility has been investigated by Drew and Veeraraghavan (2002), Brockman et al. (2009), and Pukthuanthong-Le and Visaltanachoti (2009). Drew and Veeraraghavan (2002) employing a model-free measure of idiosyncratic volatility and monthly data frequency, report that high IV stocks generate superior returns in Asian markets of Hong Kong, India, Malaysia and the Philippines for the five-year period of 1995–1999. Besides, Brockman et al. (2009) included India in their global study of 44 markets. They report a positive IV-return relation using Fu’s (2009) methodology and insignificant positive relation using Ang et al.’s (2006, 2009) methodology during the period 1990–2007 for a sample of 816 stocks. Furthermore, Pukthuanthong-Le and Visaltanachoti (2009) examined the IV-return relation in 36 markets including India using Fama and MacBeth (1973) regressions. For the Indian stock market, their sample is 936 stocks during the period 1990–2007. They find a significant coefficient of conditional IV in 33 markets including India. Thus, these studies have reported either a positive relation between IV and stock returns or no relation. Indian stock market has been given only a cursory attention in these studies and hence there was a need of an in-depth-study focusing only on the Indian stock market. This study revisits the idiosyncratic volatility and stock return relation with an updated data and numerous analysis including the application of quantile regression.

So far a considerable body of evidence on idiosyncratic risk is focused on the US or other developed stock markets. The aim of this study is to shed light on the idiosyncratic volatility puzzle with analysis of the Indian stock market. Often the anomalies which are initially discovered in developed markets are not present in other markets, and hence, country and region-specific verification is also important. Moreover, findings from emerging markets counter the data snooping bias of Lo and MacKinlay (1990).

Our main findings show that there is a positive relation between IV and stock returns. This positive relation holds after controlling for value, momentum, co-skewness and illiquidity effects. However, this relation is significant only for equally weighted (EW) portfolios and small stocks. The results are in conformity with the evidence in the literature that anomalies are more likely to persist among stocks with more arbitrage risk. In addition, this study also contests the assumption that the relationship between predictor variables and stock returns is similar across different quantiles of the

conditional distribution using quantile regressions (Koenker & Bassett, 1978). Previous findings show that the relation is mostly quantile dependent (Barnes & Hughes, 2002; Nath & Brooks, 2015).

The contribution of this paper is threefold: First, it provides evidence of the pricing of IV in the cross-section of expected stock returns in the Indian stock market with an updated data. As mentioned, there is no in-depth study that has specifically examined the IV puzzle in detail for the Indian stock market, although Indian stock market has been part of three multi-market studies. Hence, it provides new and detailed results on the relation between stock returns and IV in the context of the Indian stock market; Second, using quantile regressions (Koenker & Bassett, 1978), this study shows that even if a predictor variable is insignificant in the least square (LS) regressions it may be significant at extreme quantiles of the conditional distribution and the sign of the coefficient may be of opposite signs at the extreme quantiles. And finally, this study adds to the growing literature aimed at investigating the pricing anomalies and cross-sectional determinants of stock returns in emerging stock markets.

The rest of the paper is organized as follows: Section 2 describes the data and methodology. Section 3 presents the empirical results, Section 4 provides the discussion of the findings, and the paper concludes in Section 5.

2. Data and methodology

Our data-set is S&P BSE-500 firms from ProwessIQ, a database maintained by the Center for Monitoring Indian Economy (CMIE) for the period April 1999 to June 2014. S&P BSE-500 is a broad-based index, which accounts for 93% of the market capitalization and trading volume in the Indian stock market.¹ The rest of the market is thinly traded. Variables such as idiosyncratic volatility (IV), market beta, illiquidity, skewness, and co-skewness are computed from daily data. Idiosyncratic volatility has been computed relative to the CAPM. Here, it should be noted that the decision to use CAPM or Fama and French (1993) three-factor or Carhart's (1997) four-factor model to compute idiosyncratic volatility is inconsequential as all the measures are highly correlated as highlighted by Bali, Engle, and Murray (2016). We use monthly stock returns for computing momentum and short-term reversal. Quarterly institutional ownership and mutual fund ownership data is from March 2001 to June 2013. The market proxy is the return on BSE-500 index and the yield on 91 days Treasury bill is the surrogate for risk-free rate taken from the Reserve Bank of India (RBI) website. The variables used in this study are defined in Appendix A.

The basic methodology consists of univariate and bivariate monthly sorts and Fama and MacBeth (1973) two-pass regression. Each month, we formed decile portfolios based on the IV relative to the CAPM using a window of three months daily data. Both equal-weighted (EW) and value-weighted (VW) returns are computed for the next month. This procedure is repeated from April 2000 to June 2014 till we exhaust the sample. This procedure is similar to an E/H/M (E for estimation, H for holding and M for moving forward) plan of 3-1-1, where the numbers represent the month. We report raw returns, CAPM, three-factor and four-factor alphas of the portfolios. The construction of the risk factors is described in Appendix B. This time-series approach of risk adjustment thus controls for the market, size, value and momentum effects. Moreover, IV is also computed over an estimation window of one month and 12 months for robustness.

We control for other well-known risk factors in a bivariate sort setting. In 2×10 sorting, we first sort stock into two groups based on the control variable. Stocks are then sorted into deciles in each group based on the main variable of interest i.e. IV. Decile portfolio returns are then averaged across two groups to form decile portfolios, which have dispersion in IV but have an equal number of stocks having low and high values of control variables. We specifically control for size, value, momentum, illiquidity and co-skewness in the bivariate setting.

Fama and MacBeth (1973) regressions are run at the firm-level following Bali et al. (2011) among others. Aggregation of stocks in portfolios causes loss of information related to the idiosyncratic

volatility which defies the purpose of the investigation. In the first pass of the Fama and MacBeth (1973) regressions, variables are estimated over some window. These estimated variables are then used in the second pass cross-section regressions. Each month cross-section regressions are run and the coefficients are estimated. Time-series averages of the coefficients from the cross-section regressions and their *t*-statistics are then reported. In the cross-sectional setting, we control for a host of known predictor variables. Specifically, we control for the market beta, size, value, intermediate-term momentum, short-term reversal, illiquidity, skewness, co-skewness and the MAX effect.

Further, for examining the IV-return relation at different quantiles of the conditional distribution, we apply quantile regression instead of LS regression at the second stage of the Fama and MacBeth (1973) regressions. Before applying the quantile regressions, we verified that the coefficients of the regressors differ across quantiles of the distribution using Wald test.

3. Empirical results

3.1. Univariate sort

Table 1 presents the VW and EW average monthly returns of decile portfolios that are formed each month by sorting stocks based on IV estimated from prior three-month daily data with respect to CAPM. The results are reported for the period April 2000 to June 2014, since initial data are consumed in computing some variables.

Portfolio 1 (low IV) is the portfolio with the lowest IV during the previous quarter, and portfolio 10 (high IV) is the portfolio with the highest IV during the previous quarter. Table 1 shows that the increasing pattern in the average return is almost uniform as IV increases both in the EW and VW portfolios. For example, the EW returns are 1.29 and 4.01% for the lowest and the highest IV portfolios, respectively. The EW average raw return difference between portfolio 10 and 1 is 2.72% with a *t*-statistic of 4.07. The spread in the VW portfolios, however, is 1.20% (*t* = 1.34), that is statistically insignificant. The stronger IV effect in EW portfolios is consistent with the previous studies that high IV stocks are low-priced and small stocks.

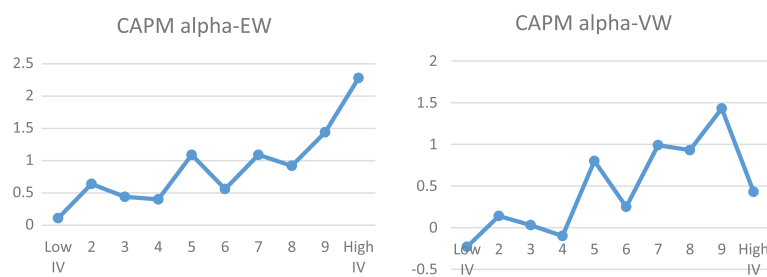
Table 1. Idiosyncratic volatility (IV) decile

Decile	EW portfolios				VW portfolios				Average IV (%)
	Average return	CAPM alpha	FF alpha	Carhart's alpha	Average return	CAPM alpha	FF alpha	Carhart's alpha	
Low IV	1.29	0.11	-0.27	-0.28	0.99	-0.23	-0.19	-0.20	1.33
2	1.95	0.64	0.01	-0.02	1.39	0.14	0.25	0.24	1.69
3	1.83	0.44	-0.25	-0.30	1.38	0.03	0.13	0.15	1.91
4	1.85	0.40	-0.35	-0.42	1.29	-0.10	-0.17	-0.21	2.11
5	2.57	1.09	0.20	0.11	2.23	0.80	0.56	0.52	2.31
6	2.14	0.56	-0.59	-0.67	1.85	0.25	-0.43	-0.49	2.52
7	2.68	1.09	-0.01	-0.06	2.61	0.99	0.77	0.74	2.77
8	2.57	0.92	-0.35	-0.41	2.69	0.93	0.24	0.12	3.09
9	3.14	1.44	0.14	-0.08	3.18	1.43	1.25	1.20	3.58
High IV	4.01	2.28	0.89	0.82	2.20	0.46	-0.06	-0.01	5.44
H-L	2.72	2.16	1.16	1.09	1.20	0.69	0.14	0.19	
	(4.07)	(3.99)	(2.17)	(2.07)	(1.34)	(0.83)	(0.6)	(0.22)	

Notes: Decile portfolios are formed each month from April 2000 to June 2014 by sorting stocks based on the idiosyncratic volatility (IV) estimated over the prior three months daily data relative to CAPM. Portfolio 1(10) is the portfolio with lowest (highest) IV over the past quarter. The table reports the equal-weighted (EW) and value-weighted (VW) average monthly returns, CAPM, three-factor and four-factor alphas of the IV decile portfolios. The last row presents the difference between the average returns of portfolios 10 and 1, CAPM, 3-factor and 4-factor alphas of the difference and their corresponding Newey-West (1987) adjusted *t*-statistics. Numbers in bold denote significance at the 5% level or better.

Figure 1. Performance of IV decile portfolios.

Notes: This figure shows the CAPM alphas of the EW and VW portfolios formed each month on the basis of IV.



In addition to raw returns, Table 1 also shows the CAPM, three-factor, and four-factor alphas of the decile portfolios. CAPM alphas have an increasing trend as we move towards the high IV portfolio which is also evident in Figure 1 that plots the CAPM alphas of the IV decile portfolios. Unlike raw returns, there is not a discernable trend in the three-factor and four-factor alphas of the IV deciles. Although, the EW portfolio (10) has the highest alphas indicating that the risk-adjusted return of the high IV portfolio is also comparatively better than other portfolios. The last row of Table 1 shows the alphas of the hedge portfolios (the difference between portfolio 10 and 1). All the three alphas of the hedge portfolio are statistically significant at the conventional levels. For VW returns, the results are weaker. Neither the raw return difference nor the alpha of the difference is statistically significant for the VW returns. Although there is some increasing trend in the raw returns from low to high IV portfolio, the difference among them fails to have statistical significance.

To get a clear picture of the composition of the high IV portfolio, Table 2 shows the summary statistics of the average of the median characteristics of the stocks in each portfolio. There is a striking pattern in the characteristics of the decile portfolios of IV. High IV stocks are relatively small and low priced (but not the smallest and lowest priced) that indicates the close relationship between IV and size previously documented by Bali, Cakici, Yan, and Zhang (2005) and Angelidis and Tessaromatis (2008), among others. High IV stocks also tend to have a slightly higher market beta. The high IV portfolio also has the highest average illiquidity. This is in line with the findings of Bali et al. (2005) where they find that a part of positive IV effect is due to the proxying effect of IV for illiquidity. In Table 2, it is clear that the portfolio with the highest IV stocks also has the highest illiquidity (1.20).

The average book-to-market ratio of the high IV portfolio is higher than the low IV portfolio indicating that high IV stocks tend to be value stocks. Similarly, high IV portfolio has an average of 13% institutional ownership as compared to low IV portfolio which has an average of 23%. This suggests

Table 2. Characteristics of IV sorted decile

Decile	IV _q	Market Cap. (₹ 10 Millions)	Price (₹)	Beta	B/M	ILLIQ (10%)	IO (%)	MOM	SSKEW	TSKEW
Low IV	1.32	5,520	429	0.61	0.41	0.26	23.0	13.8	-0.008	0.30
2	1.65	4,284	349	0.72	0.49	0.09	22.6	16.3	-0.013	0.30
3	1.86	3,488	275	0.78	0.54	0.10	22.3	16.7	-0.017	0.35
4	2.05	2,885	228	0.82	0.55	0.18	21.4	18.5	-0.024	0.39
5	2.25	2,376	198	0.88	0.64	0.27	20.1	19.4	-0.027	0.43
6	2.45	1,970	180	0.90	0.62	0.22	19.5	21.3	-0.029	0.47
7	2.70	1,747	166	0.96	0.65	0.68	18.9	25.0	-0.032	0.51
8	3.01	1,471	146	1.01	0.70	0.49	17.5	25.3	-0.038	0.57
9	4.48	1,244	129	1.04	0.68	0.40	15.0	30.8	-0.044	0.66
High IV	4.69	1,645	137	0.99	0.69	1.20	13.7	28.6	-0.042	0.18

Notes: This table reports various characteristics of the idiosyncratic volatility (IV) sorted portfolios for the period April 2000 to June 2014. The numbers are the averages of the median values of the characteristics in a portfolio.

that IV and institutional ownership are inversely related to each other. On an average, a higher proportion of institutional ownership in a stock is associated with a lower idiosyncratic risk. The cumulative return over the intermediate horizon is also high for the high IV stocks and the total skewness and systematic skewness of the high IV stocks are relatively lower. These characteristics of high IV stocks are consistent with the evidence and intuition.

3.2. Bivariate sorts

Controlling for the well-known cross-sectional determinants of stock returns is important. As a newly discovered anomaly may be subsumed by another already known effect. Subrahmanyam (2010) highlights the importance of controlling for the well-known predictors of stock returns. One method to control for other variables is the bivariate sort. To evaluate the impact of other cross-sectional predictors of average stock returns on the IV premium, we form decile IV portfolios after controlling for size, value, momentum, co-skewness, and illiquidity effects. Stocks are first grouped into two categories based on their ranked control variable. In each group, stocks are further sorted into decile portfolios based on the IV. Decile portfolios are then averaged across the two control groups to form IV deciles which have a dispersion in IV but with an equal number of control variables (for example, in the case of size, an equal number of small and big stocks). This double sort, hence, controls one variable at a time. This procedure addresses the concern that the IV effect is not subsumed by the control variable.

Table 3 reports average returns of decile portfolios after controlling for size, value, momentum, co-skewness and illiquidity. Panel A of Table 3 shows the results for the EW portfolios and Panel B reports the findings of VW portfolios. The difference between the EW returns of high IV and low IV remains statistically significant after controlling for value, momentum, co-skewness and illiquidity. In addition, the CAPM alphas of the hedge portfolios are also statistically significant at the conventional levels. The statistical significance of the IV effect, however, vanishes after controlling for the size effect. Upon looking further over the returns of the size-IV sorted 20 portfolios, it appears that the positive IV effect is confined to small size group. The difference between the returns of the high IV and the low IV portfolio is not statistically significant among large stocks (results not reported).

The presence of positive IV effect only in small stocks also explains as to why the differences between the high and low IV portfolios are not statistically significant for the VW portfolios (Panel B Table 3). The VW return differences between the high and low IV portfolios are positive for all control variables except size, yet statistically insignificant. In the case of size, the difference is negative and insignificant. The bivariate sort thus highlights that size is strongly related to the IV effect. Value, momentum, co-skewness and illiquidity, however, do not subsume the positive IV effect.

3.3. Cross-section regressions

Fama and MacBeth (1973) cross-section regressions provide the standard test for pricing of risk factors. We run firm-level cross-section regressions of stock returns on IV and other control variables known for explaining the cross-section of average stock returns. Specifically, each month the following model and its nested versions are estimated:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}IV_{i,t} + \gamma_{2,t}BETA_{i,t} + \gamma_{3,t}LnSIZE_{i,t} + \gamma_{4,t}LnBM_{i,t} + \gamma_{5,t}MOM_{i,t} + \gamma_{6,t}REV_{i,t} + \gamma_{7,t}ILLIQ_{i,t} + \gamma_{8,t}TSKEW_{i,t} + \gamma_{9,t}SSKEW_{i,t} + \gamma_{10,t}MAX_{i,t} + \varepsilon_{i,t+1} \quad (1)$$

where $R_{i,t+1}$ is the excess realized return on stock i in month $t + 1$. Each month, cross-section regression is run on IV and other lagged control variables. This model is predictive in the sense that firm characteristics in a month are used as predictors of returns in the following month. We expect a non-significant $\gamma_{1,t}$ in the context of CAPM, positive significant in the light of Merton's (1987) theory of under-diversified investors, and negative significant if Ang et al.'s (2006, 2009) results hold true in the Indian data. A similar model is used by Bali et al. (2011) among others.

Table 3. Returns on IV decile after controlling for size, BM, MOM, SSKEW and ILLIQ

Decile	SIZE	BM	MOM	SSKEW	ILLIQ
<i>Panel A: Equal-weighted portfolios</i>					
Low IV	1.75	1.62	1.62	1.97	1.63
2	1.90	1.82	1.80	1.86	1.78
3	2.24	1.91	1.95	1.93	1.90
4	2.00	1.85	2.20	2.10	2.40
5	2.34	2.17	2.27	2.72	2.17
6	2.37	2.63	2.32	2.30	2.71
7	2.67	2.60	2.58	2.78	2.28
8	2.36	2.51	2.92	2.99	2.78
9	3.13	3.21	3.00	3.50	2.87
High IV	2.69	3.41	3.62	4.06	3.41
Return difference	0.94 (1.56)	1.79 (2.75)	2.00 (3.19)	2.09 (2.65)	1.78 (2.82)
CAPM alpha	0.40 (0.91)	1.31 (2.34)	1.55 (2.85)	1.49 (2.22)	1.25 (2.44)
4-factor alpha	-0.29 (-0.62)	0.33 (0.60)	0.61 (1.11)	0.48 (0.70)	0.41 (0.81)
<i>Panel B: Value-weighted portfolios</i>					
Low IV	2.96	1.47	1.26	1.25	1.68
2	1.78	1.65	1.60	1.15	1.25
3	2.59	1.84	1.46	1.63	1.79
4	2.18	2.20	1.80	1.58	2.47
5	2.70	1.71	1.77	2.26	2.20
6	2.46	2.27	1.94	1.89	2.48
7	3.22	3.86	2.08	2.56	2.68
8	3.12	3.09	3.25	3.39	2.87
9	3.52	3.58	2.80	3.14	2.64
High IV	2.71	2.47	2.09	1.70	2.85
Return difference	-0.24 (-0.12)	1.00 (1.38)	0.82 (1.11)	0.44 (0.58)	1.17 (1.73)
CAPM alpha	-0.35 (-0.18)	0.60 (0.89)	0.44 (0.63)	-0.01 (-0.01)	0.73 (1.21)
4-factor alpha	1.035 (0.67)	-0.61 (-0.95)	-0.32 (-0.44)	-0.91 (-1.27)	-0.01 (-0.03)

Notes: Double-sorted, equal-weighted (Panel A) and value-weighted (Panel B) decile portfolios are formed every month from April 2000 to June 2014 by sorting stocks based on idiosyncratic volatility (IV_{it}) after controlling for size, value, momentum, co-skewness and illiquidity. In each case, we first sort the stocks into two portfolios using the control variable, then within each portfolio, we sort stocks into decile portfolios based on the IV over the previous quarter daily data, so that decile1(10) contains stocks with the lowest (highest) IV. This table presents average returns across the two control portfolios to produce decile portfolios with dispersion in IV but with similar levels of the control variable. "Return difference" is the difference in average monthly returns between the high IV and low IV portfolios. "Alpha difference" is the CAPM and four-factor alpha of the hedge portfolio that is long high IV and short low IV. Newey–West (1987) adjusted t-statistics are reported in parentheses. Numbers in bold denote significance at the 5% level or better.

Before estimating Fama and MacBeth (1973) regressions, we examined the correlations among the predictor variables (not reported). A high correlation exists between monthly IV (IV_m) and MAX (0.88). This correlation is bound to be high by construction since maximum daily return contributes to the IV of a stock. Bali et al. (2011) show that the MAX effect helps explain the idiosyncratic volatility puzzle of Ang et al. (2006, 2009). In fact, they report that the inclusion of MAX reverses the IV effect. Besides, the correlation between monthly IV and quarterly IV (IV_q) is 0.59. The correlation of IV_m and IV_q with REV (return in the same month) is mild at 0.37 and 0.25, respectively. The correlation of IV with other variables is not high. We estimated cross-section regressions of stock returns on IV and one control variable at a time and then the model is estimated with full specification.

Table 4 presents time-series averages of the coefficients γ_{it} ($i = 1, 2, \dots, 10$) from the cross-section regressions of equation 1 and their t -statistics. In the univariate regression of returns on IV_m , the average of the time-series of coefficients is 0.18 with a t -statistics of 1.45. The coefficient of IV_q is 0.22 ($t = 1.75$) which is statistically significant at the 10% level. The spread in the average IV_q between the high and low decile is 4.11%. Multiplying this spread by the average coefficient (0.22) gives the average risk premium of 0.90% per month. We focus more on the IV_q because of its relatively strong relation with stock returns. In the regressions with two predictive variables, the coefficients of size (LnSize), value (LnBM), and illiquidity (ILLIQ) and total skewness (TSKEW) are statistically significant at the 5% level. Size is negatively related to excess stock returns which means that small firms on an average have higher returns than bigger firms. Similarly, book-to-market ratio is positively related to stock returns which implies that value firms on an average have higher returns than the growth firms. The presence of the size and value premiums is in conformity with the existing evidence on the Indian stock market (Aziz & Ansari, 2014; Connor & Sehgal, 2003; Das, 2015; Ranjan Dash & Mahakud, 2013).

Illiquidity (ILLIQ) is also positively related to stock returns consistent with the Amihud and Mendelson's (1986) hypothesis that illiquidity is associated with higher returns. In line with Bali et al. (2005), the effect of illiquidity is stronger than the effect of IV. Total skewness (TSKEW) is also positively related to stock returns suggesting that the skewness of Harvey and Siddique (2000) is also a priced factor. The sign of beta is negative and indistinguishable from zero; this indicates the failure of CAPM in explaining the variation in returns.

Reversal (REV) does not change either the sign of the IV or impacts much of its magnitude. However, both remain insignificant. This suggests that reversal does not explain the IV effect of Ang et al. (2006, 2009) as pointed of by Huang et al. (2010). To test if MAX reverses the IV effect, stock returns are regressed on IV_m and MAX for comparability with Bali et al. (2011). The coefficient of IV_m reduces sharply (0.08) but remains positive and statistically insignificant.

In the full specification, the coefficient of IV_q is 0.02 ($t = 0.27$) indicating that the IV effect is not robust to the controls for the beta, size, value, momentum, reversal, illiquidity, skewness, co-skewness and MAX effects. The last row includes only those variables that are statistically significant. The coefficient of IV_q remains positive yet insignificant. Overall, only in 3 out of 10 specifications with two predictor variables, the coefficients of IV_q are statistically significant at the 5% level.

3.4. Separate cross-section regressions for small, medium and big stocks

One of the demerits of the cross-section regression is that it treats all stocks equally. In the context of the sorting method, VW returns are computed to counter this issue. However, Fama and French (1993) suggest estimating separate regressions for small, medium and big stocks. In this way, it can be ascertained if the anomaly is pervasive across all sizes of stocks or is concentrated in a particular group of stocks. In the similar vein, we estimate separate regressions for small, medium and big stocks. 33rd and 67th percentiles of the of market capitalization are the cut-offs for separating the sample into three size parts. Table 5 shows the results of the cross-section regressions separately for small, medium and big stocks. Interestingly, the coefficient of IV (0.37) is statistically significant ($t = 2.22$) for small stocks. For medium stocks, the coefficient of IV is negative albeit insignificant.

Table 4. Firm-level cross-section regressions

IV_m	IV_q	Beta	LnSize	LnBM	MOM	REV	ILLIQ	TSKEW	SSKEW	MAX	R^2 (%)
0.1891 (1.45)											1.96
	0.2298 (1.75)										1.90
	0.2350 (2.04)	-0.3110 (-0.42)									6.06
	0.1060 (0.92)		-0.7970 (-6.60)								3.60
	0.2081 (1.84)			1.126 (5.40)							4.16
	0.2182 (1.82)				-0.0032 (-0.88)						3.51
	0.1989 (1.58)					0.0111 (0.90)					3.72
	0.2772 (2.32)						1.09 (4.14)				3.46
	0.3894 (3.32)							0.0875 (2.54)			2.21
	0.2077 (1.58)								0.5671 (1.83)		2.76
	0.1623 (1.48)			0						0.0344 (0.75)	2.97
0.0848 (0.73)										0.0407 (0.88)	2.73
	0.0245 (0.27)	-0.0713 (-0.14)	-0.4679 (-4.33)	0.7160 (4.54)	0.0020 (0.76)	0.0046 (0.39)	0.6964 (2.22)	-0.0062 (-0.16)	0.4262 (1.55)	0.0015 (0.03)	13.5
	0.1436 (1.28)		-0.4300 (-4.16)	0.7927 (3.95)			0.8472 (2.64)				7.11

Notes: Each month from April 2000 to June 2014, we run cross-section regressions of returns in a month on IV and other lagged predictor variables. In each row, the table reports the average of the time-series of coefficients and their t -statistics in parenthesis. IV_m is the idiosyncratic volatility relative to CAPM over the prior one month; IV_q is the idiosyncratic volatility over the prior quarter; Beta is estimated over a window of one year daily data; LnSize is the natural logarithm of market capitalization; LnBM is the natural logarithm of the book-to-market ratio; MOM is the cumulative monthly return over $t - 12$ to $t - 1$; REV is the return in the previous month; ILLIQ is the ratio of absolute daily return and trading volume averaged over a month and raised by 10⁵; TSKEW is the skewness of the daily returns over one year of daily data; SSKEW is the systematic skewness or co-skewness over one year of daily data; and MAX is the maximum daily return over the previous month. The sample is BSE-500 stocks for the period April 2000 to June 2014. Numbers in bold denote significance at the 5% level or better.

Table 5. Cross-section regressions for small, medium and big stocks

	IV	LnSize	LnBM	ILLIQ	R² (%)
All	0.14 (1.28)	-0.43 (-4.16)	0.79 (3.95)	0.84 (2.64)	7.11
Small	0.37 (2.22)	-1.49 (-4.47)	0.70 (2.45)	0.42 (0.94)	5.76
Medium	-0.08 (-0.58)	-0.77 (-2.18)	0.53 (2.34)	0.34 (0.81)	6.92
Big	0.15 (1.00)	-0.12 (-0.95)	0.88 (4.04)	12.6 (3.16)	9.81

Notes: Each month from April 2000 to June 2014, we run cross-section regressions of returns in a month on IV and other lagged predictor variables separately for small, medium and big stocks. The break-points are 33rd and 67th percentile of market capitalization each month. In each row, the table reports the average of the time-series of coefficients and their *t*-statistics in parenthesis. IV is the idiosyncratic volatility over the prior quarter; LnSize is the natural logarithm of market capitalization; LnBM is the natural logarithm of book-to-market ratio; ILLIQ is the ratio of absolute daily return and trading volume averaged over a month and raised by 10⁶. The sample is BSE-500 stocks for the period April 2000 to June 2014. Numbers in bold denote significance at the 5% level or better.

This suggests that the IV effect is concentrated among small stocks. This explains why in the cross-section regressions of the whole sample the coefficients of IV are mostly insignificant.

3.5. Idiosyncratic volatility and return relation using quantile regression

The cross-sectional relationship between stock returns and predictive variables (like idiosyncratic volatility) is investigated using models like Fama and MacBeth (1973) that predict their relation at the mean of the conditional distribution. The inference from such models may be erroneous if the relation is different at different points of the conditional distribution. Keeping in view the limitations of the LS estimates, some recent studies have employed the quantile regression approach of Koenker and Bassett (1978) to model the relation between stock returns and predictor variables.

Some recent studies have used quantile regression in the asset pricing context, Barnes and Hughes (2002), Nath and Brooks (2015) and Lee and Li (2016). Barnes and Hughes (2002) applied quantile regression in assessing the relation between beta and returns and size and returns. They document that there is a disparity in the magnitude and significance of the coefficients across the quantiles. The coefficients of beta and size are significant at the extreme quantiles (0.1 and 0.9) and have opposite signs. They argue that this explains why in LS regressions these factors are mostly insignificant. Since, somewhere between the extremes of the quantile, the value of the coefficient has to pass through zero, which is generally at the median, the LS regression fails to capture the significant relation which exists at extreme levels of conditional distribution. Nath and Brooks (2015) apply quantile regression in understanding idiosyncratic risk and stock returns relation in the Australian equity market. They report a parabolic relation between stock returns and idiosyncratic volatility that is negative significant at the bottom quantile and positive significant at the top quantile of the response variable. A similar finding has been reported by Lee and Li (2016).

We apply quantile regression at the second stage of the Fama and MacBeth (1973) regressions and report the time-series averages of the coefficients of the following model:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} IV_{i,t} + \gamma_{2,t} LnSize_{i,t} + \gamma_{3,t} LnBM_{i,t} + \gamma_{4,t} ILLIQ_{i,t} + \epsilon_{i,t+1} \quad (2)$$

where IV is measured relative to the CAPM over three months daily data. The loadings on the IV in the above model ($\gamma_{1,t}$) are of our prime interest. Size, value and illiquidity are included as control variables since they are the most pervasive and significant predictors of the expected stock returns both in the time-series and cross-section.

Table 6. Fama-Macbeth estimates from quantile and LS regressions

Variable	Quantile									LS
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	
c	-7.58 (-10.06)	-4.62 (-6.14)	-2.64 (-3.50)	-0.76 (-0.95)	1.37 (1.67)	3.88 (4.22)	7.34 (6.81)	11.95 (9.83)	18.75 (12.86)	4.77 (4.45)
IV	-1.55 (-11.4)	-1.06 (-8.76)	-0.68 (-6.28)	-0.39 (-3.53)	-0.10 (-0.91)	0.17 (1.45)	0.55 (4.31)	1.08 (6.95)	1.87 (8.95)	0.14 (1.28)
LnSize	0.15 (1.91)	0.08 (1.11)	0.04 (0.64)	0.01 (0.06)	-0.07 (-0.84)	-0.16 (-1.83)	-0.38 (-3.53)	-0.66 (-5.42)	-1.14 (-7.77)	-0.43 (-4.16)
LnBM	0.71 (3.95)	0.46 (2.67)	0.36 (2.10)	0.36 (2.07)	0.40 (2.18)	0.35 (1.82)	0.31 (1.48)	0.43 (1.82)	0.48 (1.86)	0.79 (3.95)
ILLIQ	0.66 (2.26)	0.68 (2.34)	0.66 (2.61)	0.69 (2.77)	0.59 (2.42)	0.64 (2.61)	0.51 (2.06)	0.87 (2.29)	2.00 (1.95)	0.85 (2.64)
Adj. R ²	5.43	4.39	4.02	3.93	3.97	4.15	4.66	5.65	7.49	7.11

Notes: This table reports the Fama-Macbeth time-series averages of the coefficients and their t-statistics from quantile and LS regressions of the following model: $R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}IV_{i,t} + \gamma_{2,t}LnSize_{i,t} + \gamma_{3,t}LnBM_{i,t} + \gamma_{4,t}ILLIQ_{i,t} + \epsilon_{i,t+1}$. Numbers in bold denote significance at 5% or better.

Before applying the quantile regression, we verified that the returns are skewed with a fat tail. The high χ^2 -statistic in the Wald test rejected the equality of the slope hypothesis at conventional levels. This implies that the coefficients differ across quantile values. Table 6 presents the findings from the quantile regression for Equation (2). The coefficient of IV is negative and significant at the lowest quantile and positive significant at the highest quantile. The coefficient passes through zero between the quantiles 0.5 and 0.6. This perhaps explains why the LS coefficients of IV in the two models are insignificant. The upward trend in the intercept signifies the unanticipated returns at the upper quantiles. The marginal effect of *LnSize* is lowest and significant at the upper quantile and the coefficients of *LnBM* are positive across the quantiles. Similarly, the positive illiquidity effect is also pervasive across the quantiles of the distribution. Figure 2 shows the results graphically. In the figure, the relation between IV and stock returns is parabolic as found by Nath and Brooks (2015) in the Australian context.

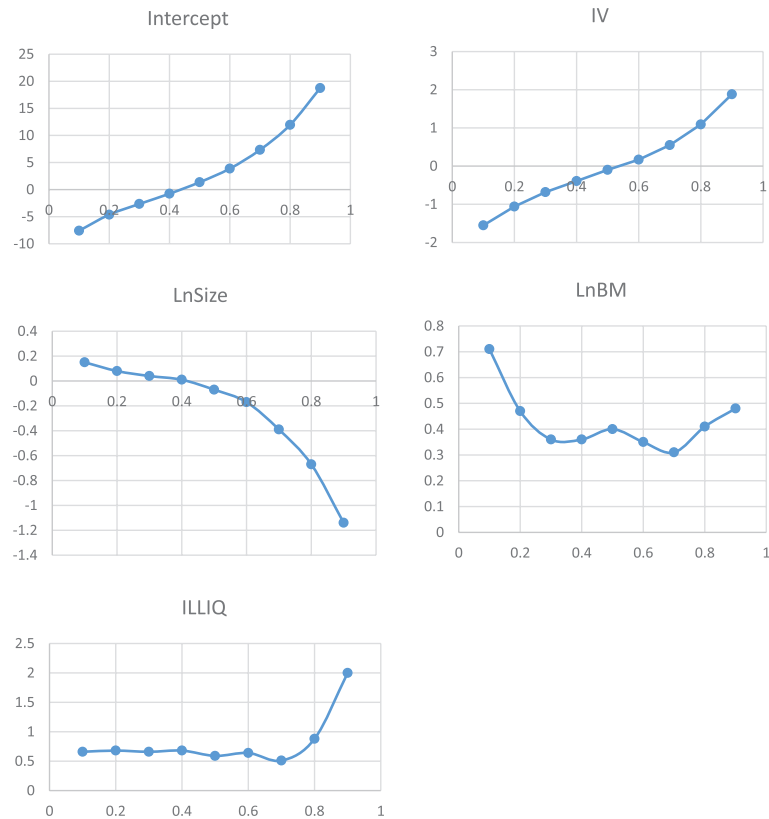
The results from the quantile regressions can be reconciled with the prospect theory of Kahneman and Tversky (1979) which states that investors value gains and losses differently. An implication of the prospect theory is that when stocks experience a sudden rise in its price investors are lured towards it making it overvalued and when price declines sharply the stock is shunned by investors making it undervalued. The tendency of retail investors to trade in such “gamble stocks” has been documented in Kumar (2009) and Bali et al. (2011). In fact, Bali et al. (2011) find that the MAX effect (stocks that experience highest daily positive return decline in the next month) reverses the idiosyncratic volatility effect documented in previous studies. This highlights the close nexus between the MAX/MIN effects and the idiosyncratic volatility puzzle. We argue that the MAX and MIN are the true effects because idiosyncratic volatility does not distinguish between a negative and positive idiosyncratic stock price movements. Moreover, this is also consistent with the findings of Bhootra and Hur (2015) that the negative idiosyncratic volatility effect exists only in stocks with unrealized capital losses but does not exist in stocks with unrealized capital gains which is expected in a word where investors value gains and losses differently.

3.6. Some robustness tests

Alternative estimation windows and data frequencies may particularly have a bearing on the empirical relation between IV and stock returns. This point has also been highlighted by Peterson and Smedema (2011) and Fink, Fink, and He (2012). Ghysels, Santa-Clara, and Valkanov (2005) find that the length of the window for risk estimation plays a crucial role in the studies of the trade-off between risk and return.

Figure 2. Quantile dependent effects of idiosyncratic volatility and other characteristics on excess stock returns.

Notes: The graphs in this figure represent the marginal effects of regressors on excess stock returns. The curves suggest the dynamic relation of regressors and excess stock returns at different conditional quartiles.



Of our particular concern is that whether the positive IV-return relation observed in this study also holds when IV is estimated over a window of one month daily data as followed by Ang et al. (2006, 2009). We estimated IV over an estimation window of one month daily data (IV_m) and form decile portfolios in a similar way. Table 7 shows the result of IV_m decile sort. The results are qualitatively similar to the sort from IV_q . The return difference between low and high IV portfolios is statistically significant in EW portfolios ($t = 3.16$) but insignificant for the VW portfolios ($t = 1.55$).

Bali and Cakici (2008) show that the relation between IV and stock returns is sensitive to the choice of data frequency. Khovansky and Zhylyevskyy (2013) demonstrate that the idiosyncratic volatility premium tends to be positive on daily return data, but negative on monthly, quarterly and annual data. Keeping this in view, we examine whether the positive IV effect observed in the daily frequency is also present in the monthly frequency. Specifically, we formed portfolios based on the IV estimated over a 24-month window. Portfolios are updated yearly. This is equivalent to a strategy of 24-12-12. Where numbers represent months. The results are reported in Table 8. Similar to the monthly sorts, returns increase as we move towards the high IV portfolio. For example, the returns for EW portfolios are 1.69 and 2.89% for the lowest and highest decile portfolios, respectively. The spread is statistically significant at the 5% level for the EW portfolios, but insignificant for the VW portfolios. This is similar to the findings from IV_m and IV_q decile sorts.

We also examined IV-return relation in two sub-periods. The choice of the breakpoint is dependent upon the regulatory change in the Indian stock market regarding the participation of institutional investors in short selling. This break-point has been opted based on the fact that the Securities and Exchange Board of India (SEBI) permitted short selling for institutional investors in January

Table 7. Returns and alphas on IV_m decile

Decile	EW portfolios				VW PORTFOLIOS				Average IV
	Average return	CAPM alpha	3-F	4-F	Average return	CAPM alpha	3-F	4-F	
Low IV	1.61	0.44	0.06	0.06	1.07	-0.16	0.01	0.02	1.14
2	2.06	0.74	-0.01	-0.04	0.95	-0.37	-0.24	-0.24	1.47
3	1.94	0.53	-0.17	-0.20	1.54	0.20	0.01	0.02	1.71
4	2.31	0.85	0.07	0.02	2.08	0.74	0.61	0.57	1.92
5	2.21	0.72	-0.27	-0.35	2.41	0.91	1.36	1.27	2.14
6	2.57	1.03	-0.20	-0.28	1.97	0.55	0.11	0.09	2.37
7	2.23	0.64	-0.36	-0.45	1.78	0.25	-0.07	-0.13	2.66
8	3.04	1.39	0.15	0.07	2.70	1.02	0.49	0.41	3.00
9	2.94	1.21	-0.07	-0.12	3.15	1.33	0.84	0.69	3.56
High IV	4.07	2.39	0.77	0.69	3.88	2.31	0.60	0.62	4.87
10-1 difference	2.45 (3.16)	1.95 (2.79)	0.70 (1.01)	0.63 (0.91)	2.80 (1.55)	2.47 (1.36)	0.59 (0.32)	0.60 (0.33)	

Notes: Decile portfolios are formed each month from April 2000 to June 2014 by sorting stocks based on the IV relative to CAPM over the past one month. Portfolio 1(10) is the portfolio with the lowest (highest) IV over the past month. The table reports the equal-weighted (EW) and value-weighted (VW) average monthly returns, CAPM, three-factor, and four-factor alphas. The last row presents the difference between the average returns of portfolios 10 and 1, the CAPM, three-factor and four-factor alphas of the difference and their corresponding Newey–West (1987) adjusted *t*-statistics. Numbers in bold denote significance at the 5% level or better.

Table 8. Returns and alphas from monthly data

Decile	EW portfolios				VW portfolios			
	Average return	CAPM alpha	3-F	4-F	Average return	CAPM alpha	3-F	4-F
Low IV	1.69	0.50	-0.12	-0.14	1.26	0.05	-0.13	-0.16
2	2.03	0.73	0.03	-0.02	1.81	0.53	0.51	0.46
3	1.99	0.60	-0.23	-0.30	1.82	0.44	0.22	0.23
4	2.16	0.76	-0.01	-0.03	1.24	-0.13	-0.02	-0.02
5	2.49	0.99	-0.02	-0.08	2.05	0.64	0.35	0.29
6	2.05	0.51	-0.75	-0.83	1.66	0.15	-0.32	-0.34
7	2.51	0.95	-0.26	-0.34	2.15	0.63	1.05	1.00
8	2.50	0.95	-0.18	-0.27	1.92	0.36	0.44	0.43
9	2.83	1.21	-0.07	-0.12	2.70	1.06	0.28	0.29
High IV	2.89	1.16	0.33	0.29	1.91	0.02	0.06	0.05
10-1 difference	1.19 (1.94)	0.65 (1.34)	0.45 (0.90)	0.43 (0.86)	0.64 (0.72)	-0.02 (-0.03)	0.19 (0.23)	0.22 (0.26)

Notes: Decile portfolios are formed each year from April 2000 to June 2014 by sorting stocks based on the IV relative to CAPM over the past 24 months (except the first sort which is based on 12 months). Portfolio 1(10) is the portfolio with lowest (highest) IV over the past 24 months. The table reports the equal-weighted (EW) and value-weighted (VW) average monthly returns, CAPM, three-factor and four-factor alphas. The last row presents the difference between the average returns of portfolios 10 and 1, the CAPM, three-factor and four-factor alphas of the difference and their corresponding Newey–West (1987) adjusted *t*-statistics. Numbers in bold denote significance at the 5% level or better.

2008. During the period 2001–2007, short selling was allowed only for retail investors. As it is argued in the literature that short selling improves market efficiency (Edelen, Ince, & Kadlec, 2016; Sobaci, Sensoy, & Erturk, 2014), we expect the decay of the IV effect during the second sub-period.

Table 9. IV decile sort for sub-periods

Decile	April 2000 to December 2007				January 2008 to June 2014			
	EW portfolios		VW portfolios		EW portfolios		VW portfolios	
	Average return	Carhart's alpha	Average return	Carhart's alpha	Average return	Carhart's alpha	Average return	Carhart's alpha
Low IV	1.92	-0.39	1.77	-0.17	0.55	-0.14	0.09	-0.13
2	2.86	-0.01	2.15	0.36	0.89	-0.01	0.51	0.18
3	2.84	-0.10	2.14	0.25	0.64	-0.40	0.49	0.14
4	2.65	-0.69	1.72	-0.45	0.91	-0.25	0.81	-0.22
5	3.72	0.44	3.24	0.81	1.23	-0.14	1.06	0.14
6	3.18	-0.96	2.87	-0.35	0.92	-0.44	0.67	-0.38
7	3.98	-0.03	3.72	1.33	1.16	-0.02	1.30	0.34
8	3.90	-0.47	3.73	0.12	1.01	-0.27	1.48	-0.09
9	5.19	0.79	4.92	1.89	0.74	-0.55	1.14	0.02
High IV	6.43	1.88	5.61	1.98	1.17	-0.01	-1.81	-2.45
H-L	4.51 (4.78)	2.27 (2.54)	3.84 (2.95)	2.15 (1.54)	0.62 (0.69)	0.13 (0.24)	-1.90 (-1.65)	-2.32 (2.05)

Notes: Results are provided for two sub-periods April 2000 to December 2007 and January 2008 to June 2014. For details see Table 1.

The two sub-periods are April 2000 to December 2007 and January 2008 to June 2014. Table 9 presents the results of the first sub-period, the period during which institutional investors were barred from participating in short selling (during 2001–2007 short selling was banned for institutional investors). The surprising result to note is that the positive IV-return relation is statistically significant only in the first half of the sample. Spreads both in the EW and VW portfolios are statistically significant ($t = 4.78$ and $t = 2.95$ for EW and VW portfolios, respectively). Even the four-factor alphas of the hedge portfolio are significant for the first sub-period. Returns on the long-short portfolios fail to have statistical significance both in the EW and VW portfolios in the second sub-period. Hence, the disappearance of the IV effect could be attributed to the participation of institutional investors in short selling post-2007. Interestingly, the lowest VW return in the second half of the sample is provided by the highest IV portfolio. This is more in line with Ang et al.'s (2006, 2009) results which hold only in VW portfolio returns (Bali & Cakici, 2008). Similar results were found for the cross-section regressions for the two sub-periods (results not reported for brevity).

Following Nath and Brooks (2015), we also included the variance version of IV in the model to check if the relation between returns and IV still holds. IV^2 is the variance version of the idiosyncratic risk. It is meant to capture the non-linearity in the relation. Table 10 shows the results of the model 2 with IV^2 . The pattern of the coefficients of IV^2 is opposite of the pattern of the coefficients of IV, positive at the lower quantile and negative at the upper quantile. The effects of both the IV and IV^2 are stronger at the extreme quantiles. However, it can be noted that the inclusion of IV^2 in the model does not make a dent in the coefficients of IV. The table also reports the LS coefficient of IV, that is positive but insignificant and the LS coefficient of IV^2 is negative and insignificant. These results are in line with the findings of Nath and Brooks (2015) for the Australian stock market and Barnes and Hughes (2002) in the US stock market.

Table 10. Fama–Macbeth estimates from quantile and LS regressions

Variable	Quantile										LS
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9		
c	-4.42 (-6.87)	-2.10 (-3.52)	-0.86 (-1.44)	0.56 (0.87)	2.20 (3.13)	3.90 (5.09)	6.41 (6.79)	10.24 (9.22)	16.77 (11.9)	4.35 (4.55)	
IV	-3.13 (-10.6)	-2.14 (-7.61)	-1.49 (-5.46)	-0.88 (-3.16)	-0.38 (-1.30)	0.35 (1.04)	1.04 (2.95)	2.04 (4.87)	3.88 (7.20)	0.41 (1.17)	
IV ²	0.1860 (6.35)	0.1188 (4.20)	0.0889 (3.44)	0.0431 (1.67)	0.0169 (0.59)	-0.0333 (-0.98)	-0.0552 (-1.69)	-0.1248 (-2.99)	-0.2683 (-4.43)	-0.0392 (-1.25)	
LnSize	0.08 (0.98)	-0.01 (-0.10)	-0.01 (-0.07)	-0.04 (-0.57)	-0.10 (-1.25)	-0.19 (-2.23)	-0.35 (-3.31)	-0.62 (-5.32)	-1.15 (-8.03)	-0.42 (-4.06)	
LnBM	0.72 (3.88)	0.44 (2.63)	0.38 (2.21)	0.36 (2.07)	0.37 (2.11)	0.32 (1.78)	0.28 (1.42)	0.35 (1.60)	0.45 (1.84)	0.78 (4.01)	
ILLIQ	0.63 (2.23)	0.55 (2.23)	0.59 (2.80)	0.67 (3.19)	0.59 (2.80)	0.72 (3.36)	0.57 (2.44)	0.10 (2.67)	2.73 (2.19)	0.91 (2.87)	
Adj. R ²	6.34	5.24	4.76	4.66	4.67	4.88	5.46	6.49	8.84	8.33	

Notes: This table reports the Fama–Macbeth time-series averages of the coefficients and their *t*-statistics from quantile and LS regressions of the following model:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}IV_{i,t} + \gamma_{2,t}IV_{i,t}^2 + \gamma_{3,t}LnSize_{i,t} + \gamma_{4,t}LnBM_{i,t} + \gamma_{5,t}ILLIQ_{i,t} + \epsilon_{i,t+1}$$

Numbers in bold denote significance at 5% or better.

4. Discussion

The positive relation between IV and stock returns is in contrast to the Ang et al.'s (2006, 2009) findings, but consistent with other studies that reported a positive or no relation between IV and stock returns (for example, Bali & Cakici, 2008; Nartea & Wu, 2013). This positive IV-return relation is more consistent with the theoretical models of Levy (1978) and Merton (1987) that posit that in the presence of under-diversification the total volatility or the idiosyncratic volatility should also be priced apart from the systematic risk.

The sorting method and the cross-section methods deliver contradictory results. The sorting method shows that the return difference between the high IV and low IV is statistically significant. On the other hand, in the cross-section regressions, the coefficient of IV is statistically insignificant. The significance of the IV effect only for EW portfolios indicates that the effect is closely related to small stocks. In order to verify this finding, we followed Fama and French (2008) in spirit and estimated separate regressions for small, medium and big stocks. The results from this exercise confirmed that the IV effect is concentrated among small stocks. This may be a reason why in the cross-section regression for all stocks the IV effect is not detected. The results are also in conformity with previous studies in the Indian context; Drew and Veeraraghavan (2002) and Brockman et al. (2009). Drew and Veeraraghavan (2002) reported a positive IV-return relation in the Indian stock market using a different methodology. In addition, Brockman et al. (2009) reported an insignificant coefficient of IV using Ang et al.'s (2006, 2009) methodology.

Next, we performed a battery of robustness tests. The results, however, reveal that the positive IV-return relation is not robust. The relation is fragile and subject to many conditions. For instance, the IV-return relation is significant (not significant) for (1) EW (VW) portfolios, (2) first (second) half of the sample period, (3) small (medium and big) stocks, and (4) raw returns (FF and Carhart's alphas). Moreover, sometimes the results from raw returns and alpha are not same i.e. raw return difference is significant but the alphas are not significant. The contradictory findings from raw returns and risk-adjusted returns are in conformity with Bali and Cakici (2008), who reported a similar phenomenon in the context of IV. Apart from the IV-return relation, the cross-section regressions show a significant negative size effect, a significant positive value premium, and a pronounced positive illiquidity effect. Beta fails to have statistical significance. Interestingly, the coefficient of the beta is negative, which is consistent with some recent findings that suggest reversing of the beta-return relation (Agarwalla, Joshy, Varma, & Vasudevan, 2014; Frazzini & Pedersen, 2014). The subperiod analysis provides a very interesting finding and points out towards the possible role of short-selling in the disappearance of the positive IV effect in the second sub-period. As it is suggested in the literature that short selling improves market efficiency.

As for the quantile regressions, the results confirm that the relationship between IV and stocks returns is quantile dependent that is parabolic in nature. Different relations (positive and negative) at the extremes of the quantile may be a cause of insignificant IV at the mean level. In other words, even if a relationship between the predictor variable and stock returns is not detectable at the mean level it may be significant at the extreme quantiles of the distribution. Further, we conjecture that the MAX and MIN effects (Bali et al., 2011) are the true effects, as the idiosyncratic volatility does not distinguish between a positive and negative idiosyncratic price movement. Both stocks with high MAX (maximum daily return) and high MIN (negative of minimum daily return) tend to be highly idiosyncratic. And since MAX and MIN effects are opposite of each other (as reported by Aziz and Ansari (2017) in the Indian context) idiosyncratic volatility is naturally bound to deliver a mixed result. The application of quantile regression also highlights the importance of dynamic relationships that may exist between predictor variables and stock returns. An insignificant relation at the mean (LS) level between the predictor variable and stock returns may be significant at the extreme quantiles of the conditional distributions. This may be a potential explanation of several cross-sectional determinants (including beta) that enter into the cross-section regression model with an insignificant coefficient.

5. Conclusion

In this study, we examined the relationship between IV and stock returns in the Indian stock market. The results tend to support a positive relation between IV and stock returns albeit with some caveats. The positive relationship holds for alternate frequencies (daily and monthly), and estimation windows (three months and one month). The relationship also holds after controlling for value, momentum, co-skewness and illiquidity effects. However, this relation is statistically significant only for EW portfolios. Separate regressions for small, medium and big stocks confirm that the positive IV effect is concentrated among small stocks. The persistence of the IV effect in small stocks may be because of the difficulty of arbitraging away anomalies that are concentrated among stocks. Further, the sub-period analysis which provides a quasi-natural setting to test the conjecture that the participation of institutional investors in short selling improves market efficiency revealed that the IV effect persisted only during the period of short sale constraint.

Finally, using quantile regressions, we show that the price of idiosyncratic volatility is not homogeneous across quantiles of the conditional distribution. Returns at the lowest quantile (which represent sharp losses) are negatively related to idiosyncratic risk and returns at the highest quantile (which represent sharp gains) are positively related to idiosyncratic risk. We conjecture that this may be because of the opposite effects of MAX and MIN documented in previous studies. Since stocks with high MAX tend to have high idiosyncratic risk similar to stocks with high MIN, the model that uses idiosyncratic volatility delivers a mixed result. Perhaps this is why returns at the median level are not significantly related to idiosyncratic risk. This is also in line with the prospect theory of Kahneman and Tversky (1979) which states that the effects of gains and losses are asymmetric.

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Note

1. http://www.bseindia.com/sensexview/DispIndex.aspx?iname=BSE500&index_Code=17.

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Appendix A

Variable definitions

Beta: We estimate the beta using market model:

$$R_{id} - Rf_d = \alpha_i + b_i(R_{md} - Rf_d) + \varepsilon_{id}. \quad (A1)$$

where R_{it} is the return on stock i on day d , Rf_d is the risk free rate, R_{md} is the market return on day d . Beta is estimated from an estimation window of one year.

SIZE: Size is measured as the market capitalization (stock price times number of shares outstanding) during month $t - 1$ for each stock.

BM: Book-to-market ratio in a month is computed as the ratio of book value and the market value of its equity. It is computed as the inverse of price-to-book (PB) ratio provided in Prowess.

IV: Idiosyncratic volatility is measured relative to the CAPM

$$R_{id} - Rf_d = \alpha_i + b_i(R_{md} - Rf_d) + \varepsilon_{id}.$$

IV is defined as the standard deviation of the error term

$$IV_{i,t} = \sqrt{\text{var}(\varepsilon_{i,d})}. \quad (A2)$$

we compute IV over an estimation window of three months daily data (IV_q) and test its robustness over a window of one month (IV_m).

MOM: Momentum for stock i in month t is computed as the cumulative returns over month $t-12$ to $t-2$

TSKEW: Skewness of a stock is calculated using daily returns over a year t .

$$\text{SKEW}_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} \left(\frac{r_{i,d} - \mu_i}{\sigma_i} \right)^3. \quad (A3)$$

SSKEW: SSKEW is the systematic skewness or the co-skewness of a stock measured over one year daily data:

$$R_{id} - Rf_d = \alpha_i + b_i(R_{md} - Rf_d) + \gamma_i(R_{md} - Rf_d)^2 + \varepsilon_{id}. \quad (A4)$$

The slope coefficient γ_i is the systematic skewness or coskewness of a stock i in a year.

REV: Following Jegadeesh (1990) and Lehmann (1990a) short-term reversal is defined as the return of stock i in month $t - 1$.

ILLIQ: Following Amihud (2002) ILLIQ is measured as the ratio of absolute daily stock return with daily volume. This measure is averaged over a month to finally get the ILLIQ.

$$\text{ILLIQ}_{it} = \left(\frac{1}{N_{it}} \right) \sum d(|r_{idt}| / \text{VOL}_{idt}). \quad (A5)$$

Following Amihud (2002) this measure is raised by 10^6 .

MAX: Max is the Maximum daily return in month $t - 1$.

$$\text{MAX}_{i,t} = \max (R_{i,d}), d = 1, \dots, D_t. \tag{A6}$$

where $R_{i,d}$ is the return on stock i on day d and D is the number of days in month t .

IO: IO is the percentage of institutional holdings in a stock.

Appendix B

Construction of risk factors

We construct SMB and HML factors as delineated in Fama and French (1993). In June of each year, we sort stocks on their market capitalization in increasing order and classify it into two portfolios small and big by the median. In each portfolio, stocks are again grouped into three portfolios based on their book-to-market ratios. The breakpoint for value is 30th and 70th percentiles. The high book-to-market stocks are value stocks and low book-to-market stocks are growth or glamour stocks. This double sort thus produces six portfolios namely, SG, SN, SV, BG, BN and BV (S for small, B for big, G for growth, N for neutral and V for value). Monthly value-weighted (VW) returns are computed for the next 12 months. The portfolios are rebalanced annually. The value-weighted difference in each month between the average of three small and three big portfolios is labelled as SMB and the difference in each month between the average of two value portfolios and the average of two growth portfolios is the HML. Momentum factor WML is computed as follows: Each month t stocks are sorted into quintile portfolios based on their cumulative return over $t - 12$ to $t - 2$, skipping one month in between. The difference between the value-weighted returns of winner portfolio and the loser portfolio is used as momentum factor. For risk adjustments, we use CAPM, Fama and French (1993) three-factor, and Carhart's (1997) four-factor model.



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