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IDIOSYNCRATIC RISK AND STOCK RETURNS: A QUANTILE REGRESSION APPROACH

Abstract:

The relation between idiosyncratic risk and stock returns is currently a topic of debate in the academic literature. So far the evidence regarding the relation is mixed. This study aims to investigate the cross-sectional relation between idiosyncratic risk and stock returns in the Indian stock market employing quantile regressions. Using quantile regressions, this study demonstrates that idiosyncratic volatility and stock returns relation is quantile dependent. The relation between idiosyncratic volatility and stock returns is parabolic. The high idiosyncratic risk is associated with high (low) excess returns at the upper (lower) quantile of the conditional distribution. This partially explains the inconclusive evidence on the idiosyncratic volatility and the stock returns relation in the literature.

Keywords:

idiosyncratic volatility; quantile regression; asset pricing; emerging markets; India,

JEL Classification: G12, C14, C21

1. Introduction

The theoretical works of Levy (1978) and Merton (1987) predict that in the presence of under-diversification and incomplete markets the idiosyncratic risk should be priced positively. In the recent empirical finance literature, this relation is currently a topic of intense debate. This debate was mainly started by the findings of Ang et al. (2006, 2009) who reported that idiosyncratic volatility is associated with abysmally low returns. In contrast, Fu (2009) shows that idiosyncratic volatility estimated using EGARCH has a positive relation to stock returns. The cross-sectional relation 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 Basset (1978) to model the relation between stock returns and predictive variables.

Quantile regression, proposed by Koenker and Bassett (1978) and explained in detail by Buchinsky (1998), is robust to least square estimates in the presence of outliers and if errors do not conform to Gaussian distribution (Buchinsky, 1998). Least square estimates use mean as a measure of location, whereas, quantile regressions can be used for different measures of the location at the extreme tails of the distribution. Information about the extreme tails of the distribution is lost in the least square estimates. A significant relation between the predictor and response variable at the tails of the distribution may not be captured by the least square estimates.

Two recent studies have used quantile regression in the asset pricing context, Barnes and Hughes (2002) and Nath and Brooks (2015). Barnes and Hughes (2002) apply 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 are of the opposite sign. 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 the 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.

In a similar vein, we investigate the idiosyncratic volatility and the stock returns relation using quantile regression on the Indian stock market. In the Indian context, Brockman, Schutte, and Wu (2009) reported a positive idiosyncratic risk premium using Fu's (2009) methodology and negative premium using Ang et al. (2006, 2009) methodology. 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 Philippines for the five year period of 1995-1999. We use quantile regressions at the second stage of the Fama and Macbeth (1973) procedure to empirically test the relation between stock returns and idiosyncratic volatility computed using Ang et al.'s (2009) method at different quantiles of the conditional distribution. The contribution of this paper is unique in two ways. First, it empirically tests the idiosyncratic volatility puzzle in the emerging stock market of India. Second, it applies quantile regression to explore the dynamic relation between stock returns and idiosyncratic volatility, which is a novel idea that helps in shedding light on why there are divergent results on the relation.

2. Empirical Framework

Our data consist of stock prices and other variables of S&P BSE-500 firms drawn from Prowess, a database maintained by the Center for Monitoring Indian Economy (CMIE) for the period April 2000 through June 2014. The variables used in this study are as follows:

Beta: *Beta* is measured from daily data over a rolling window of one month

LnSize: *LnSize* is the natural log of the market capitalization.

LnBM: *LnBM* is the natural log of the book-to-market ratio.

IVOL: Idiosyncratic volatility is measured relative to CAPM over a rolling window of one month daily data.

$$R_{id} - Rf_d = \alpha_i + \ b_i\,[R_{md} – Rf_t] + \varepsilon_{id}.$$

IVOL is defined as the standard deviation of the error term in month t.

$$IVOL_{i,t} = \ \sqrt{var(\varepsilon_{i,d}\,)}.$$

$IVOL^2$: *$IVOL^2$*is the square of the *IVOL* to capture the non-linearity in the regression.

Market proxy is the return on the BSE-500 index and the yield on the 91 days Treasury bill is the surrogate for risk free rate taken from the RBI website. The following models are estimated each month:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}Beta_{i,t} + \gamma_{2,t}LnSize_{i,t} + \gamma_{3,t}LnBM_{i,t} + \gamma_{4,t}IVOL_{i,t} + \varepsilon_{i,t+1} \quad (1)$$

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}Beta_{i,t} + \gamma_{2,t}LnSize_{i,t} + \gamma_{3,t}LnBM_{i,t} + \gamma_{4,t}IVOL_{i,t} + \gamma_{5,t}IVOL^2_{i,t_{i,t}} + \varepsilon_{i,t+1} \quad (2)$$

As it is evident from the subscripts, this is a predictive model in the sense that the conditioning variables in a month are used to predict returns in the next month. This is equivalent to an E/H/M (E for estimation, H for holding and M for moving forward) plan of 1-1-1 where numbers represent the month. This is in line with the Ang et al.'s (2009) methodology. The dependent variable consists of excess monthly returns of stocks. These variables are computed for all stocks. Since the sample period has 170 months, we have 170 cross-sections of data. At the beginning of the sample period, the number of stocks counted 287 and at the end it was 496. The average number of stocks in the cross-sectional regressions was 388. Each month cross-sectional regressions are run on the lagged variables using quantile and LS regressions and thus, we have a time series of 170 coefficients. The averages of the coefficients and their *t*-statistics are computed to provide the standard Fama and Macbeth (1973) test for non-zero risk premium.

3. Empirical Findings

Before applying the quantile regression, we verified that the returns are skewed with a fait tail. Table 1 and 2 present the findings from the quantile regression for the model 1 and 2 respectively. The main variable of our interest is the coefficient of *IVOL* in the two models. The pattern of the coefficients of *IVOL* in the two models is similar. It is negative and significant at the lowest quantile and positive significant at the highest quantile. The coefficient of IVOL increases from -1.33 for the quantile 0.1 to 1.38 for the quantile 0.9. The coefficient passes through zero between the quantile 0.5 and 0.6. The last columns of the Tables show the estimates from the LS regressions. The coefficient of IVOL is positive yet statistically insignificant in both the models. Since the coefficients of IVOL are of opposite signs at the extreme quantiles, the LS estimates are bound to be insignificant. This perhaps explains why the LS coefficients of *IVOL* in the two models are insignificant. The upward trend in the intercept signifies the unanticipated returns at the higher quantiles.

The marginal effect of beta is also similar to *IVOL*, it increases from quantile 0.1 to quantile 0.9. The coefficients of beta increases from -0.13 for the quantile 0.1 to 0.79 for the quantile 0.9. However, most of the the coefficients of beta lack statistical significance. The marginal effect of *LnSize* is lowest and significant at the upper quantile and the coefficients of *LnBM* are positive across the quantiles. Among all the factors considered here, the book-to-market effect is most pervasive. These both findings (negative size effect and positive value effect) are in conformity with the existing literature (Aziz & Ansari, 2014; Das, 2015).

$IVOL^2$ in the model 2 is the variance version of the idiosyncratic risk. It is meant to capture the non-linearity in the relation. The inclusion of the $IVOL^2$ in the model does not affect the relationship between other variables and excess stock returns. The coefficients of the predictor variables are plotted in Figure 1. The effects of both the *IVOL* and $IVOL^2$ are stronger at the extreme quantiles. The LS coefficient of *IVOL* is positive but insignificant and the LS coefficient of $IVOL^2$ is negative and insignificant. 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. These results are in conformity with the findings of Nath and Brooks (2015) in the Australian stock market.

Table 1

Fama-Macbeth estimates from quantile and LS regressions

	Quantile									
Variable	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	LS
c	-8.2150 (-11.6002)	-4.8070 (-6.7460)	-2.2720 (-3.2718)	-0.1770 (-0.2379)	2.1172 (2.6404)	4.7491 (5.4493)	8.2839 (8.3023)	13.0903 (11.1189)	22.4856 (14.8866)	6.3114 (5.7504)
β	-0.1330(-0.5055)	-0.1930 (-0.7348)	-0.1470 (-0.5439)	-0.0800 (-0.2809)	0.1222 (0.4177)	0.2442 (0.8082)	0.4853 (1.5187)	0.7620 (2.2632)	0.7998 (2.1663)	0.1745 (0.5648)
LnSize	0.1868 (2.5148)	0.0861 (1.1214)	0.0157 (0.2308)	-0.0500(-0.7017)	-0.1530 (-1.9601)	-0.2800 (-0.3.3436)	-0.4800 (-4.9201)	-0.7910 (-6.8759)	-1.4440 (-9.7731)	-0.6010(-5.1835)
LnBM	0.6720 (4.1659)	0.3993 (2.6318)	0.3272 (2.3015)	0.3005 (2.1465)	0.2766 (1.9688)	0.2648 (1.7662)	0.2718 (1.6290)	0.2890 (1.5209)	0.3051 (1.2870)	0.6731 (3.8443)
IVOL	**-1.3352 (-14.2137)**	**-0.9137 (-11.8989)**	**-0.6506 (-9.25247)**	**-0.4066 (-5.8531)**	**-0.1794 (-2.4528)**	0.0924 (1.1515)	**0.3583 (3.9597)**	**0.7936 (6.5511)**	**1.3896 (8.8744)**	0.018 (0.1850)
Adj. R^2	0.0582	0.0508	0.0488	0.0484	0.0484	0.0495	0.0535	0.0607	0.0792	0.0787

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:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} Beta_{i,t} + \gamma_{2,t} LnSize_{i,t} + \gamma_{3,t} LnBM_{i,t} + \gamma_{4,t} IVOL_{i,t} + \varepsilon_{i,t+1}$$

Numbers in bold denote significance at 5% or better.

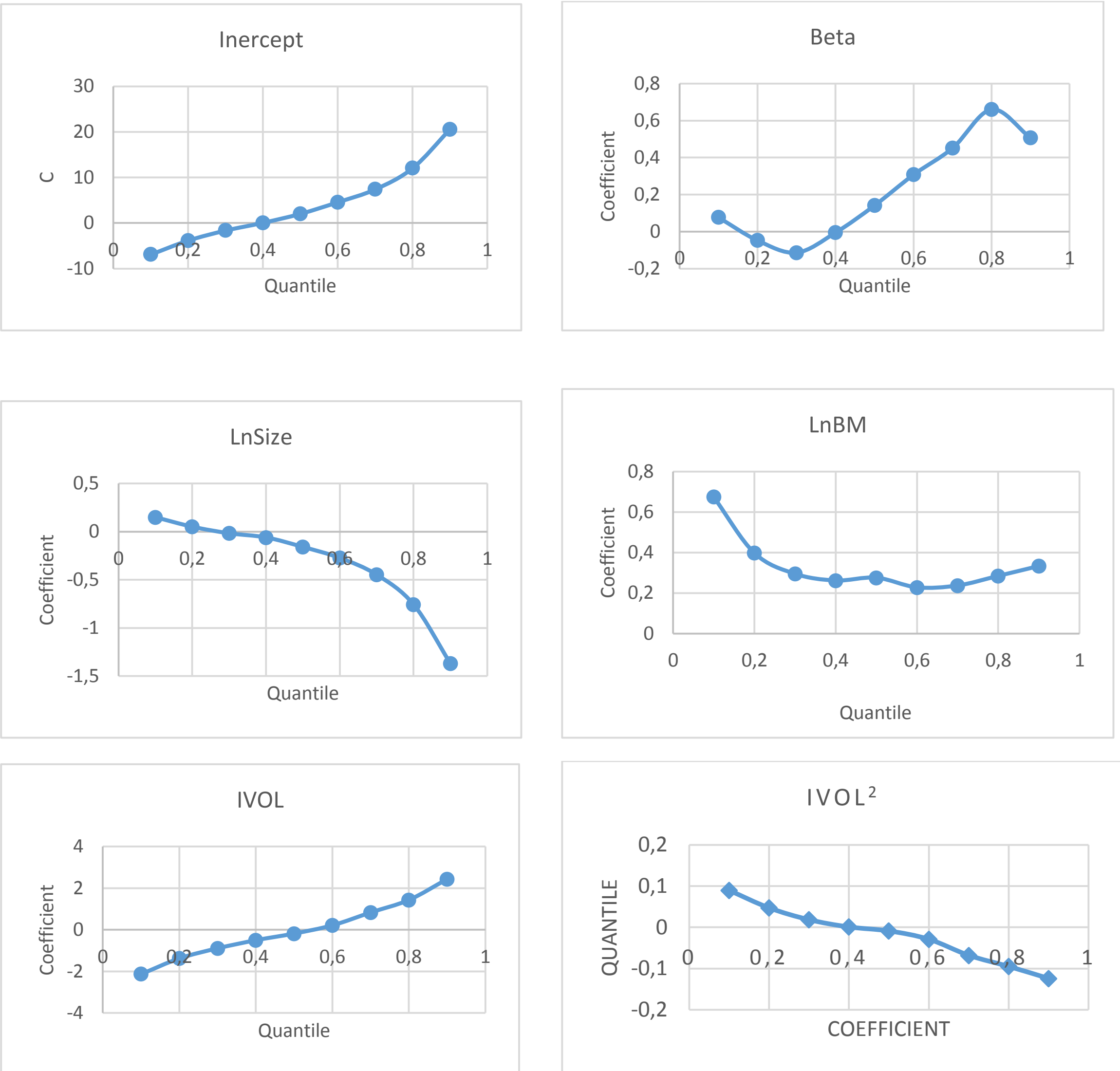
Table 2 Fama-Macbeth estimates from quantile and LS regressions

	Quantile									
Variable	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	LS
c	-6.8990 (-10.0408)	-3.843 (-5.9418)	-1.6430 (-2.5655)	0.0557 (0.0835)	2.0188 (2.8201)	4.5651 (5.8169)	7.3853 (8.1090)	12.0351 (10.9035)	20.5713 (14.7103)	5.9949 (5.3372)
β	0.0765 (0.2903)	-0.0480 (-0.1869)	-0.1140 (-0.4466)	-0.0058(-0.0209)	0.1412 (0.4949)	0.3079 (1.0549)	0.4520 (1.4573)	0.6609 (2.0128)	0.50660 (1.4218)	0.2091 (0.7022)
LnSize	0.1485 (1.9559)	0.0501 (0.7410)	-0.0180 (-0.2598)	-0.0610 (-0.8581)	-0.1360 (-1.8118)	-0.2740 (-3.3974)	-0.4480 (-4.7606)	-0.7570 (-6.7423)	-1.3700 (-9.6491)	-0.5850 (-5.1394)
LnBM	0.6742 (4.2085)	0.3978 (2.7311)	0.2953 (2.1336)	0.2619 (1.9287)	0.2756 (1.9557)	0.2283 (1.5109)	0.2370 (1.4864)	0.2843 (1.5240)	0.3330 (1.4518)	0.6702 (3.9294)
IVOL	**-2.1278 (-11.4119)**	**-1.3739 (-8.1202)**	**-0.8894 (-5.4227)**	**-0.5011 (-3.0150)**	-0.1819 (-1.0625)	0.2145 (1.1794)	**0.8312 (4.0194)**	**1.4327 (5.8184)**	**2.4338 (7.6122)**	0.1679 (0.6213)
$IVOL^2$	**0.0897 (4.1624)**	**0.0472 (2.2774)**	0.0184 (0.9695)	0.0007 (0.0361)	-0.0089 (-0.4490)	-0.0291 (-1.3317)	**-0.0681 (-2.6177)**	**-0.0951 (-3.2436)**	**-0.1242 (-3.3436)**	-0.0267 (-1.0285)
Adj. R^2	0.0646	0.0568	0.0542	0.0536	0.0536	0.0545	0.0585	0.0665	0.0866	0.0868

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:

$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}Beta_{i,t} + \gamma_{2,t}LnSize_{i,t} + \gamma_{3,t}LnBM_{i,t} + \gamma_{4,t}IVOL_{i,t} + \gamma_{5,t}IVOL^2_{i,t_{i,t}} + \varepsilon_{i,t+1}$ Numbers in bold denote significance at 5% or better.

Figure 1 through Figure 6. Quartile dependent effects of idiosyncratic volatility and other characteristics on excess stock returns.



The graphs in these figures 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 quantiles.

4. Conclusion

LS regressions are statements about how the mean of the dependent variable co-vary with the independent variables. However, this relation may be different at various levels of the conditional distribution. Using quantile regressions (Koenker & Bassett, 1978), we show that the price of idiosyncratic volatility is not homogeneous across the quantiles of the 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 the idiosyncratic risk. Returns at the median, however, are not significantly related to the idiosyncratic risk, a result similar to LS estimates. However, it is worth noting that the results may be sensitive to alternative estimation and rolling windows for computing IVOL.

Similarly, the size-return and value-return relations are also quantile dependent. The negative size effect is more pronounced at the upper quantile and the positive value effect is stronger at the lower quantile of the distribution. This study highlights the importance of testing the pervasiveness of an anomalous effect across different quantiles of the distribution. An effect which exists at the mean level (LS regression) may not be present at the extreme tails of the distribution and vice versa.

References

Ang, A., Hodrick, R. J., Xing, Y. & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, 61(1), p. 259-299.

Ang, A., Hodrick, R. J., Xing, Y. & Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further US evidence. *Journal of Financial Economics*, 91(1), p. 1-23.

Aziz, T., & Ansari, V. A. (2014). Size and value premiums in the Indian stock market. *Pacific Business Review International, 7*(4), p. 74-80.

Barnes, M. L. & Hughes, A. W. (2002). A quantile regression analysis of the cross section of stock market returns. Available from: https://www.bostonfed.org/economic/wp/wp2002/wp022.pdf [Accessed: 2nd December 2014]

Brockman, P., Schutte, M. G., & Wu, W. (2009). Is idiosyncratic risk priced? The international evidence. Available from: http://ssrn.com/abstract=1364530 [Accessed: 2nd December, 2014]

Buchinsky, M. (1998). Recent advances in quantile regression models: a practical guideline for empirical research. *Journal of Human Resources*, 33(1), 88-126.

Das, S. (2015). Empirical evidence of conditional asset pricing in the Indian stock market. *Economic Systems, 39*(2), p. 225-239.

Drew, M., & Veeraraghavan, M. (2002). Idiosyncratic volatility and security returns: evidence from the Asian region. *International Quarterly Journal of Finance, 2*(1-4), 1-14.

Fama, E. F. & Macbeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, 81(3), p. 607-636.

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics*, 91(1), p. 24-37.

Koenker, R. & Bassett, J. G. (1978). Regression quantiles. *Econometrica: Journal of Econometric Society*, 46(1), p. 33-50.

Levy, H. (1978). Equilibrium in an Imperfect Market: A Constraint on the Number of Securities in the Portfolio. *The American Economic Review*, 68(4), p. 643-658.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The Journal of Finance*, 42(3), p. 483-510.

Nath, H. and Brooks, R. D. (2015). Assessing the idiosyncratic risk and stock returns relation in heteroskedasticity corrected predictive models using quantile regression. *International Review of Economics and Finance*. Vol. 38, p. 94-111.