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Idiosyncratic Risk Matters: Evidence from India

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For a sample of US firms, Goyal and Santa-Clara (2003) find that the average stock variance is positively associated with higher returns in the subsequent month. The authors interpret the evidence as supporting the hypothesis that idiosyncratic risk matters. Several subsequent papers employing different methodologies present evidence conflicting with the findings of Goyal and Santa-Clara. We adopt the approach of Goyal and Santa-Clara in the Indian context. The results we obtain when we measure volatility on a monthly basis do not offer support for evidence documented in Goyal and Santa-Clara. However, when we compute volatility over weekly intervals, we find results consistent with those presented by Goyal and Santa-Clara. Our results in the Indian context are in line with the generally supportive evidence obtained using international data about the positive relationship between conditional volatilities and expected returns with an important difference. Supporting the arguments of Andersen, Bollerslev, Diebold, and Labys (2003), our results suggest that higher frequency data is more powerful in predicting future volatilities.

JEL Codes: G11, G12 and G17

1. Introduction

The relationship between risk and expected returns has been a subject of great interest to researchers in finance and related fields. The classical finance theory posits that risk is positively associated with future returns. Well-known asset pricing models (for example, the capital asset pricing model) predict that future stock returns depend on the systematic risk of the stock measured by its market beta. In these formulations, idiosyncratic risk ceases to matter because it can be eliminated in a well-diversified portfolio.

However, empirical research reveals that for a variety of reasons investors hold under-diversified portfolios. Levy (1978) lists studies which show that individual investors are highly undiversified. More recently, Goetzmann and Kumar (2008) find that individual investors in the US are under-diversified and the level of under-diversification is higher for younger, low-income, less-educated, and less-sophisticated investors. Collectively, these studies cast serious doubts about the validity of one of the main assumptions behind most asset pricing models: that idiosyncratic risk should not be priced.

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Empirical evidence from the US data about the relationship between conditional volatilities and expected returns is mixed with papers in the extant literature arguing that idiosyncratic risk is either positively related, or not significantly related, or even negatively related to expected returns. Evidence based on international data, however, is generally supportive of a positive relationship between firm-specific risk and expected returns. Most of the papers examining the relationship use monthly intervals to measure volatilities and expected returns.

Our paper aims to provide additional international evidence on the relationship between idiosyncratic risk and expected returns. We use data on Indian equities to construct our measures of idiosyncratic risk and returns. In the context of forecasting volatilities, Andersen et al. (2003) argue that availability of higher frequency data than just monthly or quarterly data improves the forecasting performance for two main reasons. First, there is greater predictability in the higher frequency data. Second, information in the higher frequency data is useful for predicting at longer – monthly or quarterly – horizons. Since extant research uses realized volatilities as a proxy for conditional volatilities, use of higher frequency data, weekly in our analyses, than just the monthly horizons may be more appropriate.

Our results for 24 years of data indicate that there is no evidence to support the hypothesis that idiosyncratic risk and future returns are related when volatilities and future returns are computed over monthly intervals. The conclusion, however, changes when we use weekly intervals to compute volatilities and future returns. The co-efficient on the volatility is significant in all the regressions at under 10-percent level. Our results differ from the evidence provided in other international studies by showing that the frequency of data is important in predicting future volatilities. Several international studies examining the relationship between idiosyncratic risk and expected returns find that idiosyncratic risk is important for expected returns (Estrada 2000; Harvey 2000; Brockman et al. 2009; Lee et al. 2009). We do not find such a relationship for monthly volatilities, consistent with the evidence presented in some US studies. However, when we use weekly volatilities, we find a positive relationship between idiosyncratic risk and expected returns.

Our results are consistent with the argument in Andersen et al. (2003) and contribute to the current literature on the importance of idiosyncratic risk for expected returns. We show that whether volatilities are measured at monthly or weekly intervals has an impact on the relationship between idiosyncratic risk and returns. To our knowledge, this issue has not been addressed in prior research. The paper is organized as follows. Section 2 presents a review of the relevant literature and includes our hypotheses. In section 3, we describe the data, present the method by which idiosyncratic risk is calculated, and present summary statistics. Section 4 presents the results of our analyses. We conclude in section 5.

2. Literature Review and Hypotheses

The relationship between idiosyncratic risk and expected returns has been of considerable interest to researchers in finance since the development of the capital asset pricing model (CAPM). Several papers have presented models which take into account the possibility that investors may not behave according to assumptions made by asset pricing models, such as CAPM. These papers show that in a scenario where there is departure from the assumptions of traditional asset pricing models, the level of idiosyncratic risk may have an effect on the level of expected returns.

Mayers (1976) explores the effect of nonmarketable assets and market segmentation on asset prices. In his model, Mayers finds that under the assumption of constant relative risk aversion less than or equal to one, asset prices are lower given nonmarketable assets and market segmentation. Levy (1978) allows investors to hold portfolios with some given number of securities. He finds that individual stock variance is important in his model. Merton (1987) models capital market equilibrium in an incomplete information setting and finds that less well-known stocks with fewer investors will tend to have larger expected returns and that expected returns depend on both market risk and total variance. Malkiel and Xu (2006) present a model in which if a group of investors does not hold the market portfolio, remaining investors will also not be able to hold the market portfolio and idiosyncratic risk may become important. Finally, Campbell et al. (2001) list several arguments for the importance of idiosyncratic risk to expected returns. These arguments include: a lack of investor diversification from not following the approach recommended by financial theory or due to constraint imposed by compensation policy; investors may diversify by holding a portfolio of thirty stocks or fewer which depending on the volatility of individual stocks may not be adequate; arbitrageurs who exploit mispricing of individual securities are exposed to idiosyncratic risk; idiosyncratic volatility becomes important in event studies; and option price on a stock depends on total volatility of returns which is made up of volatilities attributable to both the market and to a specific firm.

Turning attention to the empirical treatment of the issue, we note several papers which show that the relationship between idiosyncratic risk and expected returns is either positive, or non-existent, or even negative. These studies are based on US data and use monthly intervals. French et al. (1987) find a positive relationship between the expected risk premium on common stocks and predictable level of volatility. Lehmann (1990) finds that the residual risk has a significant co-efficient when he corrects for problems in the statistical methods used in prior studies. In a recent paper, Goyal and Santa-Clara (2003) (hereafter, GSC) show that average monthly stock variance is positively associated with higher returns in the subsequent month. Fu (2009) uses exponential GARCH models to estimate expected idiosyncratic volatilities and finds a positive relationship between the conditional idiosyncratic volatilities and expected returns. Malkiel and Xu (2006) control for factors like size, book-to-market, and liquidity and conduct their analyses for US and Japanese equities to find that idiosyncratic volatility is more important than β, the systematic risk, or the size measure in explaining the cross-section of returns. Huang et al. (2010) also document a positive relationship between conditional idiosyncratic volatility and expected returns.

Longstaff (1989) observes a consistently negative but insignificant relationship between variance and returns for the overall period 1926-1985 and for the three sub-periods in which he divides his sample. Bali et al. (2005) re-examine the relationship between average stock volatility and future returns to conclude that the results in GSC were driven because of small stocks traded on the NASDAQ and the GSC results disappear when instead of using equal weights to compute average volatility market values are used as weights. Wei and Zhang (2005) also examine the issue and find that the results in GSC are driven mainly by the data in the 1990s as the relationship between idiosyncratic risk and future returns disappears when they extend the sample to 2002. Wei and Zhang also raise the possibility that combining equally-weighted average volatility with value-weighted average return may be behind the results reported in GSC. Bali and Cakici (2008) employ a portfolio approach and use various different measures of idiosyncratic volatility, alternative weighting schemes, different breakpoints for the construction of portfolios, and two different samples to find no robust relationship between idiosyncratic volatility and expected returns. Finally, Ang et al. (2006) find that stocks with high idiosyncratic volatilities have low average returns, which is the opposite of that documented in GSC.

To summarize, the debate over the relationship between the idiosyncratic risk and expected returns has not been settled in the empirical literature when employing US data. We next turn to the international evidence on the relationship between idiosyncratic risk and expected returns. Estrada (2000) uses a database of 28 emerging economies and finds that idiosyncratic risk is significant in explaining the cross-section of returns. Harvey (2000) uses data from 47 different countries to construct 18 different measures of risk. He finds that collectively idiosyncratic risk is positive in explaining the cross-section of expected returns. Brockman et al. (2009) examine the relationship across 44 countries from 1980 to 2007. They find a significantly positive relationship and attribute it to under-diversification. Lee et al. (2009) obtain data for G-7 countries over the 1990 to 2000 time period and find a clear positive relationship between idiosyncratic volatility and expected returns.

From the above discussion it appears that while in the US the evidence on the relationship between the idiosyncratic risk and future returns is decidedly mixed, the international evidence seems to be weighted more in favor of a positive relationship. Most of the papers mentioned above use monthly intervals to measure volatilities and expected returns. We now present our two hypotheses to examine the relationship between idiosyncratic risk and expected returns for different measurement intervals. We use data on Indian equities to test the following hypotheses:

H1: There is a significant relationship between idiosyncratic risk and expected returns over monthly horizons.

H2: There is a significant relationship between idiosyncratic risk and expected returns over weekly horizons.

In the next section, we describe our data and the methodology and present our results in the section that follows.

3. Data

Our initial sample contained all the firms listed on the Bombay Stock Exchange (BSE) based in Mumbai, India. BSE is the oldest stock exchange in Asia and one of the largest, in terms of market capitalization, in the world with over 5,600 companies listed on the exchange as of March, 2015. We get all our data for BSE listed firms from the Prowess database maintained by the Center for Monitoring Indian Economy. The Prowess database is similar to the CRSP-Compustat merged database and is commonly used for exploring financial issues in the Indian context. To our knowledge, no other comparable database exists. The Prowess database contains daily information about stock prices and returns from 1990 onward. Therefore, our sample period starts at the beginning of January, 1990 and ends at the end of December 2013 resulting in a sample extending over 24 years. We follow GSC and compute the monthly and weekly stock variance using the approach of French, Schwert, and Stambaugh (1987).

$$V_t^i = \sum_{d=1}^{Dt} (r_{dt}^i)^2 + 2 \sum_{d=1}^{Dt-1} r_{dt}^j r_{d+1,t}^i,$$

Where r_{dt}^i is the return on stock i on the dth day in month t (week t) and D_t is the number of days in the month (the week). We conduct our analyses for the full sample spanning 24 years and the two subsamples consisting of 12 years each. We divide our sample in two subsamples because a perusal of the data reveals that in the early part of the sample, which includes observations from the 1990s, there are far fewer firms for which returns are available and many of these firms had zero returns on several days.

After computing the monthly or weekly volatility for a stock, we find the average stock volatility, $Vol,$ over a month or a week in two different ways by either attaching equal-weights or by using beginning of the period market values of the firms as weights. We compute both equally-weighted and value-weighted volatilities because Bali et al. (2005) find that the positive association between idiosyncratic risk and expected returns in GSC was driven mainly by small stocks traded on the NASDAQ and that the GSC relationship disappears when market values are used as weights to compute average stock volatilities.

In Table 1, Panel A (B), we present summary statistics for our data using monthly (weekly) intervals to calculate our variables. Although means and medians appear to be close for both monthly and weekly returns, there is evidence that our volatility measures are skewed to the right and have very high kurtosis. Returns in the subsequent month (week) are moderately skewed and have relatively lower kurtosis. Examination of the frequency distribution of volatilities and expected returns for monthly and weekly intervals also leads us to a conclusion consistent with the numbers reported in Table 1. We find strong skewness and fatter tails for volatilities for both the monthly and weekly intervals. Returns in the subsequent month (week) appear to suffer far less from the problems. Andersen et al. (2001) also find high levels of skewness and kurtosis for realized variance computed from five-minute intraday returns and much lower levels of skewness and kurtosis for daily returns for their sample of 30 Dow Jones Industrial Average stocks. The univariate statistics and graphical plots for volatilities suggest that there are periods of very high volatilities indicating strong heteroscedasticity in the data. Consequently, we employ Newey-West estimates of the variance-covariance matrix to compute *t*-statistics to control for heteroscedasticity and serial-correlations.

Table 1: Summary Statistics

Panel A: Monthly volatilities and returns

	Mean	Median	Min	Max	Skew	Kurt
R_t^{ew}	0.05	0.05	-0.32	0.65	0.68	1.88
R_t^{vw}	0.02	0.02	-0.28	0.65	1.08	5.67
Vol_{t-1}^{ew}	0.06	0.04	0.00	0.36	3.06	13.10
Vol_{t-1}^{vw}	0.02	0.01	0.00	0.33	5.75	44.39

Panel B: Weekly volatilities and returns

	Mean	Median	Min	Max	Skew	Kurt
R_t^{ew}	0.01	0.01	-0.19	0.29	0.34	1.62
R_t^{vw}	0.00	0.01	-0.16	0.20	-0.10	1.80
Vol_{t-1}^{ew}	0.02	0.01	0.00	1.51	26.04	809.90
Vol_{t-1}^{vw}	0.01	0.00	0.00	0.11	6.15	70.59

In Panels A and B of Table 2, we present the correlations for monthly and weekly intervals. For the monthly volatilities and returns, there is no statistically significant correlation between the equally-weighted returns and volatilities whether equally- or value-weighted. Value-weighted returns are positively correlated with value-weighted returns but not with equally-weighted returns. When we turn to weekly intervals, we observe that both the equally-weighted and value-weighted returns are positively correlated with equally-weighted and the value-weighted volatilities. The above results provide preliminary evidence against our hypothesis 1 but in favor of hypothesis 2 that there is a relationship between firm-specific risk and expected returns at the weekly horizon but not at the monthly horizon.

Table 2: Correlations

Panel A: Monthly volatilities and returns

	R_t^{ew}	R_t^{vw}	Vol_{t-1}^{ew}	Vol_{t-1}^{vw}
R_t^{ew}	1.00	0.86***	0.02	0.06
R_t^{vw}		1.00	0.08	0.14**
Vol_{t-1}^{ew}			1.00	0.75***
Vol_{t-1}^{vw}				1.00

Panel B: Weekly volatilities and returns

	R_t^{ew}	R_t^{vw}	Vol_{t-1}^{ew}	Vol_{t-1}^{vw}
R_t^{ew}	1.00	0.80***	0.08***	0.07***
R_t^{vw}		1.00	0.05*	0.09***
Vol_{t-1}^{ew}			1.00	0.58***
Vol_{t-1}^{vw}				1.00

*, **, ***Significant at 10%, 5%, and 1% level respectively

In Table 3, we examine autocorrelations in volatilities to find out the persistence in volatilities. Persistent becomes an important issue because we are using realized volatilities as a proxy for conditional volatilities. The relationship between risk and returns is contemporaneous; the returns in a period should depend on the risk in the same period. However, risk (volatilities in our case) is not observable and we are using realized volatilities in a month as a proxy for the next month's volatilities. Andersen et al. (2003) argue that higher frequency data is more powerful in predicting the future. Consistent with their arguments, we find that weekly value-weighted volatilities are more persistent than monthly value-weighted volatilities, although the autocorrelations for monthly equally-weighted volatilities are higher than those for weekly value-weighted volatilities. We appeal to Bali et al. (2005) who find that equal-weighting of volatilities is not appropriate and who also advocate the use of value-weighting to conclude that there is more persistence in the weekly data.

Table 3: Autocorrelations in volatilities. t-1, t-2, and t-3 are the first, second, and third lagged values of the variable.

	Vol_{t-1}^{ew}	Vol_{t-2}^{ew}	Vol_{t-3}^{ew}		Vol_{t-1}^{vw}	Vol_{t-2}^{vw}	Vol_{t-3}^{vw}
Monthly							
Vol_t^{ew}	0.28	0.24	0.13	Vol_t^{vw}	0.21	0.19	0.09
***p*-value**	0.00	0.00	0.04		0.00	0.00	**0.13**
Weekly							
Vol_t^{ew}	0.09	0.08	0.06	Vol_t^{vw}	0.32	0.28	0.26
***p*-value**	0.00	0.01	0.03		0.00	0.00	0.00

4. Results

To examine the relationship between average returns and average volatility, we employ the following specification:

$$R_t = \alpha + \beta * Vol_{t-1} + \varepsilon_t,$$

Using ordinary least square (OLS) regressions. We run a number of regressions where the returns and volatilities are a mix of equally-weighted and value-weighted returns and volatilities. To test whether recent market events have a bigger effect on the behavior of investors, we also run the OLS regressions where we use weekly returns and volatilities.

Of particular interest to us is the slope, β, of the regression. If idiosyncratic risk is important for pricing of stocks, a positive relationship between returns and lagged volatilities should exist. Empirically, a positive β will be evidence in support of idiosyncratic risk positively affecting future returns and will support our stated hypotheses. An insignificant co-efficient (β) will be consistent with the idea that idiosyncratic risk is not priced. Consistent with GSC, to account for heteroscedasticity and autocorrelation in returns, we report only the *t*-statistics computed using Newey-West estimator of the variance-covariance matrix.

In Table 4, we provide results of our various regressions when we use monthly volatilities and returns. The monthly results do not provide compelling results in favor of volatility affecting expected returns and lead us to reject our first hypothesis (H1). In the regressions using monthly volatilities and returns, we find significant β only in the case when volatilities and returns are calculated as value-weighted averages. However, this relationship is not significant for the second half of the subsample. The first subsample, which shows a significant relationship, has very few firms for which the data are available and many of the returns are zeros. Therefore, we conclude from the results that there is no conclusive evidence of a relationship between idiosyncratic risk and expected returns when we use monthly intervals for computing volatilities and future returns.

Table 4: Regressions of monthly returns on lagged volatility. Superscript *ew* implies that the variable is constructed using equal-weights and *vw* value-weights.

Monthly Regressions			
$R_t^{ew} = \alpha + \beta * Vol_{t-1}^{ew} + \varepsilon_t$	α	β	R^2
Full Sample	0.046	0.055	0.0003
	[3.92]	[0.30]	
1990-2001	0.044	0.157	0.003
	[2.37]	[0.80]	
2002-2013	0.056	-0.199	0.0028
	[3.24]	[-0.64]	
$R_t^{vw} = \alpha + \beta * Vol_{t-1}^{ew} + \varepsilon_t$			
Full Sample	0.015	0.196	0.0065
	[1.65]	[1.21]	
1990-2001	0.013	0.312	0.0162
	[0.84]	[1.68]	
2002-2013	0.026	-0.115	0.0023
	[2.27]	[-0.54]	
$R_t^{vw} = \alpha + \beta * Vol_{t-1}^{vw} + \varepsilon_t$			
Full Sample	0.014	0.512**	0.0184
	[2.07]	[2.18]	
1990-2001	0.014	0.662***	0.033
	[1.04]	[3.25]	
2002-2013	0.022	-0.101	0.0005
	[2.77]	[-0.32]	

*, **, ***Significant at 10%, 5%, and 1% level respectively

In Table 5, we present the evidence to examine the issue by computing volatilities and returns using weekly frequencies. Specifically, we compute average weekly stock volatility (where a week is defined as Monday through Friday) and average return in the subsequent week. Using weekly data has a marked impact on our results. As shown in the table, there is a positive and significant relationship between average volatility and future returns, thus supporting our second hypothesis (H2). The relationship holds whether we use equally-weighted or value-weighted volatilities and returns and is particularly stronger in the second half of our sample. It is possible that there are systematic differences between financial and non-financial firms. To check the robustness of our results, we repeat our analyses separately for financial and non-financial firms. We obtain qualitatively similar results for financial and non-financial firms suggesting that the relationship is robust.

Table 5: Regressions of weekly returns on lagged volatility. Superscript *ew* implies that the variable is constructed using equal-weights and *vw* value-weights.

Weekly Regressions			
$R_t^{ew} = \alpha + \beta * Vol_{t-1}^{ew} + \varepsilon_t$	α	β	R^2
Full Sample	0.012	0.092**	0.0071
	[5.74]	[2.01]	
1990-2001	0.010	0.241*	0.0112
	[2.39]	[1.89]	
2002-2013	0.011	0.063***	0.0067
	[4.25]	[3.02]	
$R_t^{vw} = \alpha + \beta * Vol_{t-1}^{ew} + \varepsilon_t$			
Full Sample	0.004	0.040***	0.0024
	[2.84]	[3.20]	
1990-2001	0.003	0.057	0.001
	[1.03]	[0.68]	
2002-2013	0.004	0.038***	0.0048
	[2.45]	[8.20]	
$R_t^{vw} = \alpha + \beta * Vol_{t-1}^{vw} + \varepsilon_t$			
Full Sample	0.002	0.547***	0.0073
	[1.20]	[2.85]	
1990-2001	0.000	0.653*	0.0075
	[0.02]	[1.89]	
2002-2013	0.002	0.517***	0.0082
	[1.70]	[2.56]	

*, **, ***Significant at 10%, 5%, and 1% level respectively

The results presented above differ from the evidence provided by other studies on international data by showing that the frequency of data is also important in predicting future volatilities. Several international studies (Estrada 2000; Harvey 2000; Brockman et al. 2009; Lee et al. 2009) have examined the relationship between idiosyncratic risk and expected returns and find support for the hypothesis that they are positively related. We, on the other hand, fail to find such a relationship for our sample using the monthly data which is consistent with the evidence presented in some US studies. However, when we use weekly volatilities, we find a positive relationship between idiosyncratic risk and expected returns. Our research is the first one to explore the differences between monthly and weekly volatilities. Consistent with in Andersen et al. (2003), our results show that use of higher frequency data leads to better predictability of future volatilities.

5. Conclusion

Modern asset pricing theories posit a relationship between only the systematic risk and expected returns. In these models idiosyncratic risk is diversified away and is not priced. There exists evidence, however, that individual investors are highly under-diversified. Deviations from the assumptions underlying most modern-asset-pricing models may lead to investors putting a price on the unsystematic portion of a stock's risk. Several theoretical papers have examined this issue and the empirical evidence from the US market is mixed when using monthly volatilities and returns. International evidence appears to favor a positive relationship between idiosyncratic risk and expected returns.

We examine the issue of whether idiosyncratic risk is priced in the Indian context by computing returns and volatilities over two different horizons, monthly and weekly. Our results suggest that while levels of monthly volatilities have no impact on future returns, recent levels of volatilities have a significant impact on subsequent returns. It is pertinent to note that consistent with other papers in this stream of finance literature, we use realized volatilities as our proxy for conditional volatilities. This could be justified by appealing to the evidence which suggests that volatilities exhibit persistence and mean reversion (Engle and Patton 2001). Moreover, any potential problem arising from using realized volatilities to proxy for conditional volatilities is mitigated by the fact that we also use shorter horizons for computing volatilities and returns.

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