Relationship between cross sectional volatility and stock returns: Evidence From India

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Abstract

This paper examines the relationship between cross sectional volatility (CSV) and stock returns for India. The authors use daily returns for 493 companies that form part of BSE-500 index from December 1993 to June 2010. Two measures of CSV are adopted-systematic and idiosyncratic. Systematic volatility (SV) is estimated using French, Schwert and Stambaugh (1987) and Schwert and Seguin (1990). While unsystematic volatility (UV) is estimated by computing residual variance for sample stocks using the errors of CAPM model. The authors find that high SV portfolios outperform low SV portfolios which implies dominance of speculative behavior in stock markets. The CAPM and Fama-French model are unable to fully absorb the returns on high SV portfolio which are explained by introduction of an additional CSV factor constructed on lines of Ang, Hodrick, Xing and Zhang (2003). The CSV factor possibly contains information about volatility persistence which is priced by the market. The high UV portfolios perform much better than low UV portfolios which may be consistent with finance theory that suggests compensation for imperfect diversification. The FF model is able to explain the returns on UV sorted portfolios owing to the fact that high UV portfolios comprize small size and low P/B stocks. The findings are important for market players and the present study contributes to the asset pricing anomaly literature especially for emerging markets.

Keywords: systematic volatility, unsystematic volatility, CAPM, Fama-French model, company size.
JEL Classification: C46, C51, C52, G11, G12, G14.

Introduction

Stock market volatility has for long been an issue of interest in financial literature. A wide variety of research has been done on volatility for mature as well as emerging stock markets (see Merton, 1973; Schwert, 1989; Glosten et al., 1993; Campbell et al., 2001; Ederington and; Adrian and Rosenberg, 2008; Sehgal and Vijayakumar, 2008).

The effect of stock market volatility on stock returns has for long been a subject of dispute. French et al. (1987) found a positive relation between expected risk premium and predictable volatility. But Glosten et al. (1993) report a negative relation between risk and return. While many researchers have studied the time-series relationship between market volatility and expected return on the market, the issue of how cross-sectional volatility affects stock returns has received little attention. Moreover there is a lot of disagreement on the factors explaining the cross sectional variability of returns. The Capital Asset Pricing Model developed by Sharpe (1964), Lintner (1965) and Black (1972) postulates that the returns of a stock can be explained by its exposure to systematic market risk factor and that there is a static linear relationship between the two variables. But many studies have questioned the model and accordingly there are several empirical contradictions of the CAPM. Prominent CAPM anomalies are size (Banz, 1981), book-to-market value (Stattman, 1980; Rosenberg, Reid and Lanstein, 1985), leverage (Bhandari, 1988), earning price ratio (Basu, 1983), return reversals (De Bondt and Thaler, 1985, 1987) and return momentum (Jegadeesh and Titman, 1993). Fama and French (FF) (1993) showed that beta alone does not explain the cross section of average stock returns during 1963-1990 period for the US market. They developed a three-factor model that added two additional factors namely firm size and book to market value to CAPM. Fama and French (1996) demonstrate that their multifactor model explains almost all prominent CAPM anomalies with the exception of stock momentum. Hence, the FF model has posed serious challenge to CAPM and is now an acceptable performance benchmark in empirical literature.

One important stock return anomaly which has received less focus in research is cross-sectional volatility. Cross-sectional volatility measures the dispersion of stock returns at one point in time. Empirical literature deals with two forms of cross sectional volatility: systematic and unsystematic. Systematic volatility is the cross sectional variation in stock returns owing to their sensitivity to market volatility measure (see Ang, Hodrick, Xing and Zhang, 2003). Unsystematic volatility, on the other hand, is measured by the residual variance of stocks in a given period by using error terms obtained from a standard asset pricing model such as CAPM or the FF model (see Cutler, 1989). Whether CAPM and FF can explain this or not is an empirical question. A large body of literature[1] is available dealing with other asset pricing anomalies. Even in Indian context sev-

[1] Banz (1981), Stattman (1980), Bhandari (1988), Jegadeesh and Titman (1993), Basu (1983), Fama and French (1993).

eral studies have dealt with various return anomalies[1]. However there is very limited work available on cross-sectional volatility for global capital markets.

Hwang and Satchell (2001) introduced GARCH model with cross-sectional market volatility called GARCHX model. Using US and UK data, they found that volatility of daily returns can be better specified with GARCHX models but these models are not necessarily better than conventional GARCH models for forecasting purposes. GARCHX models explain what proportion of market volatility is included in individual stock volatility. They found that 12% to 16% of individual stock's conditional volatility can be explained by market volatility. Ang, Hodrick, Xing and Zhang (2003) examined how volatility risk, both at the aggregate market and individual stock level, is priced in the cross-section of expected stock returns. Their sample period is from January 1986 to December 2000 and they have used all stocks on AMEX, NASDAQ and NYSE. They found that stocks with high exposure to changes in systematic volatility earn low returns and stocks with high idiosyncratic volatility earn abysmally low returns. Their results were robust to controlling for size, value, liquidity, volume and momentum effects and this effect persisted in bull and bear markets, recessions and expansions and volatile and stable periods. In 2004, they again brought out a paper on this issue. Their results were similar to the previous study. But in this paper they also argued that the abysmally low average returns of high idiosyncratic volatility stocks cannot be explained by exposure to aggregate volatility risk.

Connolly and Stivers (2004) studied cross-sectional volatility (CSV) in the US stock market over the period 1985 to 1999. Their main goal was to study whether CSV conveys any reliable additional information about the future traditional volatility of both firm-level and portfolio-level returns, where additional information means information in addition to what is conveyed by the own-firm lagged return shocks and the lagged market-level return shocks. The study finds that CSV conveys additional information about a firm's future volatility as compared to the lagged market level return shocks. The result holds across time and across different portfolios. Rahman (2007) intend to study whether firm-level and industry-level cross-sectional volatility gives any additional information about future volatility of market level returns. Using data of daily Australian equity returns, he found that there is a positive relationship between cross-sectional volatility and future market level volatility. The study also finds that firm-level CSV has greater impact in comparison to industry level CSV on market level volatility. Moreover, CSV has a stronger impact in relatively stable market condition. A possible explanation for information content of CSV is that it reflects firm level/industry level information flows to the market that is autocorrelated. Information content of CSV is better as compared to that of stock turnover and aggregate company announcements. The paper finds that CSV significantly explains future market volatility even after considering the impact of stock turnover, company announcements and other omitted factor shocks in returns.

Ahmed (2009) used two multiple regressions to study the relationship between liquidity and expected returns. In the first regression he included only liquidity factor while in the second regression he included liquidity factor, momentum factors and Fama-French factors. Trading volume has been used as a proxy for liquidity. The study uses a sample of 174 firms, which are selected randomly over a period from 1995 to 2000. Information was extracted from KLSE. Its findings are that (1) the level of liquidity matters in explaining the expected stock returns; (2) Fama-French factors are also important in explaining the cross-sectional variation in stock returns; and (3) momentum factor persistently explains the cross-sectional variation in stock returns. Brooks, Li and Miffre (2009) studied the cross sectional variation in returns between portfolios sorted by size and book-to-market value. Their dataset comprised 100 size and B/M sorted portfolios of Fama and French (1992). They found that there is a strong positive correlation between returns of a portfolio and their time-varying volatilities, as captured by GARCH (1,1)-M model. They further found that neither the four macroeconomic factors-inflation, industrial production, the term structure and default spread nor the market capitalization and B/M value have any impact on the importance of conditional volatility in the cross sectional pricing of stocks.

In the Indian context, the empirical work on the relationship between cross-sectional volatility and returns is virtually absent.

The primary objective of the study is to fill this important gap in asset pricing literature. We specifically seek answers to the following questions:

- Are there any return differentials amongst portfolios sorted on the basis of systematic volatility?
- Are there any return differentials for unsystematic volatility sorted portfolios?
- Do the standard asset pricing models such as Capital Asset Pricing Model and Fama-French model capture the returns on volatility sorted portfolios?

[1] Sehgal and Ilango (2002), Sehgal and Ilango (2004), Sehgal and Tripathi (2005), Sehgal and Tripathi (2006), Sehgal and Jain (2011).

- Can any abnormal returns observed on volatility sorted portfolios, which are missed by CAPM and FF model, be explained by an additional liquidity factor as suggested by Amihud and Mendelson (1986)?
- Can the missed returns be explained by an additional Cross Sectional Volatility factor as proposed by Ang, Hodrick, Xing and Zhang (2003) and what is the possible economic interpretation of this factor?

The study is organized as follows. Section 1 describes data and their sources, section 2 deals with portfolios sorted on exposure to systematic volatility, while section 3 covers unsystematic volatility sorted portfolios. The last section contains summary, concluding remarks and investment policy observations.

1. Data

The data comprises of daily adjusted share prices[1] from December 1993 to June 2010 for 493 companies that form part of BSE-500 index in India. The sample companies account for more than 90 percent of the total market capitalization and trading activity. Hence the sample set is fairly representative of market performance. The daily adjusted share prices have been converted into daily percentage returns to make it suitable for further analysis. BSE-200 has been used as a surrogate for aggregate economic wealth. BSE-200 is a broad based value weighted market proxy which is constructed on the lines of Standard & Poor 500, USA.

Market capitalization (price times number of shares outstanding) has been used to construct size factor, price to book value ratio (which is the inverse of book to market value ratio) has been used to construct value factor and liquidity factor has been constructed using daily trading volume information for the sample stocks. Relevant data has been taken from Thomson Reuters *DataStream*. The implicit yield on 91-days Treasury bills has been used as a measure of risk free return for which data has been taken from Reserve Bank of India (RBI) website (http://www.rbi.org.in).

2. Portfolios sorted on exposure to systematic volatility

We perform our analysis in two parts: Part 1 deals with portfolios based on systematic volatility while part 2 (covered in the next section) involves portfolios based on unsystematic volatility.

We start with the construction of systematic volatility sorted portfolios.

Prior research provides three estimators of systematic volatility. The first estimator is sample volatility (SVOL) which is calculated using daily returns on the market index (see French, Schwert and Stambaugh, 1987; Schwert and Seguin, 1990), second estimator is a range based estimate (RVOL) which was suggested by Alizadeh, Brandt and Diebold (2002). The third measure is volatility index (VIX) (see Whaley, 2000). VIX is a measure of the amount by which an underlying index is expected to fluctuate, in the near term, based on the order book of the underlying index options. Chicago Board Options Exchange VIX is a weighted measure of the implied volatilities of eight S&P 100 puts and calls. In this study we use the first measure i.e. sample volatility (SVOL) as a measure of systematic volatility. The range-based volatility measure has not been used as it requires high frequency intraday data which is not available in India for a longer time period, which is required for performing such cross-sectional studies. We are also unable to use volatility index owing to data paucity problems. VIX is available in India only since 2008. Its construction at our level requires data relating to option contracts which were introduced in India only in 2001. Hence our empirical work is constrained by the choice of systematic volatility measure.

Monthly SVOL (MSVOL) is the sum of squared daily returns over the past N_t days which is 22 trading days[2] in our case, adjusted for first order autocorrelation as used by French, Schwert and Stambaugh (1987):

$$MSVOL = \sum_{i=1}^{N_t} r_{it}^2 + 2\sum_{i=1}^{N_t-1} r_{it} r_{i+1,t}, \quad (1)$$

where r_{it} is the daily return and N_t is the number of trading days in a month.

Daily time series of monthly SVOL are generated on a moving average basis by skipping one day of sample market returns as suggested by Ang, Hodrick, Xing and Zhang (2003)[3]. Further following these authors we convert the monthly SVOL into

[1] The stock prices have been adjusted for capitalization changes such as stock dividends, stock splits and rights issues.

[2] Assuming approximately 22 trading days in a month, we use approximately one month daily returns for estimating SVOL.

[3] Unlike Ang, Hodrick, Xing and Zhang (2003) who used standard deviation based sample volatility measure, we use variance based sample volatility measure for further estimation. This is owing to the fact that we empirically find that cross sectional differences in returns on portfolios based on standard deviation based sample volatility measure are relatively small, i.e., 0.0222% per month (for low systematic volatility portfolio) and 0.0228% per month (for high systematic volatility portfolio). We show later in this section that sorting on the basis of our variance based systematic volatility measure results in much stronger cross sectional differences in average returns.

daily SVOL by dividing the former by number of trading days in a month, i.e., N_t. Our measure of daily systematic volatility measure has a daily mean and standard deviation of 0.000349 and 0.000437, respectively. It is not auto correlated and exhibits a correlation of -0.039 with excess market return.

In order to estimate sensitivity of stock returns to innovations in systematic volatility, the following equation is used:

$$r_{it} - r_{ft} = \alpha + \beta_1(r_{mt} - r_{ft}) + \beta_2 \Delta V_t + e_t, \quad (2)$$

where, $(r_{it} - r_{ft})$ is excess stock return, $(r_{mt} - r_{ft})$ is excess market return and $\Delta V_t = V_t - V_{t-1}$. It shows innovations in systematic volatility.

The regression given in (2) is estimated for all the sample stocks that have minimum 14 values of daily returns within that month. In January 1994, running regression (2) will give value of β_2 for each stock. On the basis of the value of β_2 (which measures the exposure to innovations in systematic volatility) stocks are sorted into quintiles. Quintile 1 (henceforth referred to as P1) is comprized of stocks with the highest systematic volatility exposure (SV) while quintile 5 (P5 in our case) is comprized of stocks with the lowest systematic volatility exposure. For each of these quintiles equally weighted monthly returns are estimated for February 1994. Similarly, β_2 values are obtained for all the stocks for February 1994, quintiles are formed on the basis of the β_2 values and for each of these quintiles returns are estimated for March 1994. The process continues till the end of the study period, i.e., June 2010. We finally end up with 197 monthly return observations for each of the quintile portfolios. The mean portfolio excess returns $(r_p - r_f)$ are then estimated which are shown in Table 1, panel A. One can clearly see that high systematic volatility portfolio exhibits high future returns. This is contrary to global market evidence where negative volatility risk premium indicates hedging motive (see Ang, Hodrick, Xing and Zhang, 2003). But in our case, volatility risk premium is positive which is indicative of speculative motive in Indian stock markets. This analysis is confirmed by the fact that trading volume in the F&O section of the stock market (which measures speculative trading activity) is many folds (almost three times) higher than open interest (which measures hedgers' trading activity). However, the relationship between systematic volatility and return is not monotonic.

Next returns on each systematic volatility portfolio are regressed on the returns for the market factor using excess return version of the market model, which is generally employed to test CAPM.

$$r_{pt} - r_{ft} = a + b(r_{mt} - r_{ft}) + e_i, \quad (3)$$

where $(r_{pt} - r_{ft})$ is excess return on systematic volatility sorted portfolio p, $(r_{mt} - r_{ft})$ is excess return on the market factor, and a, b are the estimated parameters.

CAPM constraints the intercept term of (3) to be zero. The objective is to verify if CAPM is a suitable descriptor of asset pricing in case of SV sorted portfolios. From Table 1, Panel B, it is observed that both P1 and P5 exhibit high sensitivity to market factor and display almost identical betas. Hence market factor explains some of the returns on both of these portfolios. In fact CAPM explains 23% of the return on P1 and 32% of the return on P5. The alpha values for P1 and P5 are statistically significant at 5% level. Thus implying that CAPM fails to explain cross sectional volatility effect in stock returns.

Table 1. Empirical results for portfolios sorted by exposure to systematic volatility

Portfolios have been formed every month by sorting the stocks on the basis of their sensitivity to innovations in systematic volatility. Portfolio 1 (portfolio 5) comprize high (low) volatility stocks. Panel A gives mean portfolio excess returns and associated *t*-values. Panel B gives results of CAPM model where excess returns on SV sorted portfolios are regressed on the returns for the market factor. Panel C gives results of Fama-French model in which the excess returns on SV sorted portfolios are regressed on market, size and value factors.

Panel A. Unadjusted returns					
	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5
Mean return	0.026	0.018	0.019	0.023	0.019
t-values	3.146	2.649	2.664	2.900	2.463
Panel B. CAPM regression: $(r_{pt} - r_{ft}) = a + b\,(r_{mt} - r_{ft})$					
	a	b	t_a	t_b	Adjusted R^2
Portfolio 1	0.020	1.126	4.318	20.571	0.683
Portfolio 2	0.013	1.007	3.935	25.544	0.769
Portfolio 3	0.014	0.874	3.045	15.887	0.562
Portfolio 4	0.018	1.040	3.552	17.438	0.607
Portfolio 5	0.013	1.119	3.425	24.178	0.749

Table 1 (cont.). Empirical results for portfolios sorted by exposure to systematic volatility

Panel C. Fama-French regression: $(r_{pt} - r_{ft}) = a + b\,(r_{mt} - r_{ft}) + s\,(SMB_t) + h\,(LMH_t) + e_t$									
	a	*b*	*s*	*h*	t_a	t_b	t_s	t_h	Adjusted R^2
Portfolio 1	0.011	1.068	0.620	0.164	2.565	22.258	7.411	1.904	0.768
Portfolio 2	0.005	0.964	0.555	0.071	1.865	30.176	9.947	1.238	0.855
Portfolio 3	0.007	0.844	0.544	-0.020	1.542	16.324	6.028	-0.214	0.632
Portfolio 4	0.003	0.919	0.886	0.530	0.882	25.591	14.145	8.221	0.865
Portfolio 5	0.004	1.060	0.619	0.168	1.236	28.418	9.511	2.506	0.845

The returns on quintile portfolios are then regressed on market, size and value factors in the Fama-French three factor model (1993) framework as follows:

$$(r_{pt} - r_{ft}) = a + b(r_{mt} - r_{ft}) + s(SMB_t) + \\ + h(LMH_t) + e_t, \quad (4)$$

where SMB_t and LMH_t are size and value proxies respectively. *s* and *h* are sensitivity coefficients while other terms in equation (4) have the same meaning as in equation (3). The objective is to evaluate if the FF model is able to capture returns on SV sorted portfolios that are missed by CAPM.

Our estimation of the FF model differs in two respects. First we use LMH factor instead of HML factor in the FF regression. Hence our interpretation of the value factor will be inverse. Secondly unlike Fama and French (1993) who perform 2*3 size-value partition, we construct a 2*2 size-value partition[1]. We modify the estimation of the SMB and LMH as follows. In each year of the sample period *t*, the stocks are split into two groups big (*B*) and small (*S*) – based on whether their market capitalization at the end of December of every year in the sample period is above or below the median for the stocks of the companies included. The price to book equity ratio is calculated in this month for all the companies. The stocks are now split into two equal *P*/*B* groups. Then we construct four portfolios viz. *S*/*L*, *S*/*H*, *B*/*L*, *B*/*H* from the intersection of the two size and two *P*/*B* groups. Monthly equally weighted return series are calculated for all portfolios from January of year *t* to December of year *t*.

The Fama and French model uses three explanatory variables for explaining the cross-section of stock returns. The first is the excess market return factor that is the market index return minus the risk free return. The second is the risk factor in returns relating to size portfolios (*B*/*L*, *B*/*H*) is subtracted from the average of the two small size portfolios (*S*/*L*, *S*/*H*) to get the monthly return of the *SMB* factor. This factor is free from value effects as it has about the same weighted – average price to book. SMB_t is constructed as follows such that it is independent of value factor:

$$SMB = (S/L + S/H)/2 - (B/L + B/H)/2. \quad (5)$$

The factor is relating to value. LMH_t is constructed as follows such that it is independent of size factor:

$$LMH = (S/L + B/L)/2 - (S/H + B/H)/2. \quad (6)$$

The FF results in Table 1, Panel C indicate that both P1 and P5 comprize small and low price to book value stocks. Size and value factors explain 35% of the returns on P1 and 47% of the returns on P5. FF model absorbs some of the return on P1 and almost all the returns on P5. The alpha value for high SV sorted portfolio, i.e., P1 continues to be statistically significant thus implying that the FF model may not be the optimal framework for capturing CSV patterns in stock returns. The non-validity of FF model may warrant use of additional risk factors that have a strong economic foundation in literature. Alternatively one may have to provide a behavioral explanation for the observed empirical phenomenon. We start with the first approach and augment the FF model.

A growing body of literature shows that the use of an additional liquidity factor in asset pricing models has been successful in explaining cross-sectional variation in asset returns. Lustig (2001) argues that it is solvency constraints that give rise to liquidity risk. In Lustig's model investors on average want a higher return on stocks to compensate for liquidity risk because of low stock returns in recession. Similar to solvency constraints argument of Lustig (2001), Pastor and Stambaugh (2003) argue that any investor who employs some form of leverage and faces a solvency constraint will require higher expected returns for holding assets that are difficult to sell when aggregate liquidity is low. They find that stocks with greater sensitivity to aggregate liquidity generate higher returns than low sensitivity stocks and conclude that market wide liquidity is a state variable important for asset pricing. Lee states that liquidity risk can to some extent capture any default premium. Likewise distressed firms are unattractive to investors and they will be less liquid. It is rational to believe that less liquid stocks (proxied by lower

[1] Correlation between *SMB* and *LMH* was significant at 0.7 when we used the 2*3 partition. However, the correlation was only 0.32 with 2*2 partition.

trading volume) expose investors to risk of marketability, leading to loss of asset value while trading, compared to high liquid stocks. Using the above arguments and that liquidity risk is a state variable (Pastor and Stambaugh, 2003), we start by augmenting the FF model with a liquidity factor[1]. The liquidity augmented FF model is:

$$(r_{pt} - r_{ft}) = a + b(r_{mt} - r_{ft}) + s(SMB_t) + \\ + h(LMH_t) + l(LIQ_t) + e_t, \quad (7)$$

where *LIQ* is the liquidity proxy and *l* shows the sensitivity of the portfolio returns to this factor.

The liquidity factor is constructed as follows. Stock liquidity is measured using Lee and Swaminathan's (2000) definition. Lee and Swaminathan define stock liquidity as the ratio of average daily trading volume for a stock *i* in year *t* divided by the sum of average daily trading volume for all sample stocks in the year *t*. the sample stocks were ranked on the basis of liquidity in the end of year *t* and five equally weighted portfolios were formed for which we estimate equally weighted monthly returns for the year *t* + 1. V1 and V5 comprize top 20% and bottom 20% stocks based on liquidity. The portfolios are rebalanced at the end of *t* + 1 and the process is repeated on annual basis. The *LIQ* factor is then constructed as the difference between the returns on low volume (V5) and high volume (V1).

The regression results for equation (7) are provided in Table 2, Panel A. Liquidity augmented FF model is able to capture the cross sectional volatility effect in stock returns. However it is interesting to note that both P1 (high SV portfolio) and P5 (low SV portfolio) load on the liquidity factor with latter in fact exhibiting a higher systematic exposure. Thus both P1 and P5 (with exception of P3) comprize low liquidity stocks. Despite a statistical success we are still unable to identify a rational explanation for the different return behavior of high and low SV sorted portfolios.

Table 2. Empirical results on systematic volatilty sorted portfolios based on augmented Fama-French framework

In panel A results of liquidity augmented Fama French regression are given and in panel B we provide results of CSV augmented Fama-French regression.

Panel A. Liquidity augmented Fama-French model: $(r_{pt} - r_{ft}) = a + b\,(r_{mt} - r_{ft}) + s\,(SMB_t) + h\,(LMH_t) + l\,(LIQ_t) + e_t$											
	a	*b*	*s*	*h*	*l*	t_a	t_b	t_s	t_h	t_l	Adjusted R^2
Portfolio 1	0.006	1.120	0.657	0.141	0.079	1.580	23.482	8.956	1.864	1.622	0.833
Portfolio 2	0.005	0.971	0.543	0.069	0.016	1.615	24.900	9.049	1.108	0.389	0.849
Portfolio 3	0.001	1.041	0.532	-0.074	0.438	0.118	19.238	6.397	-0.861	7.879	0.722
Portfolio 4	0.001	0.947	0.908	0.565	0.059	0.222	22.588	14.073	8.464	1.365	0.874
Portfolio 5	0.001	1.111	0.623	0.145	0.096	0.196	25.012	9.115	2.046	2.107	0.847
Panel B. CSV augmented Fama-French model: $(r_{pt} - r_{ft}) = a + b\,(r_{mt} - r_{ft}) + s\,(SMB_t) + h\,(LMH_t) + c\,(CSV_t) + e_t$											
	a	*b*	*s*	*h*	*c*	t_a	t_b	t_s	t_h	t_c	Adjusted R^2
Portfolio 1	0.006	1.062	0.619	0.167	0.753	1.798	29.576	9.887	2.589	12.348	0.870
Portfolio 2	0.005	0.964	0.554	0.071	0.062	1.704	30.181	9.953	1.243	1.133	0.856
Portfolio 3	0.007	0.845	0.544	-0.020	-0.091	1.664	16.339	6.030	-0.217	-1.038	0.632
Portfolio 4	0.003	0.920	0.886	0.529	-0.088	1.065	25.679	14.187	8.239	-1.445	0.865
Portfolio 5	0.006	1.062	0.619	0.167	-0.247	1.798	29.576	9.887	2.589	-4.046	0.856

We next augment the FF model by using a CSV factor as suggested by Ang, Hodrick, Xing and Zhang (2003). The CSV factor has been constructed by taking the difference between returns on high SV portfolio (P1) and low SV portfolio (P5)[2]. The CSV factor exhibits insignificant correlation (ρ = .046) with the liquidity factor implying that the two factors are different risk dimensions and therefore may require different economic explanations. The CSV augmented FF model is as follows:

$$r_{pt} - r_{ft} = a + b(r_{mt} - r_{ft}) + s(SMB_t) + \\ + h(LMH_t) + c(CSV_t) + e_t, \quad (8)$$

where CSV_t is the cross sectional volatility factor and *c* is a sensitivity coefficient.

The CSV factor has been used by Ang, Hodrick, Xing and Zhang (2003). When FF is augmented using CSV (Table 2, Panel B), it is observed that P1 loads strongly on CSV factor which explains its returns. This implies that P1 comprises of stocks with high volatility. The market probably believes that stocks with high pre-formation CSV tend to

[1] We find that correlation between the liquidity factor and SMB was only -0.001 and that between liquidity factor and LMH was -0.025.

[2] For construction of CSV factor Ang, Hodrick, Xing and Zhang (2003) divided the stocks into three groups but we divide the stocks into five groups so that more clear distinction can be drawn between high and low systematic volatility stocks.

exhibit higher post formation CSV thus exhibiting volatility persistence. Hence, investors demand a risk premium for high SV stocks. According to Connolly and Stivers (2004), there is no direct theory that says that cross-sectional volatility contains information about future volatility of stock returns. An economic interpretation suggesting a positive relationship between CSV and future market volatility could be that CSV reflects firm/industry level information flows to the market and if these flows are autocorrelated then an increase in CSV might also increase future volatility of market returns. We give an empirical confirmation that CSV does contain information about future market volatility and thus there is an economic rationale for the CSV factor.

In sum, both high and low SV portfolios comprize high beta, small size, small P/B ratio and low liquidity stocks. The liquidity augmented FF model is able to explain CSV patterns in stock returns but it does not help us in discerning the reason for differences in return behavior for CSV sorted portfolios. The CSV augmented FF model also explains systematic volatility sorted returns like the liquidity augmented FF model. However the CSV factor seems to have stronger economic rationale owing to volatility persistence information contained in it. High SV stocks loaded more heavily on the CSV factor vis-a-vis low SV stocks which was not the case with liquidity factor as both the portfolios loaded strongly on that factor.

3. Unsystematic volatility sorted portfolios

Next we deal with unsystematic volatility (UV) sorted portfolios. We estimate the daily CAPM regression[1] for each month t for every stock i by using the excess return version of the market model in the form:

$$(r_{it} - r_{ft}) = \alpha + \beta(r_{mt} - r_{ft}) + e_{it}, \quad (9)$$

where $(r_{it} - r_{ft})$ is the excess for stock i for month t, $(r_{mt} - r_{ft})$ is excess market return for period t. Alpha and beta are estimated parameters and e_{it} is the white noise residual term.

We run equation (9) only for those stocks for which a minimum of 14 daily return values are available in each month. The vector of errors for each stock i for the month t is then used to estimate residual variance which is a measure of unsystematic volatility for the stock i. The sample stocks are then ranked on their unsystematic volatility in t. We then divide the ranked stocks into quintiles and equally weighted return is estimated for each of the quintile portfolios for the month $t + 1$. While P1 comprizes 20% of the stocks with highest unsystematic volatility, P5 contains 20% of the stocks with the lowest unsystematic volatility. The portfolios are rebalanced at the end of $t + 1$ month and the process is continued till one reaches the end of the study period.

We estimate mean unadjusted returns for the sample portfolios which are shown in Table 3, panel A. The high UV portfolio (P1) and low UV portfolio (P5) provide an average monthly return of 3.1% and 1.3%, respectively. According to a standard asset pricing framework, idiosyncratic volatility should not be priced. Recent theories, however, predict that stocks with high idiosyncratic volatility may earn high expected returns to compensate for imperfect diversification. Hence our results are consistent with finance literature. Ang, Hodrick, Xing and Zhang (2003) reported contradictory results which they found to be puzzling.

Table 3. Empirical results for portfolios sorted by idiosyncratic volatility

Portfolios have been formed every month by sorting the stocks on the basis of idiosyncratic volatility which is measured by the variance of the residuals obtained from CAPM. Portfolio 1 and portfolio 5 comprize high and low unsystematic volatility stocks. Panel A gives mean portfolio excess returns and associated t-values. Panel B gives results of CAPM regression. Panel C provides results of Fama-French regression.

Panel A. Unadjusted returns					
	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5
Mean return	0.031	0.023	0.019	0.018	0.013
t-values	3.241	2.882	2.394	2.474	2.416
Panel B. CAPM results: $(r_{pt} - r_{ft}) = a + b\,(r_{mt} - r_{ft})$					
	a	b	t_a	t_b	Adjusted R^2
Portfolio 1	0.025	1.174	3.845	15.238	0.541
Portfolio 2	0.017	1.110	4.024	22.141	0.714
Portfolio 3	0.014	1.143	3.115	22.167	0.715
Portfolio 4	0.012	1.040	3.632	26.183	0.777
Portfolio 5	0.009	0.752	3.079	21.228	0.696

[1] We also estimated idiosyncratic volatility for sample stocks based on the Fama-French three factor model and then used these estimates for portfolio formation as well. Since the results of FF based UV sorted portfolios are similar to CAPM based UV sorted portfolios, we do not discuss them in the paper for paucity of space.

Table 3 (cont.). Empirical results for portfolios sorted by idiosyncratic volatility

Panel C. Fama-French model results: $(r_{pt} - r_{ft}) = a + b\,(r_{mt} - r_{ft}) + s\,(SMB_t) + h\,(LMH_t) + e_t$									
	a	b	s	h	t_a	t_b	t_s	t_h	Adjusted R^2
Portfolio 1	0.007	1.031	1.068	0.616	1.521	19.600	11.635	6.527	0.797
Portfolio 2	0.008	1.053	0.617	0.156	2.116	24.771	8.320	2.041	0.804
Portfolio 3	0.003	1.074	0.671	0.223	0.873	25.841	9.247	2.988	0.824
Portfolio 4	0.005	0.996	0.485	0.121	1.678	29.415	8.206	1.991	0.846
Portfolio 5	0.006	0.732	0.255	0.041	1.853	21.147	4.232	0.653	0.725

We regress the returns on UV sorted portfolios on the returns for the market factor using the CAPM specification provided in equation (3). CAPM (Table 3, Panel B) is able to explain a part of return differential on UV sorted portfolios since P1 exhibits much higher beta than P5. The extra normal returns on UV sorted portfolios continue to be statistically significant in the CAPM framework. We, therefore, regress the returns on UV sorted portfolios on the FF factors (4) to verify if the three factor model is able to capture any cross section of average returns that are missed by CAPM. We find that the FF model is able to explain the returns on UV sorted portfolios. It can be clearly seen that high UV portfolio (P1), which provides relatively higher returns, comprizes small size and low P/B companies. Thus idiosyncratic volatility based portfolio construction does not pose any challenge to asset pricing in the Indian context.

Conclusions

One important stock return anomaly which has received less focus in research is cross-sectional volatility. Empirical literature deals with two forms of cross sectional volatility: systematic and unsystematic. Systematic volatility is the cross sectional variation in stock returns owing to their sensitivity to market volatility measure. In this paper we adopt a systematic volatility estimate suggested by French, Schwert and Stambaugh (1987) and Schwert and Seguin (1990). Unsystematic volatility, on the other hand, is measured by the residual variance of stocks in a given period by using error terms obtained from a standard asset pricing model such as CAPM or the FF model. In this study we adopt CAPM based unsystematic volatility measures. We employ daily returns for 493 companies that form part of BSE 500 index in India. The study period is from December 1993 to June 2010.

We find that high SV portfolios provide higher unadjusted returns than low SV portfolios. This is in contrast to the findings of Ang, Hodrick, Xing and Zhang (2003) and implies a dominance of speculative behavior in the stock market. The high SV portfolio comprize high beta, small size and low P/B stocks compared to low SV portfolio. However CAPM as well as the FF model are not fully able to absorb the systematic volatility pattern in stock returns. We add liquidity factor to the FF model and observe that the augmented asset pricing framework is able to explain these returns. However, it is difficult to provide a rational explanation for the observed phenomenon in light of the fact that both high and low SV portfolios load on the liquidity factor, with the latter actually exhibiting a higher sensitivity coefficient. We, therefore, construct a CSV factor as suggested by Ang, Hodrick, Xing and Zhang (2003). Our CSV factor is uncorrelated to the liquidity factor implying that they represent different risk dimensions. The CSV augmented FF model is able to explain the returns on SV sorted portfolios. The CSV factor seems to contain information about volatility persistence which is priced by the market. More simply, high SV portfolios are expected to exhibit higher volatility in future compared to low SV portfolios, and thus command a risk premium.

We further find that high UV sorted portfolios provide much higher returns than low UV sorted portfolios which is consistent with finance theory that suggests a risk compensation for imperfect diversification. CAPM is able to absorb some of the return differential between high and low UV portfolios owing to the fact that former exhibit a much higher beta compared to the latter. The FF model is able to absorb the returns on UV sorted portfolios that are missed by CAPM. High UV stocks command a risk premium as they comprize small size and low P/B companies.

Thus while there is a role for CSV factor in returns for SV sorted portfolios, UV sorted portfolios do not pose an empirical challenge to standard asset pricing framework like the Fama-French model. Our findings are extremely pertinent for global portfolio managers and investment analysts who are continuously searching for trading strategies that provide extra normal returns. The CSV based trading strategy may not be rewarding in the Indian context within a multi-factor asset pricing framework. From researchers point of view, CSV augmented FF model may prove to be a better benchmark for portfolio performance evaluation. The study contributes to the asset pricing anomaly literature especially for emerging markets such as India.

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