Is Fear (VIX) a Priced Factor in Multi Factor Asset Price Modeling?

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Abstract

This study examines the effect of volatility measure VIX in the Fama and French model augmented by Durand et al. (2011) in the Indian stock market. It also tries to investigate the pricing effects and dynamic interaction of the volatility factor (VIX or market anxiety) vis. a vis. other priced factors of Fama and French (1993) by using regression methods, Granger causality test, vector auto regression method, and impulse response function method. Results indicate that the impact of risk/volatility (RVIX) is negative and consistent on almost all the portfolios, which is in congruence with the findings of Durand et al. (2011), Giot (2005), and Whaley (2000, 2008). The shocks of fear are found to be persistent for two to three consecutive months, and this is consistent with the findings of Whaley (2000, 2008). Thus, the results strongly advocate for the inclusion of change of VIX as a priced factor in the asset pricing models in India as well.

Keywords: **fear (VIX), size, P/B, asset pricing model, factor return, SMB, HML**

JEL Classification: G11, G12, G17

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The multifactor model has been developed further by accommodating several changes in the last two decades, and it was subjected to continual spatial and temporal validation in various markets. The change from traditional Sharpe Lintner CAPM model (1964, 1965) to factor models (Carhart, 1997 ; Daniel & Titman, 1997; Durand, Lim, & Zumwalt, 2011 ; Fama & French,1993) occurred mainly due to the inability of some of the investors to hold the market portfolio for exogenous reasons, that is, transaction costs, incomplete information, institutional restrictions, taxes, liquidity constraints, wealth constraints, and personal investment choice. Massa, Goetzmann, and Simonov (2004) also added that the major segment of the investors is under diversified. They complemented Merton's (1987) argument that the investors only hold those securities whose risk and return characteristics they are familiar with. Thus, these investors tend to expect a compensation for bearing idiosyncratic risks leading to positive relationship between idiosyncratic volatility and expected stock return in cross section. Durand et al. (2011), French, Schwert, and Stambaugh (1987) ; Merton (1987); and Malkiel and Xu (2002) augmented the Fama-Frech with VIX, which can address the fear of undiversified investors in the asset pricing model.

Objectives of the Study

This study was conducted with the following objectives :

(a) To appraise the pricing effects of investors' expectations of the total risk of the market (VIX) on Indian stocks using monthly unit of aggregations.

(b) To quantify the effect of VIX on other systematically priced factors of Fama and French like size premium (SML) and value premium (HML).

(c) To study the interrelationship of the market premium, SMB, HML, and VIX in the Indian stock market.

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(d) To measure the response of various priced factors with respect to one standard deviation innovations in VIX and vice versa.

Review of Literature

Sharpe (1964) and Lintner (1965) developed the CAPM independently by extending Markowitz's theory to an equilibrium theory of asset pricing under uncertainty and quantified the relationship between expected returns and risk of securities. Later, the two parameter CAPM came under sharp criticism owing to the lack of unobservable market portfolio held by all the investors and completely risk free borrowing and lending securities imposed in the model as assumptions. Furthermore, Ross (1976) used relatively weaker set of assumptions as compared to the CAPM and proposed the arbitrage pricing theory, which stated that the stochastic process generating security returns is a *k* factor linear model having expectations equal to realizations in the case of no arbitrage. Arbitrage pricing theory (APT) relies on the absence of arbitrage, while the CAPM mandates competitive equilibrium. Absence of arbitrage is an important condition for the state of equilibrium. Thus, APT emerged as a more fundamental relationship than CAPM in the sense that rejection of APT automatically leads to the rejection of CAPM, but not vice versa. Fama and French (1993) documented the five common risk factors, that is, the overall market factor, size, B/M, maturity, and default risk involved in stock returns and bond returns, which was further augmented by Carhart (1997) adding WML in the multifactor model.

➯ **Various Risk Measures and Factor Model :** Goyal and Santa - Clara (2003) observed a positive relation between lagged average stock variance and return on the market attributed to the fact that the average stock variance may be a proxy of business cycles. It may also be due to dominance of undiversified investors in the market. Xu and Malkiel (2002) found a positive relationship between idiosyncratic volatility and expected earnings growth and attributed the increasing prominence of NASDAQ market for higher volatility. Malkiel and Xu (2002) also concluded that the explanatory potential of idiosyncratic risk is much higher than that of size, BE/ME in US and Japanese stock market. Spiegel and Wang (2005) also added that idiosyncratic risk has higher explanatory potential than liquidity. However, Fu (2009) refuted the earlier findings because the earlier studies did not consider the time varying properties of idiosyncratic volatility.

Bali, Cakici, Yan, and Zhang (2005) argued that Goyal and Santa-Clara's (2003) results were driven by small stocks traded on NASDAQ as well as by liquidity premium. In addition, their results did not hold true in the extended sample period. Bali & Cakici (2008) also found no evidence of a significant link between the value-weighted portfolio returns and the median and value-weighted average stock volatility. Ang, Hodrick, Xing, and Zhang (2006) estimated a cross-sectional price of volatility risk of approximately -1% per annum, and according to them, it cannot be explained by exposures to size, book-to-market, leverage, liquidity, volume, turnover, bid-ask spreads, coskewness, or dispersion in analysts' forecasts characteristics. Thus, these studies solely reflect the pricing effects and importance of ex post measure of risk in the asset pricing model, which was further challenged by the development of forward looking volatility measures by Whaley (1993).

➯ **Development of VIX and Related Studies :** The VIX was originally introduced by Whaley (1993). He described the Chicago Board Options Exchange's market volatility index (the VIX) as “investor fear gauge”. The VIX is the proxy of expected future stock market volatility. Thus, the higher the VIX, the greater the fear. The VIX is intended to be forward looking, measuring volatility that the investors expect to see. Whaley (2000) also studied the relationship between stock market returns and change in the VIX and found it to be asymmetric. He further said that the stock market reacts more negatively to an increase in the VIX than it reacts positively when the VIX falls. Thus, it is more of a barometer of investors' fear of the downside than it is a barometer of investors' excitement (greed) in a market rally (Whaley, 2008). High levels of VIX are coincident with a high degree of market turmoil, irrespective of the cause. The VIX can also assist in judging the market anxiety by examining the persistence with which VIX remains above certain extraordinary levels. Whaley (2008) identified four anxiety periods, that is, November 1987, February 1988, September 2002, and October 2008, where market anxiety persisted for a longer duration, say for more than 25 days. He also found that VIX works reasonably well as a predictor of the expected stock index movements. Whaley (2008) also added that the VIX has the first-mover advantage, but should not be assumed as a unique stock market volatility index. The CBOE has already applied the previous methodology to create a volatility index for NASDAQ 100 (the "VXN") and the DJIA (the "VXD"). India VIX is a volatility index based on the index option prices of NIFTY. India VIX indicates the investor's perception of the market's volatility in the near term. The index depicts the expected market volatility over the next 30 calendar days, that is, higher the India VIX values, the higher is the expected volatility and vice-versa.

Giot (2005) documented a negative asymmetric relationship between the returns of the stock and implied volatility (VIX and VXN) indices. This asymmetric relationship was more pronounced in S&P100 index, indicating that negative stock index returns cause bigger changes in VIX than do positive returns. On the other hand, in the NASDAQ100 index, the asymmetric effect is rather weak, but the VXN response to the index is also somewhat muted in high-volatility trading environments. Cipollini and Manzini (2007) agreed on a widespread belief that the increase in the implied volatility value is associated with fear in the market, whereas a decline indicates complacency. Thus, prolonged and extremely high value of VIX readings indicates a high degree of anxiety or panic among traders reflecting bullish trends, whereas the prolonged and low VIX readings vindicate higher complacency in the traders, reflecting bearish trends.

Whaley (2008) stressed that VIX is more a barometer of investors' fear of the downside than it is a barometer of investors' excitement (or greed) in a market rally. He also documented the negative relationship between the movements in VIX and movements in the S&P 500 without expressing causality. Whaley tested the VIX and concluded that VIX works well as a predictor of the expected stock index movements. Similarly, VXN and VXD are created volatility indices based on NASDAQ 100 and DJIA in the U.S. Durand, Lim, and Zumwalt (2011) examined whether VIX has a direct and systematic effect on equity returns as a priced factor in three or four-factor model. They found that the VIX is not alone successful in explaining the returns of twenty five portfolios of FF (1993), indicating the presence of other priced factors.

➭ **Descriptions of Durand, Lim, and Zumwalt's (2011) Model :** Durand, Lim, and Zumwalt (2011) further proposed the five factor asset pricing model augmenting the four factor Carhart model (1997) by VIX as below :

$$R_i - R_f = a_i + b_i\,(R_m\text{-}R_f) + s_i\,(\text{SMB}) + h_i\,(\text{HML}) + m_i\,(\text{WML}) + v_i\,(\text{VIX})$$

In this study, in order to assess the pricing effects of investors' expectations of the total risk of the market (VIX) and to explore how the VIX will affect other systematically priced factors of Fama and French like size premium (SML), value premium (HML), momentum (WML), Durand et al. (2011) compared four different asset pricing models, that is, **(1)** the Fama and French model, **(2)** the Fama and French model augmented with VIX, **(3)** the Fama and French model augmented with momentum, and **(4)** the Fama and French model augmented with both the momentum factor and the VIX. They found that the returns to volatility (0.166 % per day) are higher than the returns of the market (0.0299 % per day) in the U.S. stock market. The coefficients for VIX were found to be negatively consistent with the findings of Ang et al. (2006) and were statistically significant. However, the VIX alone was not particularly successful in explaining the returns of the twenty five portfolios of FF (1993). They regressed the returns of the FF (1993) portfolios against different combinations of factors and found that the five factor Durand et al. (2011) model proved to be the best in capturing the cross-section of returns. Durand et al. (2011) also studied the interrelationship of the market premium, SMB, HML, WML, and VIX using vector auto regression (VAR). They observed that an increase in the VIX is associated with a sharp decrease in the market risk premium, but is associated with a positive effect on HML and WML premium. This indicates that the investors are likely to move from growth stocks to value stocks when volatility is expected to increase. It is suggestive of flight to quality effect (Abel, 1988). The effect of VIX on size premium is quite mixed. Durand et al. (2011) found that the Fama and French model with momentum and VIX proved to be the best model in the U.S. stock market. There are few studies that are conducted on VIX and return of the stocks, but in the Indian stock market, there is a dearth of studies pertaining to spatial and temporal testing of Durand et. al's (2011) model, leading to quantification of anxiety or fear price in the market.

Methodology and Data Sources

The closing price of shares of S&P CNX 500 at monthly frequencies BE/ME, and market capitalization were obtained from the Prowess (CMIE database) from 2009 to 2013. The data on the market index (S&P CNX 500) was collected from the official website of National Stock Exchange (www.nseindia.com). Days when there is no trading were omitted, and the price change was computed from the last day the market was open. The choice of the time period is attributed to the availability of data of VIX (fear or anxiety) in the last four years. However, the selection of monthly units of aggregations is arbitrary in the study for empirical testing. The whole study was undertaken using the monthly unit of aggregations. Moreover, we also collected data of volatility index (VIX) from the official website of NSE from 2009 to 2013. Furthermore, in order to appraise the pricing effects of fear factor in multi factor asset pricing modeling, we used Durand et al.'s (2011) model as described below.

$$R_{it} = \alpha_1 + \beta_1 (R_{mt}) + \beta_2 (\mathrm{SMB}_{it}) + \beta_3 (\mathrm{HML}_{it}) + \beta_4 (\Delta \mathrm{VIX}_t)$$

Where, VIX is used as a measure of fear or anxiety factor. In this study, the WML factor is dropped due to lack of adequate predictive ability in the Indian stock market. In this study, we used the following symbols to carry out the entire study (refer to Table 1).

Table 1. Descriptions of Notations

Symbol	Meaning
SMB	SMB is the difference between returns on portfolios of small stock firms and returns on portfolio of big stock firms.
HML	HML is the return on a zero investment portfolio long on high and short on low value book to market ratio stocks. It is meant to mimic the risk factor in returns related to values (book / market ratios).
VIX	VIX is volatility index
RVIX	Return on VIX at time t
SCR_t	Return on S&P CNX Nifty Small Cap
MCR_t	Return on S&P CNX Nifty Medium Cap
LCR_t	Return on S&P CNX Nifty Large Cap
P11	Portfolio of stocks with small size and small P/B
P12	Portfolio of stocks with big size and small P/B
P21	Portfolio of stocks with small size and moderate P/B
P22	Portfolio of stocks with big size and moderate P/B
P41	Portfolio of stocks with small size and big P/B
P42	Portfolio of stocks with big size and higher P/B

Table 1. SMB and HML are standard notations and others notations are used for calculations in Eviews.

Furthermore, in order to establish the dynamic interaction between the augmented FF (1993) factors and fear factor in Durand et al. (2011), we used the following tools :

➭ **Granger Causality Test (Granger, 1969):** This test was performed to detect the direction of relationship among priced factors, that is, SMB, HML, RVIX, and market premium of various asset pricing models. This test establishes the channels of causality using the standard "identification by ordering" methodology. This test also eliminates the simultaneity bias in the bivariate model. Furthermore, we used vector auto regression (VAR) for forecasting system of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables. In this study, we captured the dynamic interaction between market return and RVIX using unrestricted VAR without any restrictions on the structure of the system as below:

$$SCR_t = A_{11}SCR_{t-1} + A_{12}SCR_{t-2} \ldots A_{1t-n}SCR_{t-n} + B_{11}RVIX_{t-1} + B_{12}RVIX_t \ldots B_{1t-n}RVIX_{t-n} + {}_1 \ldots\ldots\ldots \quad (1)$$
$$LCR_t = A_{21}LCR_{t-1} + A_{22}LCR_{t-2} \ldots A_{2t-n}LCR_{t-n} + B_{21}RVIX_{t-1} + B_{22}RVIX_t \ldots B_{2t-n}RVIX_{t-n} + {}_2 \ldots\ldots\ldots \quad (2)$$
$$RVIX_t = A_{31}RVIX_{t-1} + A_{32}RVIX_{t-2} \ldots\ldots A_{3t-n}RVIX_{t-n} + B_{31}LCR_{t-1} + B_{32}LCR_{t-2} \ldots\ldots B_{3t-n}.LCR_{t-n} + {}_3 \ldots \quad (3)$$
$$RVIX_t = A_{41}RVIX_{t-1} + A_{42}RVIX_{t-2} \ldots\ldots A_{4t-n}RVIX_{t-n} + B_{41}SCR_{t-1} + B_{42}SCR_{t-2} \ldots\ldots B_{4t-n}SCR_{t-n} + {}_4 \ldots \quad (4)$$

Where,

SCR_t, LCR_t, $RVIX_t$ are the return on small cap indices, large cap indices, and VIX at time *t*. All the four equations have coefficients which will determine the lagged relationship of variables contained in the VAR system. The study uses VAR to quantify the impact of innovations ($_1$, $_2$, $_3$, $_4$) in market returns by RVIX and vice versa. In addition, we use impulse response function to trace the time path with varying degree of shocks on the variables contained in the VAR. In this study, we use several notations for dependent and independent variables in various models which are presented in the Table 1.

Results and Discussion

The Table 2 presents the descriptive statistics of six portfolios sorted on the basis of size and P/B at monthly aggregations. It reveals that portfolio P12 consisting of stocks with bigger size and lower P/B performed better (0.72% per month) than all other portfolios followed by P42 (0.58% per month) having stocks of bigger size and higher P/B (growth stocks). Thus, value stocks have surpassed growth stocks in the Indian stock market. On the other hand, big sized stocks are fundamentally stronger and better performers than small sized stocks. The small sized stocks, irrespective of P/B value, gained 0.35 to 0.42% per month, well below the average of performance of big sized stocks. Considering different moments of descriptive statistics, the portfolios P12 and P42 seem to be privileged among their peers in the stock market.

The Table 3 shows the regression results of six different portfolios with respect to four independent variables, that is, HML, SMB, RVIX, and market return. It is evident from the Table that return of portfolio P11 is well explained by SMB, HML, and RVIX with an adjusted *R* square (74%) negating the role of the market premium. However, out of these three factors, negative coefficients of small size premium and RVIX demonstrate an inverse relation with portfolio P11 consisting of small sized and value stocks. The portfolio P12 also exhibits a similar trend, but denies the importance of HML as a significant factor. Furthermore, it is also observed that the coefficients of RVIX vary between -0.05 to -0.06 and are also significant at the 95% confidence interval. Thus, the impact of fear is evident and consistent on almost all the portfolios in the negative direction. On the other hand, the coefficients of SMB are consistently negative, varying from -0.47 to -1.58 at 99% confidence interval in all six different regression results. This also supports the dominance of big sized stocks in the stock market. The *t* statistics (-2.7 to -8.22) of regression results indicate that SMB is the primary factor in all regressions, except P41, signifying the role of size in various portfolios. The HML factor has a mixed role in various regressions with significant strength in portfolios P11, P21, and P41, but insignificant contributions in P12, P22, and P42 at 95% confidence interval. These results show that value premium has a negligible explanatory potential in large sized portfolios, lacking consistency as a factor at monthly aggregations. The Table 3 also presents the insignificant explanatory potential of market return in explaining portfolio returns. The *R* square also varies from 37% to 74% in various regressions, indicating the prominent role of few missing factors in the asset pricing model.

The Table 4 demonstrates that the forecasting estimates (Theil inequality coefficients) are in the range of 0.2 to 0.37, indicating the moderate forecasting potential. Thus, regressions as well as forecasting estimates advocate the inclusion of missing factors at monthly aggregations. Furthermore, we also tested the residual errors (Table 5) using Breusch Godfrey Serial Correlation LM test, Jarque-Bera test, Q stata (autocorrelation test), and Breusch Pagan- Godfrey's

Table 2. Descriptive Statistics of Portfolios

Portfolio	Mean	Median	Standard Deviation	Skewness	Kurtosis	Jarque-Bera (*p* value)
P11	0.35	0.44	1.13	-0.20	2.29	0.97
P12	0.72	0.76	1.28	0.04	2.17	1.00
P21	0.38	0.49	0.89	-0.15	2.49	0.51
P22	0.56	0.45	0.88	0.48	2.45	1.80
P41	0.42	0.53	0.81	-0.33	2.63	0.86
P42	0.58	0.49	0.72	0.22	2.41	0.78

Table 2 presents the descriptive statistics of six different portfolios sorted on the basis of size and P/B

Heteroskedasticity test, and found an insignificant p value reflecting the acceptance of the augmented Fama and French asset pricing model. The Table 6 exhibits the results of different factor returns using mean, median, standard deviation, skewness and kurtosis measures. It also reveals that the extra return earned by the fear factor (RVIX) is highest among all factors subsequently followed by size (SMB) factor and value (HML) factor per unit of exposure of the factor concerned. Thus, the investors can gain or loose more with fear exposure followed by size and value factor. Moreover, the results are also in favor of mutually exclusive contribution of different predictors owing to poor degree of correlation (Table 7) among various predictors of Durand et al.'s model (2011).

However, the direction of causality is not strongly substantiated by Granger Causality results (Table 8) at monthly aggregations. It may lead to further validation using daily units of aggregations. Further VAR results (Tables 9a and 9b) strongly argue that the influence of RVIX is temporary in nature and does not lend significant contribution with lagged time zone up to two months. The same trend (Figure 1a and Figure Ib) is found with impulse response function,

Table 3. Portfolio Regression Results

Portfolio (Dependent Variables)	Particulars (Independent Variables)	Coefficient	Standard Error	*t* -Stat	Probability	Adjusted R^2	*F* -Statistics (Prob. Value)
P11	C	0.46	0.11	4.02	0.00	0.74	25.43(0.00)
	HML	1.07	0.25	4.19	0.00		
	SMB	-1.44	0.17	-8.22	0.00		
	RVIX	-0.06	0.02	-2.87	0.00		
	SCR	1.34	3.46	0.38	0.70		
P12	C	0.51	0.13	3.77	0.00	0.73	24.09 (0.00)
	HML	-0.29	0.31	-0.94	0.35		
	SMB	-1.58	0.20	-7.66	0.00		
	RVIX	-0.05	0.02	-2.08	0.04		
	LCR	3.64	5.27	0.69	0.49		
P21	C	0.41	0.12	3.44	0.00	0.53	10.93 (0.00)
	HML	0.64	0.26	2.40	0.02		
	SMB	-0.94	0.18	-5.11	0.00		
	RVIX	-0.05	0.02	-2.55	0.01		
	SCR	0.14	3.65	0.03	0.96		
P22	C	0.40	0.12	3.38	0.00	0.56	12.00 (0.00)
	HML	-0.09	0.27	-0.35	0.72		
	SMB	-0.80	0.18	-4.43	0.00		
	RVIX	-0.07	0.02	-3.15	0.00		
	LCR	1.99	4.66	0.42	0.67		
P41	C	0.54	0.12	4.24	0.00	0.37	6.03 (0.00)
	HML	0.95	0.28	3.35	0.00		
	SMB	-0.56	0.19	-2.89	0.00		
	RVIX	-0.05	0.02	-2.36	0.02		
	SCR	0.06	3.84	0.017	0.98		
P42	C	0.44	0.11	3.80	0.00	0.39	6.61 (0.00)
	HML	-0.16	0.26	-0.61	0.54		
	SMB	-0.47	0.17	-2.70	0.01		
	RVIX	-0.057	0.02	-2.68	0.01		
	LCR	4.05	4.47	0.90	0.37		

Table 3 describes the regression results of six sorted portfolios with SMB, HML, RVIX and market return as dependent variable using Durand et al.'s (2011) model. Durand et al.'s (2011) model is the extension of Fama and French model (1993) with fear factor.

reflecting the early decay of shocks or fear factor in almost two or three months despite the exposure of one standard deviation.

Table 4 Forecasting Estimates (Theil Inequality Coefficients) of Regression Results

Portfolio	Theil Inequality Coefficient	Bias Proportion	Variance Proportion	Covariance Proportion	Comments
P11	0.24	0.00	0.06	0.93	Moderate explanatory potential
P12	0.22	0.00	0.06	0.93	Moderate explanatory potential
P21	0.32	0.00	0.12	0.87	Moderate explanatory potential
P22	0.28	0.00	0.12	0.87	Moderate explanatory potential
P41	0.37	0.00	0.19	0.80	Moderate explanatory potential
P42	0.30	0.00	0.18	0.81	Moderate explanatory potential

Table 4 presents the forecasting estimates of regression results in terms of Theil Inequality Coefficients, bias proportion, variance proportion, and covariance proportion from second to fifth column.

Table 5. Residual Tests of Portfolio Regressions

Portfolios	Residual Tests for Regressions on Different Portfolio			
	Breusch-Godfrey Serial Correlation LM Test: (Prob. Chi-Square)	Jarque-Bera (Probability value)	Autocorrelation and Partial Correlation (Q stats)	Heteroskedasticity Test: Breusch-Pagan-Godfrey (Probability value)
P11	0.74	0.96	Insignificant	0.44
P12	0.86	0.09	Insignificant	0.21
P21	0.85	0.90	Insignificant	0.34
P22	0.67	0.60	Insignificant	0.38
P41	0.90	0.35	Insignificant	0.28
P42	0.70	0.63	insignificant	0.43

Table 5 shows the residual results of our regression results on six different portfolios.

Table 6. Summary Statistics of Factors

Particulars	Mean	Median	Standard Deviation	Skewness	Kurtosis	Jarque Bera (Probability)
HML	-0.033	0.010	0.607	0.662	1.80	2.10 (0.34)
SMB	-0.235	-0.30	0.418	-0.56	4.01	3.34 (0.18)
RVIX	-1.465	-0.80	4.867	-0.46	3.43	1.54 (0.46)
LCR	0.002	0.001	0.023	0.062	2.70	0.15 (0.92)
MCR	0.002	0.000	0.026	0.067	2.63	0.22 (0.89)
SCR	0.000	0.006	0.029	-0.39	2.69	1.02 (0.59)

Table 6 presents the summary of different factor returns using six moments.

Table 7. Correlation Results

	SMB	HML	RVIX
SMB	1	0.2110	0.2851
HML	0.2110	1	0.2979
RVIX	0.2851	0.2979	1

Table 8. Granger Causality Results

Null Hypothesis	*F* Statistic	Probability Value
HML does not Granger cause SMB	0.91	0.41
HML does not Granger cause SCR	1.01	0.37
HML does not Granger cause RVIX	0.71	0.49
HML does not Granger cause MCR	1.13	0.33
HML does not Granger cause LCR	1.30	0.28
SMB does not Granger cause HML	0.01	0.98
SMB does not Granger cause SCR	1.99	0.15
SMB does not Granger cause MCR	1.35	0.27
SMB does not Granger cause LCR	0.75	0.48
SMB does not Granger cause RVIX	2.74	0.08
RVIX does not Granger cause SMB	1.89	0.16
RVIX does not Granger cause HML	1.36	0.27
RVIX does not Granger cause LCR	0.17	0.83
SCR does not Granger cause SMB	0.26	0.76
SCR does not Granger cause HML	0.15	0.85
SCR does not Granger cause RVIX	1.28	0.29
MCR does not Granger cause SMB	0.09	0.90
MCR does not Granger cause HML	0.40	0.66
MCR does not Granger cause RVIX	0.48	0.62
LCR does not Granger cause SMB	0.41	0.66
LCR does not Granger cause HML	1.00	0.37
LCR does not Granger cause RVIX	1.56	0.22

Table 8 presents the results of Granger Causality with *F* value and *p* value for all hypotheses.

Table 9a. Vector Autoregression Results

Vector Autoregression Estimates Standard errors in ( ) & *t*-statistics in [ ]		
	SCR	**RVIX**
SCR(-1)	-0.02	10.55
	(0.18)	(25.71)
	[-0.12]	[0.41]
SCR(-2)	-0.24	-39.64
	(0.18)	(25.60)
	[-1.37]	[-1.54]
RVIX(-1)	-0.00	-0.15
	(0.00)	(0.17)
	[-0.87]	[-0.88]
RVIX(-2)	-0.00	0.14
	(0.00)	(0.16)
	[-0.59]	[0.91]
Adj. *R*-squared	-0.02	0.00
Akaike AIC	-3.98	5.92
Schwarz SC	-3.75	6.15

Table 9a presents the VAR results between small cap market index and RVIX.

Table 9b. Vector Autoregression Results

Vector Autoregression Estimates Standard errors in ( ) & *t*-statistics in [ ]		
	LCR	**RVIX**
LCR(-1)	-0.19	20.49
	(0.17)	(32.12)
	[-1.13]	[0.63]
LCR(-2)	-0.37	-48.98
	(0.17)	(31.83)
	[-2.15]	[-1.53]
RVIX(-1)	-0.00	-0.13
	(0.00)	(0.17)
	[-0.54]	[-0.76]
RVIX(-2)	0.00	0.14
	(0.00)	(0.15)
	[0.14]	[0.91]
Adj. *R*-squared	0.06	0.02
Akaike AIC	-4.52	5.90
Schwarz SC	-4.29	6.13

Table 9b presents the VAR results between large cap market index and RVIX

Figure 1a. Impulse Response Function Results

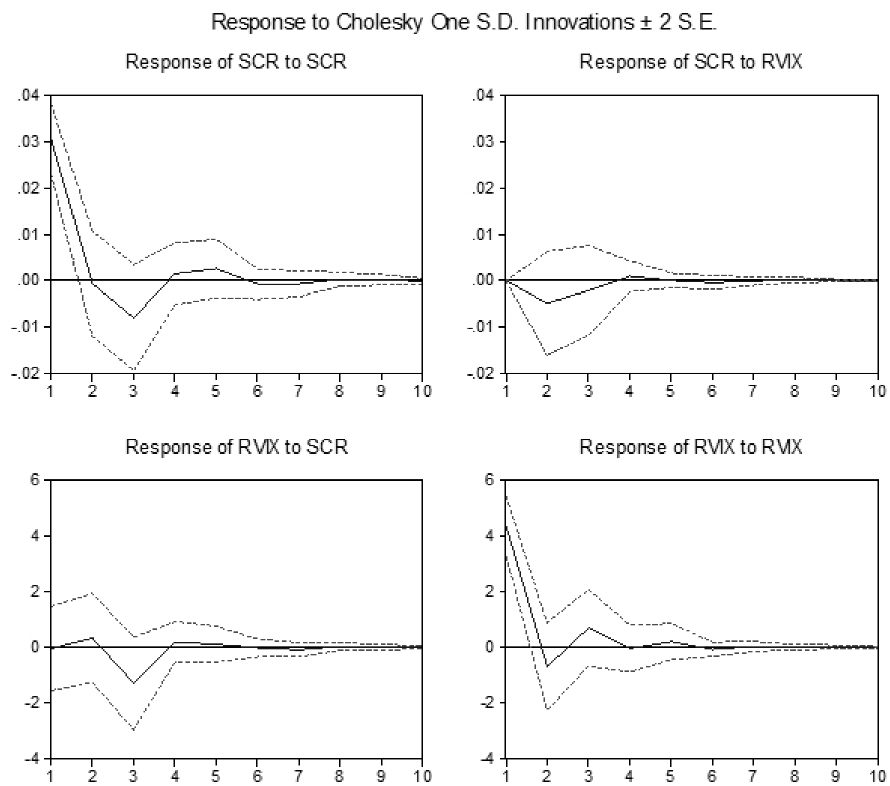
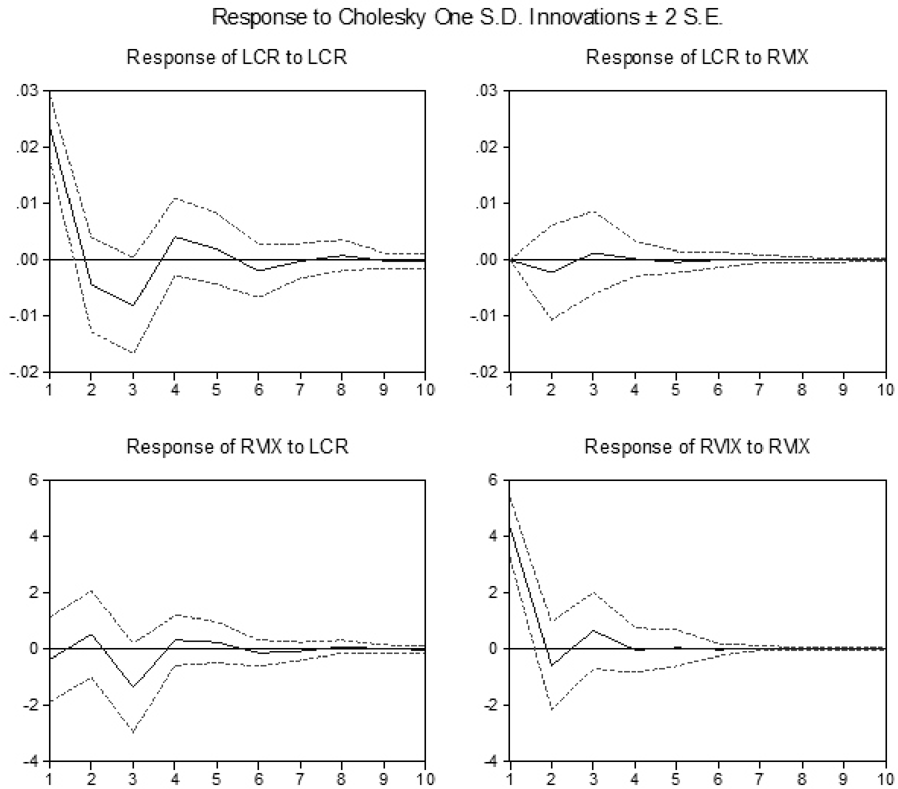


Figure 1b. Impulse Response Function Results



Conclusion and Recommendations

The objective of this study was to examine the effect of size, P/B, and fear factor in augmented Fama and French model in monthly units of aggregation for empirical testing of Durand et al.'s (2011) model in the Indian stock market. The study tried to investigate pricing effects and dynamic interaction of fear factor (VIX or market anxiety) vis. a vis. other priced factors of Fama and French (1993). Results indicate that the value stocks have surpassed growth stocks in the Indian stock market. On the other hand, big sized stocks are fundamentally stronger and better performers than small sized stocks. SMB is the primary factor in portfolios, whereas the value premium has a negligible explanatory potential in large sized portfolios, lacking consistency as a factor at monthly aggregations. Thus, the lack of pricing effects of value premium in large sized portfolios is contrary to the findings of Durand et al. (2011). However, it can be further tested by extending the sample space and time in further studies. On the other hand, the impact of fear (RVIX) is evident and consistent on almost all the portfolios in a negative direction, which is consistent with the findings of Giot (2005), Whaley (2000, 2008), Durand et al. (2011), and Ang et al. (2006). It was also revealed that the extra return earned by the fear factor (RVIX) is highest among all factors subsequently followed by size (SMB) factor and value (HML) factor per unit of exposure of the factor concerned. The impulse response function demonstrates that the shocks of fear factor die out in almost two or three months. Thus, change in VIX seems to be a prominent candidate for inclusion in the augmented Fama and French model at monthly aggregations as well. Thus, the augmented asset pricing model with RVIX can be more informative for portfolio managers, financial analysts, fund managers, and individual investors. However, the current study has its own implications in terms of units of aggregations (month) and liquidity bias of sampled stocks in S&P CNX 500 stocks. Thus, the significance of VIX in asset pricing can be well understood by extending the present study with daily units of aggregations and highly liquid stocks with different sampled portfolios.

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