IIMB Management Review (2017) xx, 1–11

available at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/iimb

IIMB Management Review

Volatility effect and the role of firm quality factor in returns: Evidence from the Indian stock market

Asheesh Pandey [a,*], **Sanjay Sehgal** [b]

[a] *Fortune Institute of International Business, New Delhi, India*
[b] *Department of Financial Studies, Delhi University, New Delhi, India*

Received 19 July 2014; revised 1 March 2015; accepted 13 January 2017; available online

KEYWORDS
Return volatility;
CAPM;
Fama French model;
Volatility anomaly;
Firm quality factor

Abstract In the study, we examine if there are any volatility patterns in stock returns for India. Data are employed for 493 companies that form part of BSE 500 index from March 2000 to November 2013. Unlike previous international evidence, no volatility anomaly is observed. Consistent with theory, high volatility stocks significantly outperform low volatility stocks. Alternative risk models fail to explain the volatility effect. Consistent with prior research, we confirm the role of firm quality factor in explaining these volatility patterns. Cash flow variability seems to be a more appropriate measure of firm quality compared to profitability.

Introduction

The efficient market hypothesis as propounded by Fama in the 1970s has been sufficiently challenged in the last few decades by researchers around the world. Academics have found various anomalies, popularly referred to as capital asset pricing model (CAPM) anomalies, to counter the efficient market hypothesis, such as the value effect (Stattman, 1980), size effect (Banz, 1981), momentum effect (Jegadeesh & Titman, 1993), liquidity effect (Amihud, 2002) and net stock issues effect (Loughran & Ritter, 1995) to name a few. On similar lines, one of the prominent inconsistencies persisting in the past few decades has been the volatility anomaly. The volatility anomaly suggests that low volatile stocks tend to provide significant positive abnormal returns over high volatility stocks, and a long–short strategy can be adopted by traders to make riskless profits out of it.

Prior studies, particularly in the U.S., have acknowledged that low volatility stocks tend to outperform high volatility stocks. Clarke, De Silva, and Thorley (2006) find that minimum variance portfolios, based on 1000 large capitalisation U.S. stocks, result in a 25% volatility reduction and provide higher returns than the market portfolio. Ang, Hodrick, Xing, and Zhang (2006) find that over the period

* Corresponding author.
E-mail address: asheeshpandey@rediffmail.com (A. Pandey).
Peer-review under responsibility of Indian Institute of Management Bangalore.

http://dx.doi.org/10.1016/j.iimb.2017.01.001
0970-3896

1963–2000, U.S. stocks with high volatility earned abnormally lower returns. They based their research on a short term of the 1 month volatility measure. Blitz and Vliet (2007) extend the work of Ang et al. (2006) beyond the U.S. to other developed markets covering Europe and Japan, and use short term (1 month) as well as long term (36 months) volatility measure to test volatility anomaly. They find annual premium of 12% per year on a trading strategy which involves buying low volatility and (short) selling high volatility stocks. Further, they observe that the volatility effect cannot be explained by popular risk based models. Similarly, Baker, Bradley, and Wurgler (2011) show that contrary to basic risk principles, low volatility stocks outperform high volatility stocks. They show that such an anomaly has been in existence in the U.S. for the past four decades and provide various behavioural explanations for the same. Dutt and Humphery-Jenner (2013) confirm the presence of low volatility anomaly in developed markets outside the U.S. as well as in some emerging markets. Walkshausl (2013) tried to associate low volatility anomaly with the quality of the firm and provided a trading strategy of going long on high quality firms and short on low quality firms. Wang and Ma (2014) document a significant positive relationship between excess volatility and cross section of stock returns over a sample period of 1963–2010. Further, they show that these returns cannot be explained either by risk models using size, value and momentum factors, or by liquidity, bid-ask bounce and risk aversion related inventory effects.

There have been various explanations given in the international literature for the low volatility anomaly. Blitz and Vliet (2007) provide three possible explanations for volatility effect. One reason could be that leverage restrictions in low volatility stocks may not allow investors to arbitrage away the opportunity presented by them. It has been argued that it is not possible for low volatile firms to borrow at a scale needed to exploit the opportunity offered by low volatile stocks. The second reason could be that the volatility effect may be the result of the inefficient decentralised investment approach. The approach suggests that in the institutional investment industry, an investment decision is taken in two stages: first, asset allocation decision, and second, to buy securities within an asset class. In order to beat the benchmark, and if CAPM holds, asset managers are better off buying more volatile companies which make them overpriced, and selling low volatile stocks which makes them underpriced. Further, managers tend to outperform the benchmarks during upturns rather than during downturns and thus are willing to pay more for high volatile stocks during market upturns. The third explanation could be the behavioural biases, as explained by Shefrin and Statman (2000). They argue that investors tend to overpay for risky stocks as they have a characteristic of lottery tickets and do not pay much attention to low volatile stocks. This results in overpayment for risky stocks which reduces their returns while keeping the upside potential of low volatile stocks intact.

Baker et al. (2011) provide certain behavioural explanations for the existence of low volatility anomaly. One reason that they quote is that of the irrational behaviour of market participants wherein their preference for lottery like securities leads to higher demand for high volatility securities and decreases their returns. This was called "loss aversion" by Kahneman and Tversky (1979). The second reason could be behavioural biases of representativeness[1] (Tversky & Kahneman, 1974) and overconfidence[2] (Alpert & Raffia, 1982; Fischhoff, Slovic, & Lichtenstein, 1977). They cite benchmarking as another reason for the persistence of low volatility anomaly. Herein, they argue that this anomaly has gained importance over the years as participation of institutional investors in portfolio management has doubled from 30% to 60%. In order to beat benchmarks, these institutional investors always follow high volatile stocks and pay little attention to less risky stocks which obstruct the arbitrage opportunity.

Dutt and Humphery-Jenner (2013) show that low volatile stocks have high operating performance, and this improves a firm's ability to access the capital market which can help it take long dated entrepreneurial projects. This investment in projects improves the firm's efficiency and returns in the long term. They further state that high operating performance could be unexpected, and when it happens, the firm will experience higher stock returns as suggested by Core, Guay, and Rusticus (2006). There could also be a situation wherein the operating performance is not a surprise, but is uncertain. It is possible that such performance could result in high stock prices. They provide three reasons for it. One could be the revelation of information over time to investors, and as and when information reaches them, they reevaluate the company. The second reason could be risky information content of expansion options. Herein, due to increase in operating performance, firms make risky investments and thus increase their returns. The last factor, according to Dutt and Humphery-Jenner (2013), could be return persistence which has been found in emerging markets. Alti, Kaniel, and Yoeli (2012) argue that in emerging markets, quality of information flow is poor and investors tend to wait for subsequent confirmation news to set stock prices which leads to persistence in returns.

Walkshausl (2013) shows that the volatility effect is associated with the quality of firms. Quality is measured by profitability factor and cash flow variability factor. He adds a quality factor to the Fama French model to explain the return behaviour of volatility portfolios, and finds that the return behaviour of low volatility portfolios is partially explained. Rambhia, Joshipura, and Joshipura (2013) examine low risk anomaly in the Indian context and find the presence of low volatility anomaly using data from 2001 to 2011.

One can see that a large body of literature on volatility anomaly exists for developed markets. However, limited empirical work on the subject is available for emerging markets, including India. Most empirical work has defied theory as low volatility stocks seem to outperform high volatility stocks across different market settings. Several behavioural expla-

[1] Representativeness bias: It means that investors tend to take one or two successful examples of success as the representative of the entire lot and pay a high price for volatility. For example, looking at the success of Infosys in the era of the 1990s, investors may have thought it to be representative of the entire technology industry, and that the road to riches is to buy volatile new technology stocks and pay a high price for them.

[2] Overconfidence bias: It means that prices in the stock market are generally set by optimists, and stocks with a wider range of opinions will have more optimists among their shareholders. This will result in selling of such stocks at higher prices and hence lower future returns.

nations have been provided for these anomalous findings. The role of firm quality factor in explaining the volatility effect has also been explored more recently. However, the research is still not fully conclusive and poses an empirical challenge. The present study attempts to fill this important research gap in the literature. We specifically pursue the following objectives: to test if the volatility anomaly exists for the Indian equity market, to evaluate if such an anomaly can be explained by various asset pricing models, and to verify if the firm quality factor can explain the volatility effect in the absence of empirical success of risk models.

We divide the rest of the paper into the following sections. In the second section we present the data and their sources, and in the third section we examine the relationship between volatility and stock returns. In the fourth section we test if the standard asset pricing models capture the returns on volatility sorted portfolios. In the fifth section we evaluate the role of firm quality factors in the returns on volatility sorted portfolios. A summary and concluding remarks are given in the last section.

Data

The data comprise 493 companies belonging to the BSE 500 Index for the period July 2000 to November 2013. BSE 500 companies account for about 95% of market capitalisation as well as trading activity on the Indian exchanges. Monthly stock prices, adjusted for stock dividends, rights issues and stock splits, have been taken for the sample companies. These monthly share prices have been used to compute percentage returns which are then employed for further estimations. The BSE 200 Index has been used as a market proxy. The index is broad based and free float weighted, and has been constructed on the lines of the S&P – 500, U.S.

Average month end trading volumes based on the past 12 months for the sample companies have been used to form the liquidity factor. In addition, market capitalisation (price times the number of shares outstanding) and price to book value (P/BV) ratio has been employed to construct the size and value factors. We use profitability (return on assets) and cash flows (cash flow from operations) to construct alternative firm quality measures. The data source is CMIE Prowess, a popularly used financial software in India.

Implicit yield on 91 day treasury bills has been used to proxy risk free return. The data have been obtained from the Reserve Bank of India (RBI) monthly handbook of statistics available on the RBI website (www.rbi.org.in).

Volatility and stock returns

In this section, we test if the volatility effect exists in the Indian equity market. The findings, if confirmative, will help portfolio managers in strategy design. We begin our investigation by estimating stock volatility and forming portfolios based on volatility measures which are described subsequently. Stock volatility is measured as the standard deviation of returns for the past 12 months. In June of year (t), securities are ranked on the basis of volatility variable. Then the ranked stocks are divided into 10 portfolios, i.e. P1 to P10, and equally weighted monthly excess returns are estimated for these portfolios for next month (t). P1 is the low volatility portfolio, which contains the least 10% volatile stocks, while P10 is the high volatility portfolio consisting of 10% of the most volatile stocks. We call this strategy as 12/1 strategy, i.e. 12 months formation period and 1 month holding period. Portfolios are rebalanced at the end of each month and the process continues from June 2002 until the last month of our sample period i.e. November 2013. The high-low zero investment portfolio (P10-P1) implies taking long position in P10 and short position in P1. Table 1 Panel A shows the average monthly returns on 12/1 volatility based portfolios. In contrast to results reported in developed markets we find that unadjusted returns increase monotonically from P1 to P10. P1 provides unadjusted return of 1.1% per month, translating into 13.2% per year, whereas P10 provides unadjusted return of 4.5% per month which is about 54% on an annualised basis. Thus, the high volatility stocks outperform the low volatility stocks in the Indian context.[3] Our results confirm the power of volatility information in portfolio formation which is theoretically consistent. Low volatility anomaly seems to be negated in India, unlike prior evidence for other world markets. Further, an investor can make a profit of 3.3% per month, i.e. 39.6% per year, by adopting a long-short strategy by buying P10 and selling P1.

We check the robustness of our results in two ways: 1) by changing portfolio formation period and 2) by altering the portfolio holding period. First, we change the portfolio formation period by estimating volatility using past 36 months and keeping the holding period as 1 month. We call it as 36/1 strategy. Portfolios are ranked and constructed in a similar manner as reported for 12/1 strategy. Next, we change the portfolio holding period to 12 months in both the above mentioned strategies and call them as 12/12 strategy and 36/12 strategy. We report the results of all the three strategies in Table 1 (Panels B, C and D). The results are similar to that of our original (12/1) strategy. In all the three cases P10 provides superior unadjusted returns as compared to P1. Thus, we confirm the presence of strong volatility effect on returns for the Indian stock market. The findings are robust as shown by evidence on trading strategies based on alternative constructions. Low volatility anomaly is rejected in the Indian context which is in contrast to the international literature. A possible explanation could lie in the nature of investors and their trading behaviour. It may be noted that the Indian market has far less institutional investor participation as compared to the U.S. Retail investors are more risk averse, and hence focus on low volatility stocks, leading to their overpayment and subsequent observable low returns. Unlike institutional investors, they are also not expected to cross high benchmarks for performance evaluation, and hence have little motivation to choose high volatility stocks in the absence of strong gambling behaviour. Our results are also in contrast to Rambhia

[3] Our results may however be interpreted with some caution as the volatility premium when measured as the difference between returns on P9 and P1 is relatively moderate i.e. 73% per month as compared to the volatility premium of 3.4% per month when measured as a difference between P10 and P1. This is owing to the fact that there is a large difference in returns for the two high volatility portfolios i.e. P10 and P9. Perhaps P10 comprises very thinly traded stocks which experience irregular but large price spurts resulting in high observable returns.

Table 1 Mean unadjusted returns for volatility sorted portfolios. We form 10 portfolios based on 12/1 strategy involving 12 months for volatility estimation and one month portfolio holding period. Decile portfolios are also constructed for 12/12, 36/1 and 36/12 strategies. The mean excess returns for P1 (low volatility portfolio), P10 (high volatility portfolio), intermediate portfolios (P2-P9) and long-short portfolio (P10-P1) for different strategies are shown below.

Descriptives	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1
Panel A: 12/1 strategy											
Mean	0.0119	0.0180	0.0183	0.0169	0.0191	0.0212	0.0255	0.0259	0.0283	0.0458	0.0339
Standard error	0.0044	0.0068	0.0076	0.0076	0.0086	0.0089	0.0099	0.0105	0.0115	0.0126	0.0129
t stat	2.7273	2.6270	2.4051	2.2189	2.2129	2.3646	2.5739	2.4553	2.4614	3.6209	2.6347
Panel B: 12/12 strategy											
Mean	0.0170	0.0177	0.0190	0.0180	0.0179	0.0210	0.0259	0.0234	0.0270	0.0437	0.0268
Standard error	0.0048	0.0070	0.0075	0.0083	0.0083	0.0089	0.0094	0.0100	0.0115	0.0124	0.0091
t stat	3.5342	2.5171	2.5154	2.1747	2.1411	2.3550	2.7532	2.3362	2.3531	3.5320	2.9347
Panel C: 36/1 strategy											
Mean	0.0143	0.0173	0.0171	0.0191	0.0201	0.0207	0.0239	0.0268	0.0302	0.0427	0.0284
Standard error	0.0043	0.0043	0.0065	0.0076	0.0081	0.0086	0.0089	0.0095	0.0109	0.0116	0.0101
t stat	3.3187	2.6617	2.2448	2.3645	2.3414	2.3222	2.5228	2.4510	2.6079	3.3217	2.8204
Panel D: 36/12 strategy											
Mean	0.0168	0.0199	0.0164	0.0199	0.0194	0.0175	0.0254	0.0251	0.0285	0.0409	0.0241
Standard error	0.0047	0.0068	0.0074	0.0083	0.0085	0.0086	0.0095	0.0106	0.0116	0.0127	0.0097
t stat	3.5619	2.9056	2.2357	2.3973	2.2832	2.0348	2.6740	2.3807	2.4572	3.2315	2.4862

et al. (2013) owing to the different time periods used in both studies. Our study provides for a more recent period, i.e. from 2000 to 2013, suggesting that the return behaviour in the Indian stock market might have changed. Further we have also checked the robustness of our results by altering the volatility calculation period (12 months and 36 months) and portfolio holding period (2 months and 1 month).

It is further observed that both high as well as low volatility stocks provide significant unadjusted returns with the former outperforming the latter. High returns on low volatility portfolios may not favour the implementation of long-short strategy as market borrowings may be much lower than the profit forgone on short selling. From the portfolio manager's perspective it seems more feasible to go long on high volatility stocks which promise a mean monthly return in the range of 4.1%–4.6% for the alternative strategies. In our analysis, we have thus far focussed on unadjusted returns. A large part of these returns may be associated with risk exposure(s). In the next section we test if prominent asset pricing models can explain the returns on volatility sorted portfolios.

Volatility sorted portfolios and asset pricing models

In the previous section we found that the return behaviour of portfolios sorted on volatility was in conformity with the risk story, i.e. P10 the highest volatile portfolio is providing the highest return and P1 the least volatile portfolio provides lowest returns. We now examine if the observed volatility pattern in stock returns can be explained by risk models. Tests are performed for all the four above mentioned strategies. We start with the standard CAPM model to evaluate if the market factor is able to absorb the cross section of average returns for the sample portfolios, the results for which are shown in Panel A of Table 2. The familiar excess return version of the market model is used to operationalise CAPM wherein excess asset returns are regressed on excess market returns as shown below,

$$Rp_t - Rf_t = \alpha + \beta(Rm_t - Rf_t) + e_t \quad (1)$$

where $Rp_t - Rf_t$ = Excess Return on sample portfolio; $Rm_t - Rf_t$ = Excess Return on the market factor; α and β are the estimated parameters; and e_t = error term.

The CAPM results provide consistent risk–return relationship for our analysis as low volatility portfolios (which provide low expected returns) exhibit smaller betas while high volatility portfolios (which exhibit higher expected returns) exhibit large betas.[4]

As expected, betas of P10 are substantially higher (almost three times) than those for P1. In fact, the market factor is able to explain about one third of the return differential on our long-short portfolios. The alphas (measure of abnormal return) are statistically significant at 5% level for all high volatility portfolios (P10), as well as for three out of four low volatility portfolios (P1) with the exception of 12/1 strategy. Further, alpha differentials are a measure of profitability as long–short positions are also statistically significant for all sample trading strategies barring 36/12 strategy.

Large CAPM alphas may not imply extranormal performance and actually represent compensations for missing risk factors. We extend our analysis by employing a multifactor

[4] The betas in CAPM framework increase monotonically as one moves from low to high volatility portfolios. However, they have not been reported for intermediate portfolios (P2 to P9) owing to paucity of space.

Table 2 Risk adjusted returns on volatility sorted portfolios. We regress excess returns on volatility sorted portfolios on (1) the market factor (CAPM Framework), (2) market size and value factors (the F-F model), (3) momentum factor in addition to the F-F factors (momentum augmented F-F model), (4) liquidity factor in addition to the F-F factors (liquidity augmented F-F model) and (5) momentum and liquidity factors in addition to the F-F factors (momentum and liquidity augmented F-F model). Alpha (α) is the risk adjusted returns which measures the extra normal performance.

Panel A: CAPM model results

	α	β	t_α	t_β	Adjusted R^2
12/1 strategy					
P1	0.0054	0.4834	1.9277	13.7215	0.6016
P10	0.0271	1.3855	3.2913	13.3157	0.5871
P10-P1	0.0217	0.9022	2.8587	9.3932	0.4130
12/12 strategy					
P1	0.0102	0.5911	3.6165	15.6541	0.6631
P10	0.0266	1.4967	3.5290	14.8173	0.6380
P10-P1	0.0164	0.9056	2.3493	9.6746	0.4275
36/1 strategy					
P1	0.0082	0.5327	3.2587	15.7587	0.6661
P10	0.0250	1.5453	3.1637	14.5751	0.6303
P10-P1	0.0168	1.0125	2.2029	9.9018	0.4390
36/12 strategy					
P1	0.0101	0.5869	3.7108	16.0993	0.6756
P10	0.0235	1.5279	3.0281	14.7189	0.6349
P10-P1	0.0134	0.9410	1.7674	9.2887	0.4075

Panel B: F-F model results

	α	β	SMB	LMH	t_α	t_β	t_{SMB}	t_{LMH}	Adjusted R^2
12/1 strategy									
P1	0.0027	0.5043	0.0297	0.0058	0.9858	14.7161	3.5696	0.3703	0.6340
P10	0.0189	1.4390	0.0941	−0.2525	2.6947	16.5911	4.4650	−6.4146	0.7214
P10-P1	0.0162	0.9347	0.0644	−0.2582	2.5012	11.6930	3.3143	−7.1184	0.6051
12/12 strategy									
P1	0.0076	0.5523	0.0238	−0.0078	2.4692	14.4541	2.5588	−0.4496	0.6248
P10	0.0178	1.4259	0.0844	−0.2289	2.5818	16.7109	4.0712	−5.9126	0.7190
P10-P1	0.0102	0.8737	0.0607	−0.2211	1.6398	11.3741	3.2498	−6.3445	0.5806
36/1 strategy									
P1	0.0070	0.5429	0.0135	−0.0100	2.7023	15.8949	1.7204	−0.6857	0.6699
P10	0.0148	1.6292	0.1172	−0.2667	2.4158	20.3133	6.3603	−7.7672	0.7952
P10-P1	0.0077	1.0863	0.1037	−0.2566	1.2767	13.6699	5.6800	−7.5447	0.6720
36/12 strategy									
P1	0.0088	0.5979	0.0142	0.0024	3.1439	16.1918	1.6688	0.1543	0.6777
P10	0.0136	1.6088	0.1130	−0.2597	2.2484	20.3362	6.2203	−7.6707	0.7947
P10-P1	0.0047	1.0109	0.0989	−0.2622	0.7888	12.9077	5.4965	−7.8214	0.6571

Panel C: Momentum augmented F-F model results

	α	β	SMB	LMH	w	t_α	t_β	t_{SMB}	t_{HML}	tw	Adjusted R^2
12/1 strategy											
P1	0.0039	0.5144	0.0322	−0.0152	−0.0656	1.3465	14.7787	3.8075	−0.7202	−1.4614	0.6374
P10	0.0180	1.4307	0.0921	−0.2353	0.0537	2.4614	16.1099	4.2642	−4.3718	0.4690	0.7196
P10-P1	0.0141	0.9162	0.0599	−0.2201	0.1193	2.1073	11.2436	3.0206	−4.4567	1.1353	0.6060
12/12 strategy											
P1	0.0091	0.5657	0.0271	−0.0354	−0.0865	2.8639	14.6261	2.8771	−1.5112	−1.7345	0.6310
P10	0.0161	1.4103	0.0806	−0.1968	0.1006	2.2446	16.1811	3.8033	−3.7258	0.8948	0.7185
P10-P1	0.0070	0.8447	0.0535	−0.1614	0.1871	1.0938	10.8850	2.8379	−3.4316	1.8695	0.5891
36/1 strategy											
P1	0.0083	0.5538	0.0163	−0.0339	−0.0747	3.1118	16.1003	2.0558	−1.7193	−1.7842	0.6758
P10	0.0140	1.6227	0.1155	−0.2523	0.0449	2.1913	19.8467	6.1233	−5.3774	0.4511	0.7938
P10-P1	0.0056	1.0689	0.0992	−0.2184	0.1196	0.8951	13.2652	5.3356	−4.7224	1.2194	0.6733
36/12 strategy											
P1	0.0102	0.6089	0.0170	−0.0217	−0.0753	3.5009	16.3453	1.9773	−1.0132	−1.6604	0.6823
P10	0.0119	1.5956	0.1096	−0.2306	0.0912	1.9049	19.8392	5.9078	−4.9961	0.9315	0.7945
P10-P1	0.0018	0.9867	0.0926	−0.2089	0.1664	0.2887	12.5018	5.0870	−4.6129	1.7330	0.6627

(*continued on next page*)

Please cite this article in press as: Asheesh Pandey, Sanjay Sehgal, Volatility effect and the role of firm quality factor in returns: Evidence from the Indian stock market, IIMB Management Review (2017), doi: 10.1016/j.iimb.2017.01.001

Table 2 (*continued*)

Panel D: Liquidity augmented F-F model results

	A	β	SMB	LMH	L	t_α	t_β	t_{SMB}	t_{LMH}	tL	Adjusted R^2
12/1 strategy											
P1	0.0029	0.5036	0.0284	0.0074	0.0443	1.0250	14.6790	3.3460	0.4689	0.8593	0.6332
P10	0.0185	1.4414	0.0993	−0.2586	−0.1714	2.6363	16.6655	4.6448	−6.5448	−1.3181	0.7231
P10-P1	0.0156	0.9377	0.0709	−0.2660	−0.2158	2.4344	11.8380	3.6221	−7.3489	−1.8113	0.6124
12/12 strategy											
P1	0.0080	0.5505	0.0200	−0.0033	0.1250	2.6120	14.6347	2.1474	−0.1923	2.2096	0.6365
P10	0.0172	1.4295	0.0922	−0.2381	−0.2558	2.5141	16.9604	4.4242	−6.1839	−2.0186	0.7260
P10-P1	0.0092	0.8790	0.0722	−0.2348	−0.3808	1.5440	11.9420	3.9686	−6.9830	−3.4408	0.6151
36/1 strategy											
P1	0.0072	0.5413	0.0112	−0.0074	0.0739	2.7909	15.9252	1.4141	−0.5032	1.5328	0.6736
P10	0.0139	1.6368	0.1274	−0.2786	−0.3316	2.3406	21.0647	7.0141	−8.3212	−3.0085	0.8079
P10-P1	0.0066	1.0956	0.1161	−0.2712	−0.4055	1.1533	14.5198	6.5864	−8.3427	−3.7887	0.7046
36/12 strategy											
P1	0.0092	0.5951	0.0103	0.0070	0.1259	3.3273	16.4351	1.2165	0.4465	2.4506	0.6905
P10	0.0125	1.6176	0.1249	−0.2736	−0.3863	2.1731	21.4277	7.0798	−8.4130	−3.6075	0.8132
P10-P1	0.0033	1.0226	0.1146	−0.2806	−0.5122	0.6100	14.3127	6.8643	−9.1158	−5.0537	0.7150

Panel E: Momentum and augmented liquidity based F-F model results

	α	β	SMB	LMH	w	L	t_α	t_β	t_{SMB}	t_{HML}	tw	tL	Adjusted R^2
12/1 strategy													
P1	0.0040	0.5142	0.0308	−0.0144	−0.0687	0.0500	1.4072	14.7690	3.5904	−0.6820	−1.5270	0.9716	0.6372
P10	0.0174	1.4314	0.0970	−0.2381	0.0648	−0.1767	2.3757	16.1733	4.4447	−4.4357	0.5665	−1.3517	0.7215
P10-P1	0.0133	0.9172	0.0662	−0.2237	0.1336	−0.2267	2.0004	11.3773	3.3289	−4.5752	1.2814	−1.9035	0.6144
12/12 strategy													
P1	0.0096	0.5651	0.0233	−0.0333	−0.0949	0.1328	3.0678	14.8893	2.4942	−1.4474	−1.9330	2.3677	0.6446
P10	0.0151	1.4115	0.0880	−0.2010	0.1173	−0.2655	2.1335	16.4192	4.1517	−3.8556	1.0551	−2.0902	0.7262
P10-P1	0.0055	0.8463	0.0647	−0.1677	0.2121	−0.3982	0.9061	11.4515	3.5481	−3.7413	2.2199	−3.6471	0.6273
36/1 strategy													
P1	0.0087	0.5527	0.0140	−0.0326	−0.0796	0.0803	3.2417	16.1859	1.7559	−1.6636	−1.9108	1.6795	0.6806
P10	0.0127	1.6274	0.1251	−0.2578	0.0654	−0.3369	2.0546	20.5735	6.7551	−5.6767	0.6780	−3.0418	0.8071
P10-P1	0.0041	1.0747	0.1110	−0.2252	0.1450	−0.4172	0.6804	14.1071	6.2269	−5.1485	1.5604	−3.9111	0.7081
36/12 strategy													
P1	0.0107	0.6070	0.0132	−0.0195	−0.0833	0.1326	3.7517	16.6793	1.5529	−0.9322	−1.8777	2.6015	0.6969
P10	0.0105	1.6011	0.1208	−0.2371	0.1153	−0.3956	1.7484	20.9261	6.7482	−5.3964	1.2353	−3.6929	0.8141
P10 -P1	−0.0002	0.9941	0.1076	−0.2176	0.1986	−0.5282	−0.0388	13.9366	6.4464	−5.3130	2.2832	−5.2888	0.7246

model. We examine if the Fama French Three factor model (F-F model) could explain portfolio returns that are not fully explained by CAPM. The F-F model equation is as follows:

$$Rp_t - Rf_t = \alpha + \beta(Rm_t - Rf_t) + s(SMB_t) + l(LMH_t) + e_t \quad (2)$$

where SMB and LMH are proxy size and value factors; and s and l are coefficients of SMB and LMH factors respectively. Other terms have the same meaning as in Eq. (1).

SMB and LMH factors are constructed by the intersection of five independently sorted size as well as value portfolios (5 × 5 formations) as in the case of Fama and French (1993). SMB is defined as the difference between average return on small and big stocks, while LMH is measured as the difference between average return on low and high P/B stocks on period to period basis. Any multicollinearity problem is sorted out before introducing these factors in the F-F framework. The results pertaining to the F-F model are shown in Table 2 (Panel B). P10 (high volatility portfolios) tend to load more strongly on the size factor as compared to P1 (low volatility portfolios). In contrast P10 seems to be composed of relatively high P/BV stocks vis-à-vis P1. The contradictory role of size and value factor reduces the power of the Fama French model in explaining returns. Almost all P1 and P10 portfolios provide significantly positive abnormal returns at the 5% level. On an overall basis, returns on three of the four P10-P1 portfolios, with the exception of 12/1 strategy, are absorbed by the Fama French model. These results must be interpreted with caution as they may be an outcome of self-cancelling pattern owing to high returns reported by the cornered portfolios i.e. P10 as well as P1.

In general CAPM and F-F model do explain a major part of returns on volatility sorted portfolios. However, given that alphas for some of the volatility portfolios have still not been fully explained, we further evaluate if returns on the sample portfolios could be explained by augmenting the Fama French model with an additional risk factor(s). Three versions of the augmented Fama French model are implied involving: 1)

Please cite this article in press as: Asheesh Pandey, Sanjay Sehgal, Volatility effect and the role of firm quality factor in returns: Evidence from the Indian stock market, IIMB Management Review (2017), doi: 10.1016/j.iimb.2017.01.001

Carhart (1997) stock momentum factor, 2) liquidity (Amihud, 2002) factor and 3) both momentum as well as liquidity factors. The liquidity factor has been constructed by ranking stocks on average daily trading volumes[5] and making five equally weighted portfolios wherein P1 is a portfolio of least liquid stocks and P5, the portfolio of most liquid stocks. Liquidity factor is constructed by taking difference of P1 and P5 (P1-P5). Similarly, momentum factor has been constructed by ranking stocks on past 12 month average returns and making 5 portfolios out of it. Momentum factor is created by taking the difference of P5 (portfolio providing highest return) and P1 (portfolio providing lowest returns) i.e. P5-P1. The full blown equation for our augmented F-F versions is as follows:

$$\begin{aligned} Rp_t - Rf_t = \alpha + \beta(Rm_t - Rf_t) + s(SMBt) + l(LMH_t) \\ + w(WML_t) + L(L1 - L10) + e_t \end{aligned} \quad (3)$$

where WML and (L1–L10) are proxies for price momentum and liquidity factors and w and L are the sensitivity coefficients. Other terms have the same meaning as in Eq. (2).

Equation (3) describes the five factor model. The momentum and liquidity augmented versions of the F-F model are estimated using the above said equation by eliminating one of the factors which does not find a place in our four factor framework. In order to create momentum factor each year starting June end 2003, we rank the sample stocks on the basis of average past 12 months excess returns and form 10 portfolios which are then held for the next 12 months i.e. from July to June. We rebalance the portfolios on a yearly basis, and continue until the end of the sample period. Finally, we take a difference of P10 and P1 to form momentum factor where P10 comprises past winners while P1 contains past losers. We adopt a similar process to construct the liquidity factor. However, the ranking criterion now is past 12 months average trading volumes. The liquidity factor is defined as L1-L10, where L1 and L10 consist of the bottom 10% and top 10% stocks based on trading volumes. The results relating to our augmented F-F versions are provided in Table 2 (Panels C to E). The additional factors do not play an important role in explaining asset returns with an exception of momentum factor in case of 36/12 strategy.

The failure of CAPM as well as our versions of multifactor model is not able to fully explain the returns on volatility sorted portfolios. Thus, in the Indian stock market, we experience volatility anomaly of a different kind. Both high and low volatility stocks provide extranormal returns on a risk adjusted basis. Further, the former outperform the latter in general. The long–short 12/1 strategy continues to provide an extranormal monthly return of 1.3%, even after using a five factor benchmark (Panel E). Following Walkshausl (2013), in the next section we examine the role of firm quality factor in asset returns, especially relating to the volatility anomaly. This, however, poses its own challenges. There can be several measures of firm quality and asset pricing results may or may not be impacted by choice of alternative measures.

Volatility anomaly and the role of firm quality factor

Measuring the firm quality

In this section we examine the association between return volatility and firm quality. McGuire, Schneeweis, and Branch (1990) show that profitability and operating income growth are important determinants for investors' perception of firm quality. Following Walkshausl (2013), two measures of firm quality are employed, namely, profitability and cash flow variability. Profitability has been measured using return on assets ratio (ROA), while cash flow variability is estimated as the standard deviation of the cash flow from operations over the last five years prior to portfolio formation. Following Huang (2009), cash flow from operations is used as a proxy for economic earnings as accounting earnings may underestimate the variability in operational profit due to earnings smoothing. According to prior evidence firms with higher profitability and low cash flow variability should provide higher returns (Allayannis, Rountree, & Weston, 2005; Bali & Cakici, 2008; Fama & French, 2006; Walkshausl, 2013). To form firm quality sorted portfolios, we rank the sample stocks in March of year t-1 and use the information to form 10 equally weighted portfolios from July of year t-1 to June of year t. Portfolio rebalancing is performed in March of each year over the sample period. P1 and P10 comprise the bottom 10% and top 10% stocks based on profitability. A similar exercise is done using cash flow variability as sorting criterion, resulting in P1 and P10 as portfolios with lowest and highest cash flow variability. The returns on quality sorted portfolios are shown in Table 3 (Panel A). The two measures of firm quality provide inconsistent results in the Indian context. Low cash flow variability stocks outperform high cash flow variability stocks resulting in a quality premium of 3.2% per month. These findings are in line with international evidence. Against expectations, high profitability stocks underperform low profitability stocks creating a negative quality premium of −1.2% per month. Our results are in contrast with international research and consistent with Sehgal and Subramaniam (2012)[6] in the Indian context. Thus, the results relating to firm quality factor are conflicting and not robust for alternative measures of risk attributes.

We next examine the association between the two measures of firm quality. Correlations are estimated between ROA and cash flow variability for the sample firms on a yearly basis. Mean correlation is then estimated by taking the average of annual correlations. The mean correlation between ROA and cash flow variability is −0.06 which is statistically insignificant. Thus, profitability measured by ROA and firm quality measured by the cash flow variability seem to be two independent dimensions associated with stock returns. In the Indian context, cash flow variability seems to be an appropriate measure of firm quality given its strong positive association with returns. Profitability measure should be avoided as a proxy for firm quality. More evidence needs to be collected

[5] It may be noted that average trading volume has been consciously chosen as a liquidity measure. Sehgal, Subramaniam, and De La Morandiere (2012) show that liquidity based portfolio results are robust for alternative measures of liquidity including more complex measures.

[6] Sehgal and Subramaniam (2012) suggest that less profitable firms exhibit low payout ratios, and hence are perceived to be more risky by investors, vis-à-vis highly profitable firms, which demand higher returns to hold them.

Please cite this article in press as: Asheesh Pandey, Sanjay Sehgal, Volatility effect and the role of firm quality factor in returns: Evidence from the Indian stock market, IIMB Management Review (2017), doi: 10.1016/j.iimb.2017.01.001

Table 3 Firm quality factor and its role in asset pricing. We form 10 portfolios based on firm quality characteristic. Two sets of portfolios are formed based on alternative measures of firm quality i.e. ROA and cash flow variability, results for which are shown in Panel A. In Panel B we provide the results for firm quality augmented F-F model which involves regressing excess returns of volatility sorted portfolios on F-F factors and the additional firm quality factor which is measured on the basis of cash flow variability.

Panel A: Relationship between firm quality factor and returns

Profitability unadjusted returns				Cash flow variability unadjusted returns			
Descriptives	P1	P10	P1-P10	Descriptives	P1	P10	P1-P10
Mean	0.0338	0.0215	0.0122	Mean	0.0468	0.0150	0.0318
Standard error	0.0100	0.0067	0.0064	Standard Error	0.0088	0.0094	0.0073
t stat	3.3677	3.2089	1.8974	t stat	5.3018	1.6005	4.3527

Panel B: Firm quality augmented F-F results

	α	B	SMB	LMH	QCFV	t_α	t_β	t_{SMB}	t_{HML}	tQCFV	Adjusted R^2
12 by 1 strategy											
P1	−0.0002	0.5368	0.0174	0.0343	0.1107	−0.0786	14.5703	1.7552	1.7086	2.1982	0.6452
P10	0.0061	1.5798	0.0409	−0.1290	0.4786	0.8175	17.6353	1.6951	−2.6441	3.9098	0.7508
P10-P1	0.0063	1.0430	0.0235	−0.1633	0.3680	0.9047	12.3941	1.0360	−3.5628	3.1997	0.6331
12 by 12 strategy											
P1	0.0027	0.6067	0.0032	0.0399	0.1850	0.8046	15.1535	0.2960	1.8301	3.3820	0.6546
P10	0.0085	1.5284	0.0457	−0.1391	0.3484	1.1298	16.8632	1.8713	−2.8170	2.8129	0.7342
P10-P1	0.0058	0.9217	0.0425	−0.1790	0.1634	0.8403	11.0352	1.8887	−3.9339	1.4313	0.5842
36 by 1 strategy											
P1	0.0040	0.5763	0.0006	0.0196	0.1155	1.4179	15.9908	0.0678	1.0516	2.4861	0.6835
P10	0.0078	1.7056	0.0877	−0.1988	0.2646	1.1789	20.1306	4.0264	−4.5412	2.4219	0.8031
P10-P1	0.0038	1.1293	0.0871	−0.2184	0.1490	0.5717	13.2358	3.9696	−4.9537	1.3549	0.6742
36 by 12 strategy											
P1	0.0043	0.6475	−0.0050	0.0465	0.1717	1.4567	17.0138	−0.5085	2.3620	3.4993	0.7051
P10	0.0064	1.6881	0.0824	−0.1894	0.2746	0.9728	20.2525	3.8474	−4.3962	2.5551	0.8037
P10-P1	0.0020	1.0406	0.0874	−0.2358	0.1029	0.3038	12.3268	4.0282	−5.4057	0.9452	0.6568

for other emerging markets before drawing general conclusions.

Firm quality factor and portfolio returns

Following Walkshausl (2013), we construct the firm quality factor (QCFV) as a difference between the returns on low cash flow variability and high cash flow variability stocks. The returns on our volatility sorted portfolios constructed in the previous section are regressed on the three Fama-French factors and the additional quality factor, the results for which are shown in Table 3 (Panel B). We refer to our four factor framework as the quality enhanced F-F model. Interestingly, the quality enhanced F-F model is able to explain returns on high volatility (as well as low volatility) portfolios which were missed by the F-F model. Further, it also captures the return on 12/1 long-short strategy (buying high volatility and short selling low volatility stocks) which the F-F model fails to explain. Consistent with international evidence, the firm quality factor thus plays an important role in explaining cross section of returns. However, unlike global findings wherein it partially absorbs the abnormal returns on low volatility portfolios, it plays a pivotal role in explaining abnormal returns on high volatility portfolios in the Indian scenario. Thus, in the Indian environment, firms with low cash flow variability (hence better quality) tend to exhibit higher stock return volatility. This observable inconsistency between measures of operational variability and return variability seems puzzling and needs to be further examined for a longer time period and across a cross section of emerging market economies. One possible explanation could be that institutional investors, who are playing an increasingly important role in emerging markets including India, chase high quality firms which exhibit low cash flow variability, and at the same time look for more volatile stocks that promise higher returns which may help them cross performance benchmarks. This may particularly be true for foreign institutional investors who have experienced a dampening of dollar/international currency denominated returns owing to a trend resulting in the slide of emerging market currency values vis-à-vis the dollar. The institutional investor behaviour of selecting stocks based on firm quality as well as return volatility may explain the empirical association between the two attributes. We conclude that the quality factor absorbs the volatility anomaly and hence has an important role to play in the multifactor asset pricing framework.

Volatility sorted portfolios after controlling for firm quality factor

We re-examine the relationship between volatility effect and firm quality. In March of t-1 we rank the sample firms on cash flow variability, and form two groups based on median breakpoint IE low and high firm quality groups. Next, we rank the sample stocks within each group on their past volatility and

Please cite this article in press as: Asheesh Pandey, Sanjay Sehgal, Volatility effect and the role of firm quality factor in returns: Evidence from the Indian stock market, IIMB Management Review (2017), doi: 10.1016/j.iimb.2017.01.001

form five portfolios for each quality group. The objective is to analyse the relationship between volatility and stock returns after controlling for the firm quality factor. As expected, volatility effect is more prominent for low quality firms than for the high quality group. The monthly differential returns between high and low volatility portfolios (P5-P1) for low cash flow variability group are 3.5%, 2.6%, 3.1% and 2.3% for 12/1, 12/12, 36/1 and 36/12 strategies respectively, as shown in Table 4 (Panel A). Similar returns for high cash flow variability group are 0.7% to 0.8 % per month for different strategies. Our findings are in contrast with prior research. In line with previous work, portfolios within low cash flow variability exhibit stronger volatility effect vis-à-vis those in the low volatility group. However, there is no volatility anomaly in India as high volatility stocks outperform low volatility stocks within each group, consistent with theoretical arguments.

The returns on these double sorted portfolios are then regressed on the market factor using CAPM framework, the results for which are shown in Table 4 (Panel B). We also regress returns of our conditional double sorted portfolios on the F-F factors (see Table 4 Panel C). Again, as expected, both CAPM and the F-F model are unable to explain the returns on higher volatility and a few long-short portfolios for low quality group. This provides scope for firm quality factor in returns which we empirically examined in the previous subsection. Thus, our results on volatility effect and the role of firm quality factor in returns are inherently consistent. To sum up, there is a strong volatility effect in stock returns, which is however explained by the quality enhanced F-F model in the Indian context. Our findings are in contrast with prior international work. Thus, the empirical issue under examination still remains unresolved and may warrant further research.

Summary and conclusions

In this paper, we examine if there is a volatility effect in stock returns for the Indian equity market. Data are employed for 493 stocks that form part of the BSE 500 Index from March 2000 to November 2013. In contrast with prior research, it is observed that high volatility stocks outperform low volatility stocks to the tune of 3.3% per month for a 12/1 strategy involving volatility estimation based on the past 12 months and fixing the holding period of volatility sorted portfolios to one month. The findings are robust for alternative strategies involving a different time period for volatility estimation and/or a different holding period. Our results are consistent with the theory, and negate the volatility anomaly argument observed in previous international work.

We observe that CAPM, Fama French Three Factor model and our versions of augmented F-F models involving stock momentum or/and the liquidity factor(s) are unable to absorb the volatility patterns in returns. High volatility stocks exhibit comparatively higher betas and comprise small size firms vis-à-vis low volatility stocks, which is consistent with the risk argument. However, more volatile firms seem to load less on the value (P/BV) factor as compared to low volatility firms. This may possibly explain the lower explanatory power of the F-F model.

We next explore the role of firm quality factor in returns with focus on volatility sorted portfolios. Following Walkshausl (2013), two measures of firm quality, namely profitability (measured by ROA) and cash flow variability, are used for the study. Unlike Walkshausl, our results with regard to these two firm quality measures are inconsistent. We find that low profitability and low cash flow variability firms outperform high profitability and high cash flow variability firms. The findings relating to profitability measure are not in line with international work (see Fama & French, 2006) but consistent with prior Indian evidence (Sehgal & Subramaniam, 2012). Thus, in the Indian context, profitability and firm quality seem to be two different dimensions with the latter being more appropriately measured by cash flow variability. Our argument is confirmed by the fact that quality premium based on the cash flow variability measure is large and to the tune of 3.2% per month.

We verify if the returns on volatility sorted portfolios are explained by the firm quality factor (based on cash flow variability). The quality enhanced F-F model is able to explain returns on all volatility sorted portfolios as well as long–short portfolios that involve buying high volatility and short selling low volatility stocks. We reconfirm our results by forming volatility sorted portfolios after controlling for the firm quality factor. As expected, volatility effect is mainly observed for the low cash flow variability group than for the high cash flow variability group. Further, both CAPM and the F-F model fail to explain the returns on our quality controlled volatility sorted portfolios in the low cash flow variability group. These results provide support for the role of firm quality factors in explaining the volatility pattern in returns. The present study is significant in many ways. First, unlike prior international evidence (including those for emerging markets) no volatility anomaly is observed in India. In fact, high volatility stocks outperform low volatility stocks, which is consistent with the theory. Thus, the behavioural explanations provided for superior performance of low volatility stocks in world markets may not be very relevant in the Indian context. Second, the measures of firm quality factor which have been used in recent literature to explain the volatility effect provide inconsistent results in India. The profitability premium is in fact negative, and the correlation between profitability and cash flow variability measures of firm quality is statistically insignificant. Profitability and cash flow variability seem to be two different dimensions and cash flow variability seems to be a better measure of the latter. Finally, the firm quality factor is able to fully absorb volatility patterns in returns for India, unlike international evidence where the firm quality factor does play an important role but still leaves some possibility for arbitrage opportunities. The research findings should be interpreted in light of the fact that we have focussed on gross returns and not included transaction costs in our analysis. However, given the fact that portfolio rebalancing exercise is annually in our case, the transaction cost may not play as important a role as in the case of high frequency trading strategies.

The research is pertinent for global fund managers, policy makers as well as the academic community. From an investment perspective, there is a volatility effect, but it does not pose any serious challenge to asset pricing. Thus, the profitability of volatility based trading strategies may be debatable in the Indian environment. From the policymaker's perspective, it provides some understanding of volatility patterns in returns as well as the institutional investor response to this information. Emerging markets like India, owing

Table 4 Results for volatility sorted portfolios after controlling for firm quality factor. We form two groups based on firm quality using median breakpoint. Firms with low cash flow variability represent the high quality group while firms with high cash flow variability are categorised into the low quality group. Next, we form five volatility portfolios within each quality group. This exercise helps us in evaluating the relationship between firm volatility and return after controlling for the quality characteristic, as shown in Panel A. Next, we verify if returns on our conditional double sorted portfolios can be explained by (1) CAPM and (2) F-F model, the results for which are shown in Panels B and C.

Panel A: Unadjusted returns

Descriptives	P1	P5	P5-P1	Descriptives	P1	P5	P5-P1
12/1 strategy: Low CFV based portfolios				**12/1 Strategy: High CFV based portfolios**			
Mean	0.0175	0.0526	0.0350	Mean	0.0131	0.0212	0.0081
Standard error	0.0051	0.0117	0.0084	Standard error	0.0066	0.0124	0.0070
t stat	3.4539	4.5033	4.1570	t stat	1.9866	1.7170	1.1579
12/12 Strategy: Low CFV based portfolios				**12/12 Strategy: High CFV based portfolios**			
Mean	0.0220	0.0480	0.0260	Mean	0.0125	0.0201	0.0076
Standard error	0.0053	0.0119	0.0084	Standard error	0.0067	0.0120	0.0065
t stat	4.1693	4.0404	3.1062	t stat	1.8549	1.6816	1.1645
36/1 Strategy: Low CFV based portfolios				**36/1 Strategy: High CFV based portfolios**			
Mean	0.0201	0.0508	0.0307	Mean	0.0122	0.0202	0.0080
Standard error	0.0051	0.0118	0.0086	Standard error	0.0061	0.0126	0.0077
t stat	3.9554	4.2963	3.5719	t stat	1.9866	1.6027	1.0478
36/12 Strategy: Low CFV based portfolios				**36/12 Strategy: High CFV based portfolios**			
Mean	0.0247	0.0482	0.0234	Mean	0.0130	0.0208	0.0078
Standard error	0.0054	0.0119	0.0084	Standard error	0.0066	0.0124	0.0071
t stat	4.5454	4.0625	2.7903	t stat	1.9785	1.6702	1.0997

Panel B: CAPM based results for double sorted portfolios

Portfolios	α	β	t_α	t_β	Adjusted R^2
12/1 Strategy: Low CFV					
P1	0.0108	0.5842	3.2507	13.0822	0.5784
P5	0.0370	1.3587	4.9008	13.4272	0.5912
P5-P1	0.0262	0.7744	3.8516	8.5048	0.3652
12/12 Strategy: Low CFV					
P1	0.0148	0.6280	4.4992	14.2735	0.6205
P5	0.0320	1.3918	4.2143	13.6604	0.5995
P5-P1	0.0173	0.7638	2.5471	8.4066	0.3597
36/1 Strategy: Low CFV					
P1	0.0133	0.5950	4.0781	13.6316	0.5985
P5	0.0352	1.3616	4.5349	13.0965	0.5790
P5-P1	0.0219	0.7666	3.1121	8.1294	0.3442
36/12 Strategy: Low CFV					
P1	0.0173	0.6530	5.1462	14.5373	0.6291
P5	0.0323	1.3844	4.2327	13.5326	0.5949
P5-P1	0.0151	0.7314	2.1610	7.8306	0.3272

Panel C: F-F model results for double sorted portfolios

Portfolios	α	β	SMB	LMH	t_α	t_β	t_{SMB}	t_{HML}	Adjusted R^2
12/1 Strategy: Low CFV									
P1	0.0075	0.5482	0.0336	−0.0005	2.0880	12.3998	3.1283	−0.0251	0.5506
P5	0.0282	1.2925	0.0882	−0.2575	4.2569	15.8174	4.4385	−6.9454	0.7100
P5-P1	0.0207	0.7443	0.0545	−0.2570	3.6738	10.7006	3.2259	−8.1434	0.5971
12/12 Strategy: Low CFV									
P1	0.0130	0.5726	0.0159	−0.0118	3.5228	12.5687	1.4336	−0.5731	0.5574
P5	0.0224	1.3287	0.0970	−0.2458	3.3351	16.0260	4.8113	−6.5321	0.7115
P5-P1	0.0094	0.7562	0.0811	−0.2339	1.6890	11.0070	4.8560	−7.5034	0.6018
36/1 Strategy: Low CFV									
P1	0.0127	0.5996	0.0064	−0.0169	3.7516	13.4708	0.6296	−0.8865	0.5958
P5	0.0260	1.4359	0.1046	−0.2638	4.2419	17.8278	5.6522	−7.6527	0.7554
P5-P1	0.0133	0.8364	0.0981	−0.2469	2.4532	11.7461	6.0001	−8.1024	0.6380
36/12 Strategy: Low CFV									
P1	0.0168	0.6563	0.0050	−0.0250	4.8331	14.3670	0.4758	−1.2788	0.6287
P5	0.0226	1.4638	0.1107	−0.2514	3.7670	18.5791	6.1185	−7.4550	0.7674
P5-P1	0.0058	0.8075	0.1057	−0.2264	1.0657	11.3212	6.4535	−7.4155	0.6201

Note: CFV stands for cash flow variability.

to low dividend paying behaviour of firms, exhibit high return volatility as investors focus more on the capital gains component. These investors prefer firms with higher quality (low cash flow variability), and at the same time chase more volatile stocks in pursuit of higher returns. For the academic community, the study provides several results inconsistent with prior literature. Thus, it is a future empirical challenge to reconcile these conflicting findings in the light of nuances in investor behaviour as well as microstructure effects across different global market settings. The study contributes to the return volatility and asset pricing literature for emerging markets such as India.

References

Allayannis, G., Rountree, B., & Weston, J. P. (2005). Earnings volatility, cash flow volatility, and firm value. Darden Graduate School of Business, University of Virginia, Working Paper.

Alpert, M., & Raffia, H. (1982). A progress report on the training of probability assessors. In D. Kahneman, P. Slovic, & A. Tversky (Eds.), *Judgment under uncertainty: Heuristics and biases* (pp. 294–305). New York: Cambridge University Press.

Alti, A., Kaniel, R., & Yoeli, U. (2012). Why do institutional investors chase return trends? *Journal of Financial Intermediation*, *21*(4), 694–721.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time series effect. *Journal of Financial Markets*, *5*(1), 31–56.

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

Baker, M., Bradley, B., & Wurgler, J. (2011). Benchmarks as limits to arbitrage: Understanding the low volatility anomaly. *Financial Analyst Journal*, *67*(1), 40–54.

Bali, T. G., & Cakici, N. (2008). Idiosyncratic volatility and the cross section of expected returns. *Journal of Financial and Quantitative Analysis*, *43*(1), 29–58.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3–18.

Blitz, D., & Vliet, V. (2007). The volatility effect: Lower risk without lower return. *Journal of Portfolio Management*, *34*(1), 102–113.

Carhart, M. M. (1997). On persistence in Mutual Fund Performance. *The Journal of Finance*, *52*(1), 57–82.

Clarke, R., De Silva, H., & Thorley, S. (2006). Minimum-variance portfolios in the U.S. equity market. *The Journal of Portfolio Management*, *33*(1), 10–24.

Core, J. E., Guay, W. R., & Rusticus, T. O. (2006). Does weak governance cause weak stock returns? An examination of firm operating performance and investor's expectations. *Journal of Finance*, *61*(2), 655–687.

Dutt, T., & Humphery-Jenner, M. (2013). Stock return volatility, operating performance and stock returns: International evidence on drivers of the "low volatility" anomaly. *Journal of Banking and Finance*, *37*(3), 999–1017.

Fama, E. F., & French, K. R. (1993). Common risk factors in returns on stocks and bonds. *Journal of Financial Economics*, *33*, 3–56.

Fama, E. F., & French, K. R. (2006). Profitability, investment and average returns. *Journal of Financial Economics*, *82*(3), 491–518.

Fischhoff, B., Slovic, P., & Lichtenstein, S. (1977). Knowing with certainty: The appropriateness of extreme confidence. *Journal of Experimental Psychology. Human Perception and Performance*, *3*(4), 552–564.

Huang, A. G. (2009). The cross section of cash flow volatility and expected stock returns. *Journal of Empirical Finance*, *16*, 409–429.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications of stock market efficiency. *Journal of Finance*, *48*(1), 65–91.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, *47*(2), 263–291.

Loughran, T., & Ritter, J. R. (1995). The New Issues Puzzle. *The Journal of Finance*, *50*(1), 23–51.

McGuire, J. B., Schneeweis, T., & Branch, B. (1990). Perceptions of firm quality: A cause or result of firm performance. *Journal of Management*, *16*, 167–180.

Rambhia, R., Joshipura, M., & Joshipura, N. (2013). Low risk anomaly: A new enemy of market efficiency. *The IUP Journal of Financial Risk Management*, *10*(3), 7–17.

Sehgal, S., & Subramaniam, S. (2012). An empirical investigation of the profitability anomaly in the Indian stock market. *Asian Journal of Finance and Accounting*, *4*(2), 347–361.

Sehgal, S., Subramaniam, S., & De La Morandiere, L. P. (2012). A search for rationale sources of stock return anomalies: Evidence from India. *International Journal of Economics and Finance*, *4*(4), 121–134.

Shefrin, H., & Statman, M. (2000). Behavioural portfolio theory. *Journal of Financial and Quantitative Analysis*, *35*(2), 127–151.

Stattman, D. (1980). Book values and stock returns. *The Chicago MBA: A Journal of Selected papers*, *4*, 25–45.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124–1131.

Walkshausl, C. (2013). The high returns to low volatility stocks are actually a premium on high quality firms. *Review of Financial Economics*, *22*(4), 180–186.

Wang, Y., & Ma, J. (2014). Excess volatility and the cross-section of stock returns. *The North America Journal of Economics and Finance*, *27*, 1–16.

Please cite this article in press as: Asheesh Pandey, Sanjay Sehgal, Volatility effect and the role of firm quality factor in returns: Evidence from the Indian stock market, IIMB Management Review (2017), doi: 10.1016/j.iimb.2017.01.001