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Sanjay Sehgal Vibhuti Vasishth

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Past price changes, trading volume and prediction of portfolio returns

Evidence from select emerging markets

Sanjay Sehgal
Department of Financial Studies, University of Delhi, New Delhi, India, and
Vibhuti Vasishth
Department of Commerce, Kamala Nehru College, University of Delhi, New Delhi, India

Abstract

Purpose – The purpose of this paper is to evaluate the profitability of investment strategies based on past price changes and trading volumes.
Design/methodology/approach – Data are employed from January 1998 to December 2011 for select emerging markets. Portfolios are formed on the basis of past information on prices and/or volumes. Unrestricted and risk adjusted returns for sample portfolios are analyzed. The risk models employed in study are Capital Asset Pricing Model (CAPM), Fama-French (F-F) Model and Fama-French augmented models.
Findings – Price momentum patterns are observed for Brazil, India, South Africa and South Korea, while there are reversals in Indonesia and China. Low-volume stocks outperform high-volume stocks for all sample countries except China. Further, volume and price based bivariate strategies do a better job than univariate strategies in case of India, South Africa and South Korea. The past price and volume patterns in stock returns are not fully explained by CAPM as well as the F-F Model. Price and volume momentum factors do play a role in explaining some of these return patterns. Finally, the unexplained returns seem to be an outcome of investor under or overreaction to past information. The sources of price and volume momentum seem to be partly risk based and partly behavioral.
Originality/value – The study analyzes combined role of price and volume in portfolio formation with post holding analysis. The work is useful for global portfolio managers, policy makers, market regulators and the academic community. The study contributes to asset pricing and behavioral finance literature for emerging markets.

Keywords Behavioural finance, Asset pricing, Investment strategies, Price momentum, Volume momentum
Paper type Research paper

1. Introduction

Efficient Market Hypothesis, given by Fama, 1970 suggests that as information gets reflected in security prices quickly and accurately, it is not possible to earn abnormal profit by using a trading strategy based on past and current public or private information. But, asset pricing anomalies help practitioners earn abnormal profits that are not explained by risk-return relationship suggested by asset pricing models. It is possible to earn abnormal returns by making use of past information in a weak form inefficient market. Two famous trading rules that successfully exploit past information on security prices are momentum and contrarian strategies.

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Momentum trading rule suggests that securities that have been earning profits in the past will continue to do so in future and vice versa. In their work, Jegadeesh and Titman (1993) have shown that on buying past winner stocks and selling past loss making stocks, significant profit is earned over the next three to 12 months. On the other hand, Contrarian trading rule suggests that securities that have been winner in the past, will be losers in future, and past loser securities will be future winners. Empirical evidence shows that while momentum strategies work well for intermediate portfolio formation periods (upto 12 months, see Jegadeesh and Titman, 1993), contrarian strategies seem to dominate in long-term horizons (for portfolio formation windows between 36 and 60 months, see De Bondt and Thaler, 1985).

Apart from the information contained in past security prices, traders can also exploit other sets of information to earn abnormal profits in an inefficient market. One such information is the past trading volume of securities. Information on past trading volume for long attracted attention of researchers and practitioners. Theory suggests that securities that have had low-trading volume in the past must demand an illiquidity premium compared to securities with high trading volume. Henceforth we refer to this phenomenon as volume momentum. Another trading strategy could be devised by combining information on past prices and past volumes, as both the variables may provide different information that could be profitable for portfolio formation. Theory would suggest that stocks that have been low-volume winners in the past must outperform high-volume losers.

Amihud and Mendelson (1986) introduced the effect of trading volume in asset pricing. They find that average return increases with illiquidity. After this, there have been many researchers who have analyzed the relation between trading volume and stock returns. Campbell *et al.* (1993) report a lower first daily autocorrelation of stock returns on days with high volume. Blume *et al.* (1994) examine informational content of volume and discuss its role in technical analysis. They prove that differential information is provided by volume and price, thus the information provided by volume can be successfully employed for technical analysis. Conrad *et al.* (1994) report positive auto covariance in weekly returns for securities with low-trading activity, whereas price reversals are observed for securities with high trading activity.

Lee and Swaminathan (2000) conclude that low-volume firms provide higher returns in future. Also, continuation of price momentum can be predicted by past trading volume. They depict the interaction between trading volume, price momentum and reversals with the help of momentum life cycle hypothesis. They propose that trading volume can help in finding the position of stock in this cycle. Chen *et al.* (2001) find that stocks with a relatively higher trading volume in the past six months, are skewed negatively. Gervais *et al.* (2001) report results different from what have been observed in earlier studies. They find the existence of high-volume return premium. Stocks with high trading volume over a day or week are observed to be rising in the following month. Lee and Rui (2002) analyze the cause and effect relation between trading volume and stock returns. Contrary to prior research, they find no causality running from trading volume to stock market returns. Amihud (2002) proves the concept of illiquidity premium. Pastor and Stambaugh (2003) find that sensitivity to aggregate liquidity and expected returns are directly related. Gagnon and Karolyi (2009) examine relation between return and trading volume for cross listed securities on the US market. They report that when returns in home market are accompanied by large shocks in volume, stocks with higher level of home or US market illiquidity have higher chance of experiencing continuations. Florackis *et al.* (2011) introduce a new price impact ratio (return to turnover ratio). They use the price impact factor along with the momentum factor to augment the Fama-French (F-F) Model. They observe an inverse relation between price impact ratio and subsequent return. They also document that introduction of this factor helps in partial explanation of momentum. Chen (2012) explores if empirical linkages between stock returns and trading volume are asymmetric in market upswings and downswings. With respect to contemporaneous correlation, he reports a positive and negative correlation in rising and falling market, respectively.

There has not been much work on this subject for emerging markets. Few studies that have analyzed the relation between stock returns in trading volume in various developing countries are mentioned below.

Saatcioglu and Starks (1998) study the relation between stock price and trading volume for six Latin American markets. They find that volume and returns are correlated positively. They also conclude that returns follow volume. Hameed and Yuanto (2002) work on six pacific basin stock markets to analyze the profitability of momentum investment strategy. They find the presence of momentum in securities with high turnover, but in all the markets these profits are not found to be significant. Sehgal and Balakrishnan (2008) report stronger momentum profits for low-volume stocks for the Indian market. Tripathy (2011) analyzes the relation between trading volume and stock return for the Indian market. He reports two-way causality between stock return volatility and trading volume. He also finds that trading volume and increase in return volatility are asymmetrically related. Chuang *et al.* (2012) examine the cause and effect relation between trading volume and stock returns, and trading volume and stock return volatility for ten Asian markets. They report a positive two-way causality between trading volume and stock returns for certain countries; and between trading volume and return volatility for some economies. Sehgal and Subramaniam (2012) work on various asset pricing anomalies including liquidity affect for the Indian market. They find that liquidity enhanced F-F Model does a better job in explaining portfolio returns as compared to Capital Asset Pricing Model (CAPM) and F-F Model. Gebka and Wohar (2013) examine the causal link between past trading volume and index returns for nine pacific basin countries. No causal linkage is found between trading volume and returns according to OLS results. But, his Quantile regression results indicate non-linear causality between the variables. They find positive (negative) impact of volume for high (low) returns of next day.

It can be clearly seen that current literature on volume momentum focusses more on developed capital markets, while similar work for emerging markets is limited. Further, very few studies have examined the combined role of price and volume in portfolio formation. Also there are limited attempts to evaluate profitability of price and volume-based trading strategies *vis-à-vis* multifactor benchmarks beyond the F-F Model. In other words the power of additional risk factors based in explaining price/volume momentum is relatively unexplored. Moreover, the post holding patterns of these portfolios have been less examined to diagnose if there are any behavioral biases which possibly explain observable momentum profits. The present study attempts to fill these important gaps in research for select emerging markets, namely, Brazil, India, China, South Africa, South Korea and Indonesia. Out of the popular group of emerging economies;

BRICS, Russia has been excluded from the analysis as enough data were not available for it. Two more important developing Asian economies; South Korea and Indonesia have been added to the group.

The study specifically attempts to answer the following questions:

(1) Are price momentum and volume momentum strategies profitable?

(2) Are trading strategies based on combined information on past price and volume profitable?

(3) Is trading strategy based on combined information more profitable than any of the strategies based on either past price or volume?

(4) Do the returns on sample strategies get explained by standard risk models such as CAPM and F-F Model?

(5) Is there a role for price momentum (Carhart, 1997) and illiquidity (Amihud and Mendelson, 1986) factors in explaining cross section of returns for portfolios formed on basis of past prices and/or volume?

In Section 2, we describe data and their sources. Methodology and estimation procedures are discussed in Section 3. In Section 4, we provide empirical results and their analysis. Summary and concluding observations are given in the last section.

2. Data

The data comprises of month end stock prices that are adjusted for stock splits, stock dividends and rights issues. They are then converted into percentage returns for further analysis. The information about daily number of shares traded and number of shares outstanding is also collected, which is then used to construct daily turnover (number of shares traded/ number of shares outstanding). Daily data for volume have been taken as suggested by prior work; including Lee and Swaminathan (2000). Data on price to book value ratio and market capitalization (price times number of shares outstanding) for each security at the end of each six months are collected to construct value and size factors, respectively. Month end stock index values are used to proxy market performance, which are again converted into percentage returns. In all, 91 day US Treasury Bill yields are used as risk free surrogate. Data for the sample countries have been collected in dollar terms as this will facilitate comparison for a global portfolio manager.

It was initially planned that data for all the sample countries would be taken from the time period January 1998 to December 2011. This period was chosen because the focus of this paper is on Asian economies, and the impact of Asian crises was visible on concerned economies till December 1997. But, the starting time period for all countries is not the same as sufficient data were not available for most of the sample markets from January 1998. Thus the beginning of the study period for each sample country has been chosen to ensure that sufficient stocks (at least ten) are present in each portfolio, so that sample portfolios are well diversified and hence their returns do not reflect any compensation for unsystematic risk.

The table below gives information on time period of analysis, number of stocks and market proxy (with its construction methodology) for the sample countries.

The data source: Bloomberg database:

Country	Time period of analysis	Number of stocks	Market proxy (construction methodology)
Brazil	July 2000-December 2011	195	BOVESPA Index (Market value of free float is used to assign weights to securities. This index is constructed using 1968 as the base year, with base value being 100)
India	January 1998-December 2011	500	BSE-200 Index (It is constructed using 1989-1990 as the base year, with free float market capitalization)
China	January 2000-December 2011	599	Shanghai stock exchange A share index (It traces price trends of all A-shares, which are limited to local and qualified institutional foreign investors. This capitalization weighted index has a base value of 100, and was developed in December 1990)
South Africa	January 2000-December 2011	238	FTSE/JSE Africa ALL SHARE (It comprises of the top 99% of all the listed companies on the Johannesburg Stock Exchange. It is a free float market capitalization weighted index)
South Korea	January 2001-December 2011	500	South Korea Stock Exchange KOSPI index (It was developed with 100 as the base value on January 4, 1980. It is a market capitalization weighted index which comprises of all common stocks traded on the South Korea stock exchange)
Indonesia	January 2001-December 2011	443	Jakarta stock exchange composite index (It was developed with 100 as the base value on August 10, 1982. It is a modified capitalization weighted index that comprises of all stocks listed on the Indonesia stock exchange)

3. Methodology

The methodology used to test profitability of various strategies; univariate (based on past price or past volume) and bivariate (based on combined information on past price and volume) is described in this section. We employ 6-6 and 12-12 strategies. The former involves six-month portfolio formation and holding periods, while the latter uses 12-month periods. We concentrate on these two strategies as most prior work deals with them. We consciously avoid 6-12 and 12-6 strategies as they shall result in overlapping portfolio formation and holding windows. The strategy choice is justified on following counts:

(1) no significant result differences were reported for non-overlapping and overlapping portfolios in Jegadeesh and Titman (1993) work; and

(2) when strategies are formed on overlapping basis, portfolio managers will have to hold many sub portfolios, and transaction costs may wipe off arbitrage profits. Strategies less than 6-6 months are avoided as they require high-frequency price data which may in turn reflect microstructure impacts (see Lo and MacKinlay, 1990).

First, the methodology used for construction of portfolios based on 6-6 strategy is illustrated.

In June end of each year, securities are ranked in ascending order on the basis of average of past six month's excess returns. On the basis of these rankings the stocks are divided into five portfolios, P1 to P5, where P1 consists of top 20 percent of the stocks and P5 is comprised of bottom 20 percent stocks. Then, equally weighted returns on the sample portfolios are estimated for the next six months (July to December). We skip six months and re-rank and re-form the portfolios and the process is continues till the end of study period.

We similarly form past volume-based trading strategy with a difference that six months average daily turnover is used as ranking variable instead of past returns. The five volume ranked portfolios are labeled V1-V5 with V1 comprising of 20 percent of the stocks with highest volume and V5 consists of bottom 20 percent stocks in terms of volume.

Besides the above described univariate strategies (involving a single ranking criterion), two bivariate ranking strategies are also employed. First we adopt an independent bivariate strategy. Under this we first rank the stocks on the basis of six months' past return and form three equally weighted portfolios. P1 (top 33-1/3 percent), P2 (middle 33-1/3 percent) and P3 (bottom 33-1/3 percent). Next, we independently rank the sample companies based on past six-month daily turnover and form three equally weighted portfolios. While V1 comprises of top 33-1/3 percent stocks, V3 contains bottom 33-1/3 percent stocks. From the intersection of three past return and three past volume sorted portfolios, we form nine bivariate independently sorted portfolios. In this case, V3P1 comprises of stocks with bottom 33-1/3 percent past trading volume and top 33-1/3 percent past returns. In contrast V1P3 refers to the portfolio with stocks having highest (top 33-1/3 percent) past trading volume and lowest (bottom 33-1/3 percent) past returns.

Further we use two bivariate conditional trading strategies, namely, volume-price and price-volume. In the first case 3 equally weighted portfolios are formed on the basis of past volumes. And then, three past return-based sub portfolios are formed within each volume group.

The procedure is reversed in the second case, i.e., portfolios are first formed on past returns followed by volume sorted sub portfolios within each past return group. Each of the estimation procedure results in nine bivariate conditional sorted portfolios. All bivariate (independent and conditional portfolios) have been rebalanced using six-month roll over period. Similar estimation procedures are adopted for 12-12 univariate and bivariate strategies, with a difference that portfolio formation and holding periods are taken to be 12 months.

We estimate mean returns for the sample portfolios. They are referred to as unrestricted returns, as no filtering has been done as yet for the risk factors. We report returns only for the corner portfolios which are lowest and highest on a single ranking criterion in case of univariate strategies. In case of bivariate strategies, the corner portfolios comprise of lowest volume/highest return groups and highest volume/lowest return groups. The portfolio choice is guided by prior research which shows that while high past return stocks outperform low past return stocks (price momentum), low past volume stocks do better than high past volume stocks in the future (volume momentum). Such an analysis is likely to provide a clearer picture for two extremely distinct groups. Results for intermediate portfolios have not been reported owing to paucity of space and can be obtained on request.

We then evaluate if the cross section of returns on our univariate and bivariate sorted portfolios can be explained by standard risk models. Two asset pricing models are used for this purpose, namely, CAPM, F-F Model. The CAPM is operationalized using the familiar excess return version of market model equation as shown below:

$$R_{pt}–R_{ft} = a_p + b_p\left(R_{mt}–R_{ft}\right) + e_{pt} \tag{1}$$

where $R_{pt} - R_{ft}$ is the excess return on portfolios at time "t", i.e., return on portfolio at time "t" minus risk free return at time "t"; $R_{mt} - R_{ft}$ the excess return on market factor; a_p the intercept, which is the measure of abnormal profits; b_p the slope coefficient which shows the sensitivity of portfolio returns to market returns; e_{pt} the error term.

CAPM implies that portfolio returns must be fully explained by market returns. If the intercept is significantly positive (or negative), CAPM is unable to explain the portfolio returns. Thus, the portfolios are observed to be earning abnormal profits (or losses). If this is the case, we adopt the F-F three-factor model to verify if it is a better descriptor of asset returns *vis-à-vis* one factor CAPM. The F-F equation is as follows:

$$R_{pt}–R_{ft} = a_p + b_p\left(R_{mt}–R_{ft}\right) + s_p(R_{SMB}) + l_p(R_{LMH}) + e_{pt} \tag{2}$$

where SMB and LMH are mimicking portfolios for size and value factors, respectively. s_p and l_p are sensitivity coefficients.

Other variables have the same description as in Equation (1).

Our estimation procedure of F-F Model is different from the methodology applied by Fama and French (1993) in two ways. First we construct LMH factor rather than HML factor in the F-F regression. Therefore we interpret value factor in an inverse manner. Second, we do not make use of 2×3 size-value partition. Instead, we use 2×2 size-value partition. Our construction procedure ensures that the size and value factors are only mildly correlated. We abandon 2×3 procedure owing to serious multicollinearity problems. At the end of every six months/12 months, sample stocks are divided on the basis of their market capitalization into two groups. Stocks with market capitalization more than the median value are classified as Big (B) and the remaining as Small (S). Similarly, stocks are categorized into High (H) and Low (L) groups on the basis of their price to book value ratio. Then four portfolios, namely, S/L, S/H, B/L, B/H are formed using the intersection of the two size and two P/B groups. SMB factor is the difference between average return of small stocks and big stocks for each holding period. This factor is used because small stocks are supposed to have higher risk than big stocks, thereby giving higher returns. LMH factor is the difference between average return of low-P/B and high-P/B stocks. This factor is used because low-P/B stocks are supposed to be undervalued stocks which theoretically must give higher returns than high-P/B stocks.

These factors have been constructed with six months and 12 months formation and holding periods for 6-6 and 12-12 strategies, respectively.

A significantly positive intercept for the F-F Model may imply superior performance on risk adjusted basis, which shall be encouraging for global portfolio managers. However, superior selection skills are to be interpreted with caution. Growing body of empirical literature has traced role of additional risk factors in returns. For instance, Carhart (1997) suggested a four-factor model which augments the F-F framework by including a stock momentum factor. Stock momentum factor is described to be the difference between the average return on past winners and past losers. The economic foundation for this factor can be traced to Chordia and Shivakumar (2002), who show that past returns reflect macroeconomic fundamentals as they contain information about future returns which are predicted by these fundamentals.

Amihud and Mendelson (1986) introduced the role of illiquidity factor in asset pricing models. This factor has been used since theory suggests that low-volume stocks must give higher returns *vis-à-vis* high-volume stocks as investors demand a premium for less liquid stocks. Earlier studies did not focus on the impact of liquidity, but recent studies show that liquidity needs to be considered specifically (see Chordia *et al.*, 2001; Amihud, 2002; Lee and Swaminathan, 2000 and Keene and Peterson, 2007.

Based on prior work, we extend the F-F Model by including additional risk dimension(s). Three versions of enhanced F-F Model is used, namely, price momentum enhanced F-F Model, illiquidity enhanced F-F Model and Price momentum and illiquidity enhanced F-F Model. While the first two versions provide a four factor performance benchmark, the last version results in a five-factor model. The five-factor model is described below:

$$R_{pt}–R_{ft} = a_p + b_p\left(R_{mt}–R_{ft}\right) + s_p(R_{SMB}) + l_p(R_{LMH}) + m_p(R_{WML}) + v_p(R_{v5t}–R_{v1t}) + e_{pt} \tag{3}$$

where WML is the stock momentum factor; V5t-V1t the illiquidity factor; m_p, v_p are sensitivity coefficients.

WML is defined as the average return on past winners (P1) and past losers (P5). On the other hand, illiquidity factor is constructed as the difference between average return on low-liquidity portfolio (V5) and high-liquidity portfolio (V1).

The five factor version is estimated using above said equation, while the two four factor versions are estimated by suppressing one additional variable at a time, while retaining the three F-F factors. An insignificant α from the enhanced models shall imply that the extra normal performance observed in the case of F-F Model is merely a compensation for missing risk factor(s). In contrast, a significantly positive α shall provide stronger support for strategy design as well as arbitrage.

Existing finance theory does not provide a universal asset pricing model and hence, the nature and number of risk factors relevant for a country or a group of countries is more of an empirical debate. For instance, αs filtered from enhanced F-F benchmarks may indicate superior performance but the findings may not be conclusive. All or some part of these abnormal returns may actually be outcomes of behavioral biases, i.e., do investors over/under react to past information. In the final phase, we examine the post holding pattern of our price/volume momentum sorted portfolios whose return behavior was not fully explained by alternative multifactor models used in the study.

We observe returns for select portfolios for a period of 36 months following the holding window. After estimating the average return for each month starting from holding period, we cumulate the returns for all months in holding and post holding window. We then estimate the average of cumulative returns for each month. Post holding period has been restricted to 36 months owing to limited length of our data period. Most prior studies dealing with momentum also tend to use three to five years post holding periods (see Lee and Swaminathan, 2000; Jegadeesh and Titman, 2001, etc.).

4. Empirical results

In this section we estimate time series of unrestricted returns for univariate sorted (price/volume-based) as well as bivariate sorted (price- and volume-based) portfolios. We further examine if cross section of returns for the above said portfolios can be explained by risk model(s).

4.1 Unrestricted returns

We define unrestricted returns as the mean excess unadjusted returns which are shown in Table I for our sample portfolios[1].

Using past returns as ranking criterion, for 6-6 strategy winner portfolio in South Africa is earning 4.04 percent P.M., followed by those in India and Brazil with mean monthly return of 3.71 percent and 3.48 percent, respectively. In contrast to momentum for these markets, contrarian behavior is observed for Indonesia, where the loser outperforms the winner and provides return of 3.6 percent P.M. For 12-12 strategy, momentum profits shrink for South Africa, India and Brazil mainly due to the decline in returns of winner portfolios. Interestingly, contrarian profits become stronger over time for Indonesia, mainly due to superior performance of the loser portfolio which provides return of 4.19 percent P.M.

It is observed that, loser portfolios in Brazil, India and South Africa and winner portfolio in Indonesia provide high returns. Hence, a long-short strategy may not be economically feasible owing to high financing costs. Instead, going long in winners (loser in case of Indonesia) promises higher profits. Weak momentum and contrarian patterns are witnessed for South Korea and China, respectively, for both 6-6 and 12-12 strategies. Winner portfolio in South Korea provides a mean monthly return of about 1.7 percent for both the strategies, which though statistically insignificant, cannot be ignored in the economic sense.

Using past volume as the ranking criterion, for 6-6 strategy, low-volume portfolios in Indonesia, South Africa, India and South Korea are earning mean monthly returns of 3.58, 3.33, 3.22 and 1.69 percent, respectively. But, a contrary pattern is observed in Brazil where high-volume portfolio is earning a return of 2.68 percent P.M. which is better than return on low-volume portfolio. The results for Brazil are surprising as they defy the illiquidity premium argument. An optimal strategy would be to go long in low-volume portfolios of Indonesia, South Africa, India and South Korea, and in high-volume portfolio of Brazil. Long-short strategy is again not beneficial as high-volume portfolios of Indonesia, South Africa, India and South Korea; and low-volume portfolio of Brazil provide high returns making the financing strategy expensive.

For 12-12 strategy, all the above mentioned countries (including Brazil) exhibit volume momentum which implies that low-volume stocks outperform high-volume stocks in the next period. Low-volume portfolios provide a mean monthly return of 5.45, 3.31, 3.3, 2.87 and 1.7 percent for Indonesia, Brazil, India, South Africa and South Korea, respectively.

Low-volume portfolios tend to provide stronger profits in all cases with exception of South Africa as one expands the strategy's window from 6-6 to 12-12 months. Like price momentum, there are no significant volume momentum results for China.

Comparing the two univariate sorted strategies, it can be clearly seen that price momentum winners perform the best in Brazil, India and South Africa based on 6-6 strategy, whereas low-volume stocks give highest returns in case of South Korea and Indonesia based on 12-12 strategy. Thus, global investors who are scanning emerging markets should keep in mind that past price changes contain better information than past volumes for portfolio formation purposes in case of Brazil, India and South Africa. In contrast, past volumes seem to be better asset selection criterion *vis-à-vis* past price

	Brazil	India	China	South Africa	South Korea	Indonesia
Panel A: price momentum sorted portfolios						
Mean (P1)	0.0348	0.0371	0.0098	0.0404	0.0166	0.0310
t-Value	3.4809	4.0312	1.1354	3.8200	1.7792	2.9957
Mean (P5)	0.0250	0.0232	0.0102	0.0195	0.0157	0.0359
t-Value	2.0969	2.2351	1.1124	2.8249	1.6920	2.8959
Mean (P1-P5)	0.0098	0.0139	(0.0004)	0.0208	0.0009	(0.0049)
t-Value	1.1823	2.3122	(0.0819)	2.4095	0.2178	(0.6142)
Panel B: volume momentum sorted portfolios						
Mean (V1)	0.0269	0.0244	0.0097	0.0165	0.0102	0.0215
t-Value	2.0736	2.2932	1.0286	2.3501	1.0050	1.8580
Mean (V5)	0.0247	0.0322	0.0090	0.0333	0.0169	0.0358
t-Value	2.4845	4.0316	1.1234	3.3435	2.2840	3.9092
Mean (V5-V1)	(0.0022)	0.0078	(0.0006)	0.0168	0.0067	0.0143
t-Value	(0.2575)	1.5355	(0.1830)	1.9563	1.2652	2.1973
Panel C: portfolios framed using Independent sorting						
Mean (V3P1)	0.0321	0.0383	0.0142	0.0320	0.0149	0.0388
t-Value	3.6024	4.3545	1.5253	3.3030	1.8947	3.8973
Mean (V1P3)	0.0215	0.0198	0.0106	0.0138	0.0130	0.0156
t-Value	1.7498	1.7614	1.0643	1.6472	1.2517	1.2054
Mean (V3P1-V1P3)	0.0105	0.0186	0.0036	0.0182	0.0019	0.0232
t-Value	1.1591	2.3547	0.5248	2.1519	0.3252	2.3504
Panel D: portfolios framed using Conditional I sorting						
Mean (V3P1)	0.0312	0.0356	0.0109	0.0492	0.0182	0.0376
t-Value	3.4836	4.4186	1.2763	3.1710	2.3276	3.8258
Mean (V1P3)	0.0204	0.0208	0.0115	0.0138	0.0154	0.0171
t-Value	1.7455	1.8406	1.1760	1.8379	1.4692	1.3451
Mean (V3P1-V1P3)	0.0109	0.0148	(0.0006)	0.0354	0.0029	0.0205
t-Value	1.2718	2.0689	(0.1186)	2.4307	0.4759	2.2352
Panel E: portfolios framed using Conditional II sorting						
Mean (P1V3)	0.0324	0.0356	0.0118	0.0514	0.0182	0.0391
t-Value	3.5952	4.2150	1.4117	3.2328	2.2193	3.9297
Mean (P3V1)	0.0211	0.0193	0.0102	0.0174	0.0142	0.0169
t-Value	1.7715	1.7339	1.0315	2.0967	1.3675	1.3802
Mean (P1V3-P3V1)	0.0113	0.0164	0.0016	0.0341	0.0040	0.0222
t-Value	1.3284	2.2519	0.2777	2.2439	0.7192	2.4713

Notes: We show mean excess returns for price momentum-based winner and loser portfolios and low- and high-volume-based stock portfolios for univariate strategies. For bivariate strategies, we show similar returns for low-volume-price winners and high-volume-price losers. All mean returns are tested for significance at 5 percent level on two-tailed basis

Table I. Unrestricted returns for sample portfolios

changes for South Korea and Indonesia. Volume-based strategies seem to perform better on expanded time windows, i.e., 12-12 months compared to price based strategies which seem to do better for 6-6 windows. No past volume or price based return patterns are observed in China, implying that prior information based trading strategies are irrelevant.

Two results seem to be inconsistent with most of previous empirical work:

(1) Short-term (upto 12 months) contrarian behavior is observed in Indonesia for strategies based on past returns. Short run contrarian may arise due to short run liquidity imbalances in the market (see Lehmann, 1990).

(2) More liquid stocks seem to enjoy premium for 6-6 strategy in Brazil, which is puzzling. One plausible explanation could be that visibility of a stock is affected by the shocks it experiences in its trading activity. Thus, the demand and price of the stock is affected by its volume (see Gervais *et al.*, 2001).

Next, we analyze three bivariate sorted strategies, namely, Independent, Conditional I (based on price sub portfolios nesting within each volume momentum portfolio) and Conditional II (based on volume sub portfolios nesting within each price momentum portfolio).

Analyzing 6-6 bivariate independent strategy, one can see that low-volume-winner portfolios outperform high-volume-loser portfolios for all the sample countries. The returns on low-volume-winner portfolios are statistically significant for all markets except South Korea and China.

With expansion of time window, returns on low-volume-winner portfolios of India and Indonesia have increased from 3.83 to 4.06 percent P.M. and 3.88 to 4.49 percent P.M., respectively, whereas it has decreased for Brazil and South Africa.

For bivariate Conditional I and Conditional II sorts, low-volume-winner portfolios outperform high-volume-loser portfolios, and in fact provide statistically significant returns for all markets except China. Further, low-volume-winner portfolios perform better for 12-12 strategy compared to 6-6 strategy in case of India only in Conditional I (return has increased from 3.56 to 4.10 percent P.M.), South Korea only in Conditional II (return has increased from 1.82 to 1.9 percent P.M.), and for Indonesia both in case of Conditional I and II strategies (return has increased from 3.76 to 4.5 percent P.M. for Conditional I, and from 3.91 to 4.79 percent P.M. in case of Conditional II). The converse is true for South Africa and Brazil.

For all bivariate strategies, a long position in low-volume winners is advisable compared to long-short strategy owing to high returns on high-volume losers, implying exorbitant cost of financing. It is observed that bivariate strategies are not always better than univariate strategies. Conditional sorting works well for markets of India, South Africa and South Korea. In the Indian context, the best strategy is when securities are sorted first on the basis of past volume, then on past returns (Conditional I) using 12-12 windows. For other two countries the best strategy is when securities are sorted first on the basis of past returns then on past volume (Conditional II) using 6-6 and 12-12 windows, respectively. Thus, only in these markets, it is profitable to use combined information on past return and volume. Further, it is observed that in India, price has additional significant information apart from information contained in volume. Whereas, reverse is true in case of South Africa where volume contains significant incremental information[2].

4.2 Momentum profits and risk models

After observing the unrestricted returns, excess return on all portfolios are regressed on excess market return using CAPM framework. Results based on this model are given in Table II.

For 6-6 strategy, winner stocks in Brazil and India, as well as winner and loser stocks in South Africa provide statistically significant returns. Further the market beta for winners is lower than that for losers in case of first two countries, which is surprising. The CAPM is able to explain returns on all other portfolios for the sample countries. For 12-12 strategy, winners in India, losers in Indonesia and winners as well as losers in South Africa outperform the market factor. Further as expected, winner portfolio for these countries, except Indonesia exhibit higher betas *vis-à-vis* losers.

When securities are sorted on the basis of past volume for 6-6 strategy, low-volume stocks outperform the market for South Africa, India, Indonesia and Brazil. Interestingly,

	Brazil	India	China	South Africa	South Korea	Indonesia
Panel A: price momentum sorted portfolios						
a(P1)	0.0223	0.0221	0.0052	0.0339	0.0032	0.0084
t-Value	3.7207	5.1537	1.0749	3.4977	0.7512	1.3856
b	0.8020	1.2259	1.0249	0.9007	1.0501	1.0237
t-Value	15.5314	24.4916	17.2340	7.9557	22.3656	16.2377
Adjusted R^2	0.6471	0.7881	0.6836	0.3126	0.7997	0.6776
a(P5)	0.0092	0.0076	0.0055	0.0110	0.0031	0.0081
t-Value	1.4678	1.2532	0.9885	2.5121	0.6115	1.1880
b	1.0161	1.2714	1.0377	0.8184	0.9871	1.2536
t-Value	18.8448	17.9683	15.1948	14.6553	17.7614	17.5440
Adjusted R^2	0.7300	0.6666	0.6266	0.6094	0.7156	0.7105
Panel B: volume momentum sorted portfolios						
a(V1)	0.0111	0.0068	0.0048	0.0063	(0.0034)	(0.0060)
t-Value	1.3641	1.4429	0.8598	2.1918	(0.5846)	(1.1150)
b	1.0135	1.4359	1.0769	0.9678	1.0611	1.2440
t-Value	14.4702	26.0575	15.7328	26.2568	16.5966	22.2846
Adjusted R^2	0.6140	0.8081	0.6428	0.8340	0.6871	0.7986
a(V5)	0.0117	0.0202	0.0048	0.0260	0.0067	0.0162
t-Value	2.1635	4.3510	1.0487	2.9066	1.7359	2.9051
b	0.8348	0.9813	0.9473	0.6973	0.7991	0.8872
t-Value	17.9505	18.1326	17.0340	6.0997	18.6165	15.2629
Adjusted R^2	0.7103	0.6706	0.6785	0.2090	0.7344	0.6498
Panel C: portfolios framed using Independent sorting						
a(V3P1)	0.0211	0.0256	0.0099	0.0314	0.0041	0.0195
t-Value	3.8752	4.6251	1.5318	3.1967	0.9882	2.7819
b	0.7074	1.0327	0.9631	0.0631	0.8450	0.8726
t-Value	15.1153	15.9438	12.2392	0.5028	18.5304	11.9453
Adjusted R^2	0.6346	0.6113	0.5206	(0.0055)	0.7325	0.5313
a(V1P3)	0.0059	0.0025	0.0057	0.0116	(0.0003)	(0.0124)
t-Value	0.8248	0.4003	0.8892	1.3856	(0.0513)	(1.6040)
b	1.0030	1.4068	1.0885	0.2108	1.0412	1.2645
t-Value	16.2632	19.3494	13.9344	1.9643	14.7387	15.6973
Adjusted R^2	0.6679	0.6987	0.5851	0.0204	0.6337	0.6625
Panel D: portfolios framed using Conditional I sorting						
a(V3P1)	0.0202	0.0234	0.0066	0.0414	0.0072	0.0179
t-Value	3.6648	5.0456	1.2492	2.7776	1.8705	2.6968
b	0.7098	0.9940	0.9628	0.7445	0.8587	0.8917
t-Value	14.9681	18.3291	14.9742	3.9035	20.0202	12.9049
Adjusted R^2	0.6300	0.6754	0.6197	0.0941	0.7618	0.5698
a(V1P3)	0.0052	0.0033	0.0067	0.0038	0.0021	(0.0111)
t-Value	0.8061	0.5317	1.0632	0.9214	0.3192	(1.5444)
b	0.9738	1.4263	1.0764	0.9500	1.0373	1.2770
t-Value	17.5185	19.8421	13.9663	17.9169	14.3603	16.9986
Adjusted R^2	0.7002	0.7092	0.5862	0.7002	0.6215	0.6973
Panel E: portfolios framed using Conditional II sorting						
a(P1V3)	0.0211	0.0230	0.0075	0.0433	0.0065	0.0193
t-Value	3.9624	4.6033	1.4912	2.8377	1.6841	2.8439
b	0.7308	1.0292	0.9527	0.7790	0.9096	0.8964

(*continued*)

Table II.
CAPM based results

	Brazil	India	China	South Africa	South Korea	Indonesia
t-Value	15.9638	17.6206	15.5255	3.9933	21.1122	12.6449
Adjusted R^2	0.6596	0.6578	0.6366	0.0984	0.7806	0.5597
a(P3V1)	0.0054	0.0021	0.0053	0.0072	0.0008	(0.0106)
t-Value	0.8486	0.3385	0.8399	1.3555	0.1284	(1.5660)
b	1.0099	1.4034	1.0879	0.9653	1.0417	1.2419
t-Value	18.4755	19.7516	14.0502	14.1406	14.9522	17.6437
Adjusted R^2	0.7221	0.7073	0.5891	0.5922	0.6404	0.7128

Table II.

Notes: Excess portfolio returns are regressed on the returns for market factor using CAPM specifications. α (a) is a measure of extra normal return

these low-volume portfolios exhibit lower betas compared to their high-volume counterparts, thus implying that stocks with greater illiquidity may not necessarily be riskier in terms of operational and financial risk. For 12-12 strategy, returns on low-volume stocks are again not fully explained by CAPM. In addition, CAPM fails to explain return for high-volume stocks in South Africa for both 6-6 and 12-12 strategy.

For all the three bivariate strategies, low-volume-winner portfolios in India, South Africa, Brazil and Indonesia are earning statistically significant returns for both 6-6 and 12-12 strategies.

Surprisingly, for all the double sort strategies at both the levels, market beta of low-volume winner portfolio is lower than that of high-volume-loser portfolio for the above mentioned countries.

Table III provides results based on F-F Model. Focussing on price momentum, we find that F-F Model fails to absorb returns for sample portfolios which were missed by CAPM except for loser portfolio for South Africa and Indonesia in case of 12-12 strategy. In case of volume momentum, the F-F Model again fails to capture the cross section of returns that are missed by CAPM with the exception of low-volume portfolio for Brazil for 6-6 and 12-12 strategy and low-and high-volume portfolio for South Africa for 12-12 strategy. Returns on low-volume portfolios for Indonesia and India for both the strategies remain unexplained.

For bivariate strategies, the F-F Model again does not perform a better job than CAPM except for Brazil (in case of 12-12 strategy).

The poor performance of F-F Model can be attributed to the fact that price winners in case of South Africa, seem to comprise of small size and high-P/B firms. While those in Brazil and India contain big size and high-P/B firms, which is confirmed by their factor loadings. Low-volume portfolios in India are composed of big size and low-P/B firms, whereas low-volume portfolios of South Africa and Indonesia comprise of small size with high-P/B firms. Similarly, low-volume-winner stocks for South Africa and Indonesia comprise of small stocks and high-P/B firms, while in case of India they seem to contain large-size and low-P/B firms. For 6-6 bivariate strategies, low-volume-winner portfolios for Brazil are comprised of big stocks with high-P/B. The factor loadings are inconsistent with the risk story. Hence, the F-F size and value factors do not seem to play an important role in explaining momentum patterns for stock returns.

Next we test if price or/and volume momentum factors explain returns that are missed by the F-F Model. Results of our enhanced F-F Models are shown in Table IV. The number of unexplained portfolios comes down from 33 to 20 as one employees enhanced F-F Models in place of F-F Model. Thus, a part of momentum patterns in stock returns for the sample countries can be attributed to illiquidity risk and/or risk associated with price momentum which has its tracks in macroeconomic fundamentals (see Chordia and

	Brazil	India	South Africa	Indonesia
Panel A: price momentum sorted portfolios				
a(P1)	0.0175	0.0163	0.0328	
t-Value	3.1225	3.9388	3.7832	
b	0.8365	1.1602	0.8979	
t-Value	17.6388	23.5440	8.2933	
s	0.5839	0.4706	1.1804	
t-Value	5.3266	5.5555	3.7504	
l	(0.1673)	0.0009	(0.3513)	
t-Value	(1.2712)	0.0117	(0.9737)	
Adjusted R^2	0.7091	0.8205	0.3719	
a(P5)	0.0002	(0.0043)	0.0091	
t-Value	0.0409	(0.7689)	2.1420	
b	1.0506	1.1138	0.8214	
t-Value	23.2091	16.7059	15.5495	
s	0.8044	0.6839	0.5622	
t-Value	7.6877	5.9665	3.6612	
l	0.1399	0.3754	0.3656	
t-Value	1.1137	3.6009	2.0771	
Adjusted R^2	0.8140	0.7412	0.6508	
Panel B: volume momentum sorted portfolios				
a(V1)	0.0072	(0.0016)	0.0063	0.0002
t-Value	0.8636	(0.3639)	2.1831	0.0388
b	1.0269	1.3332	0.9679	1.1678
t-Value	14.6333	25.5479	27.0082	24.2488
s	0.3351	0.5964	0.3287	0.1713
t-Value	2.0661	6.6472	3.1545	1.9678
l	0.0863	0.1179	0.0100	0.7116
t-Value	0.4433	1.4449	0.0839	7.4598
Adjusted R^2	0.6213	0.8496	0.8432	0.8634
a(V5)	0.0062	0.0114	0.0269	0.0244
t-Value	1.3027	2.6238	3.0614	4.5111
b	0.8711	0.8640	0.6958	0.8348
t-Value	21.5262	16.7570	6.3330	15.6870
s	0.6366	0.4908	1.1594	0.2691
t-Value	6.8062	5.5366	3.6295	2.7971
l	(0.1464)	0.2949	(0.1824)	0.5888
t-Value	(1.3032)	3.6585	(0.4982)	5.5870
Adjusted R^2	0.7856	0.7387	0.2699	0.7326
Panel C: portfolios framed using Independent sorting				
a(V3P1)	0.0198	0.0161	0.0285	0.0302
t-Value	3.9017	3.0344	2.8305	4.0932
b	0.7432	0.9041	0.0676	0.8641
t-Value	17.3376	14.2962	0.5383	11.8836
s	0.4115	0.5105	0.0883	0.4043
t-Value	4.1531	4.6960	0.2416	3.0755
l	(0.4447)	0.3465	0.3550	0.3305
t-Value	(3.7382)	3.5042	1.3253	2.2946
Adjusted R^2	0.7004	0.6761	(0.0067)	0.5768

(*continued*)

Table III.
Fama-French Model based results

	Brazil	India	South Africa	Indonesia
a(V1P3)	(0.0055)	(0.0078)	0.0093	(0.0093)
t-Value	(0.8901)	(1.3047)	1.0865	(1.2341)
b	1.0275	1.2759	0.2143	1.1495
t-Value	19.7964	17.9491	1.9982	15.5540
s	0.8340	0.6613	(0.2645)	0.0223
t-Value	6.9518	5.4115	(0.8481)	0.1670
l	0.4668	0.2337	0.4392	0.9199
t-Value	3.2409	2.1027	1.2286	6.2846
Adjusted R^2	0.7701	0.7483	0.0217	0.7412
Panel D: portfolios framed using Conditional I sorting				
a(V3P1)	0.0187	0.0150	0.0439	0.0278
t-Value	3.5775	3.4195	2.9501	3.9678
b	0.7433	0.8831	0.7406	0.8876
t-Value	16.8303	16.8992	3.9802	12.8377
s	0.4013	0.4869	1.5782	0.3793
t-Value	3.9310	5.4193	2.9175	3.0346
l	(0.3956)	0.2592	(0.4847)	0.2799
t-Value	(3.2282)	3.1718	(0.7816)	2.0439
Adjusted R^2	0.6864	0.7365	0.1386	0.6075
a(V1P3)	(0.0053)	(0.0069)	0.0027	(0.0102)
t-Value	(0.9516)	(1.1780)	0.6302	(1.5206)
b	0.9911	1.2976	0.9518	1.1477
t-Value	21.2284	18.5223	17.9167	17.4571
s	0.7163	0.6729	(0.0453)	(0.0724)
t-Value	6.6378	5.5870	(0.2936)	(0.6090)
l	0.5082	0.2104	0.2183	0.9709
t-Value	3.9224	1.9206	1.2329	7.4563
Adjusted R^2	0.7933	0.7586	0.6993	0.7888
Panel E: portfolios framed using Conditional II sorting				
a(P1V3)	0.0198	0.0149	0.0458	0.0306
t-Value	3.8829	3.0712	3.0204	4.3364
b	0.7614	0.9212	0.7751	0.8825
t-Value	17.6682	15.9877	4.0923	12.7039
s	0.3611	0.4640	1.7341	0.4195
t-Value	3.6256	4.6839	3.1492	3.3405
l	(0.3674)	0.2613	(0.4829)	0.3837
t-Value	(3.0720)	2.9000	(0.7651)	2.7886
Adjusted R^2	0.7052	0.7089	0.1508	0.6148
a(P3V1)	(0.0040)	(0.0089)	0.0068	(0.0062)
t-Value	(0.7131)	(1.5430)	1.2391	(0.9695)
b	1.0261	1.2627	0.9660	1.1386
t-Value	21.5430	18.4826	14.0546	18.1732
s	0.6502	0.6805	(0.0784)	0.0810
t-Value	5.9060	5.7935	(0.3921)	0.7152
l	0.4474	0.2760	0.0798	0.8665
t-Value	3.3844	2.5840	0.3483	6.9831
Adjusted R^2	0.7938	0.7635	0.5870	0.7927

Note: Excess returns on the sample portfolios are regressed on the returns on market factor and two mimicking portfolios that proxy for size and value factors in returns

Table III.

(1) Fama-French Model augmented with price momentum factor

Panel A: price momentum sorted portfolios

	Brazil	India	South Africa
a(P1)	0.0085	0.0098	0.0121
t-Value	2.3147	2.5916	2.8908
b	0.9479	1.1456	0.8313
t-Value	29.9258	26.2170	16.2510
s	0.6986	0.5376	0.6424
t-Value	9.8149	7.1022	4.2680
l	(0.0074)	0.1186	0.2727
t-Value	(0.0864)	1.6820	1.5803
m	0.5205	0.3142	0.8704
t-Value	0.0000	6.6657	21.6668
Adjusted R^2	0.8791	0.8592	0.8603
a(P5)	0.0085	0.0098	0.0121
t-Value	2.3147	2.5916	2.8908
b	0.9479	1.1456	0.8313
t-Value	29.9258	26.2170	16.2510
s	0.6986	0.5376	0.6424
t-Value	9.8149	7.1022	4.2680
l	(0.0074)	0.1186	0.2727
t-Value	(0.0864)	1.6820	1.5803
m	(0.4795)	(0.6858)	(0.1296)
t-Value	(12.3933)	(14.5511)	(3.2263)
Adjusted R^2	0.9151	0.8891	0.6737

Panel B: volume momentum sorted portfolios

	India	South Africa	Indonesia
a(V1)	0.0039	0.0062	0.0026
t-Value	0.9148	2.0980	0.5367
b	1.3455	0.9677	1.1595
t-Value	27.6738	26.8541	24.0006
s	0.5399	0.3271	0.2582
t-Value	6.4102	3.0851	2.9141
l	0.0188	0.0118	0.8727
t-Value	0.2394	0.0972	7.5964
m	(0.2647)	0.0025	(0.2642)
t-Value	(5.0476)	0.0889	(4.1934)
Adjusted R^2	0.8697	0.8421	0.8645
a(V5)	0.0151	0.0101	0.0262
t-Value	3.4670	1.5802	4.8007
b	0.8723	0.6417	0.8295
t-Value	17.4263	8.2197	15.4523
s	0.4525	0.7216	0.3360
t-Value	5.2181	3.1417	3.4133
l	0.2277	0.3253	0.7190
t-Value	2.8204	1.2350	5.6326
m	(0.1795)	0.7081	(0.2026)
t-Value	(3.3239)	11.5510	(2.8937)
Adjusted R^2	0.7543	0.6328	0.7319

Panel C: portfolios framed using Independent sorting

	Brazil	India	South Africa	Indonesia
a(V3P1)	0.0168	0.0106	0.0196	0.0269

(*continued*)

Table IV. Excess returns of sample portfolios are regressed on the three Fama-French factors and price momentum or/and volume momentum factor(s)

t-Value	3.3797	2.0180	2.0000	3.9278
b	0.7803	0.8916	0.0390	0.9031
t-Value	18.2459	14.7842	0.3268	13.3946
s	0.4497	0.5680	(0.1430)	0.3126
t-Value	4.6797	5.4372	(0.4068)	2.5282
l	(0.3914)	0.4475	0.8232	0.3207
t-Value	(3.3836)	4.5999	2.0430	2.0001
m	0.1735	0.2696	0.3740	0.3051
t-Value	3.3211	4.1446	3.9879	3.4692
Adjusted R^2	0.7222	0.7062	0.0940	0.6414
a(V1P3)	0.0002	0.0047	0.0107	(0.0026)
t-Value	0.0293	0.9692	1.2107	(0.3781)
b	0.9578	1.3039	0.2188	1.1043
t-Value	19.7352	23.4427	2.0316	16.5918
s	0.7622	0.5323	(0.2289)	0.2406
t-Value	6.9891	5.5242	(0.7224)	1.9718
l	0.3668	0.0071	0.3979	1.1962
t-Value	2.7946	0.0796	1.0953	7.5581
m	(0.3255)	(0.6050)	(0.0576)	(0.6853)
t-Value	(5.4902)	(10.0842)	(0.6812)	(7.8949)
Adjusted R^2	0.8127	0.8463	0.0178	0.7932
Panel D: portfolios framed using Conditional I sorting				
	Brazil	India	South Africa	Indonesia
a(V3P1)	0.0156	0.0111	0.0102	0.0253
t-Value	3.0457	2.5319	1.2204	3.7705
b	0.7819	0.8743	0.6317	0.9188
t-Value	17.7591	17.2814	6.2154	13.9498
s	0.4410	0.5271	0.6987	0.3073
t-Value	4.4578	6.0143	2.3363	2.5441
l	(0.3402)	0.3299	0.5353	0.2752
t-Value	(2.8573)	4.0424	1.5612	1.7572
m	0.1803	0.1889	1.4227	0.2401
t-Value	3.3533	3.4611	17.8244	2.7948
Adjusted R^2	0.7096	0.7536	0.7439	0.6490
a(V1P3)	0.0007	0.0058	0.0031	(0.0037)
t-Value	0.1441	1.2408	0.7146	(0.6151)
b	0.9175	1.3262	0.9532	1.1057
t-Value	22.0355	24.7479	17.8583	18.9044
s	0.6405	0.5415	(0.0336)	0.1406
t-Value	6.8454	5.8326	(0.2141)	1.3107
l	0.4025	(0.0204)	0.2047	1.2514
t-Value	3.5744	(0.2364)	1.1366	8.9972
m	(0.3441)	(0.6164)	(0.0189)	(0.6666)
t-Value	(6.7658)	(10.6635)	(0.4519)	(8.7397)
Adjusted R^2	0.8468	0.8591	0.6975	0.8353
Panel E: portfolios framed using Conditional II sorting				
	Brazil	India	South Africa	Indonesia
a(P1V3)	0.0170	0.0098	0.0117	0.0276
t-Value	3.3888	2.0475	1.3532	4.2147
b	0.7954	0.9097	0.6652	0.9201
t-Value	18.3690	16.5732	6.3052	14.3079
s	0.3962	0.5168	0.8463	0.3368

Table IV.

(*continued*)

t-Value	4.0717	5.4355	2.7262	2.8557
l	(0.3185)	0.3541	0.5467	0.3875
t-Value	(2.7191)	3.9997	1.5358	2.5341
m	0.1592	0.2479	1.4361	0.2773
t-Value	3.0097	4.1882	17.3334	3.3068
Adjusted R^2	0.7227	0.7365	0.7375	0.6747
a(P3V1)	0.0017	0.0038	0.0092	0.0006
t-Value	0.3405	0.8557	1.6453	0.1045
b	0.9552	1.2912	0.9737	1.0919
t-Value	22.0569	25.1311	14.2745	20.7033
s	0.5772	0.5494	(0.0161)	0.2992
t-Value	5.9311	6.1722	(0.0800)	3.0942
l	0.3456	0.0458	0.0075	1.1349
t-Value	2.9506	0.5528	0.0328	9.0486
m	(0.3313)	(0.6148)	(0.1008)	(0.6862)
t-Value	(6.2623)	(11.0932)	(1.8810)	(9.9765)
Adjusted R^2	0.8412	0.8666	0.5946	0.8552

(2) Fama-French Model augmented with volume momentum factor

Panel A: price momentum sorted portfolios

	Brazil	India	South Africa
a(P1)	0.0175	0.0148	0.0320
t-Value	3.1117	3.4943	3.8379
b	0.8282	1.2136	1.0339
t-Value	17.1518	19.8820	9.2739
s	0.5998	0.4827	1.0126
v	5.4018	5.6918	3.3005
l	(0.1796)	(0.0192)	(0.4792)
t-Value	(1.3569)	(0.2467)	(1.3723)
v	(0.0529)	0.1138	0.4184
t-Value	(0.9201)	1.4719	3.4256
Adjusted R^2	0.7088	0.8218	0.4185
a(P5)	0.0003	(0.0034)	0.0083
t-Value	0.0529	(0.5947)	2.3489
b	1.0612	1.0822	0.9495
t-Value	23.0856	13.0317	20.0331
s	0.7838	0.6768	0.4041
t-Value	7.4156	5.8660	3.0983
l	0.1557	0.3873	0.2452
t-Value	1.2360	3.6508	1.6518
v	0.0680	(0.0674)	0.3941
t-Value	1.2433	(0.6405)	7.5905
Adjusted R^2	0.8148	0.7403	0.7545

Panel B: volume momentum sorted portfolios

	India	South Africa	Indonesia
a(V1)	0.0051	0.0064	0.0007
t-Value	1.2854	2.2335	0.1543
b	1.0926	0.9474	1.2096
t-Value	19.3406	24.8182	29.3337
s	0.5422	0.3540	0.2246
t-Value	6.9085	3.3699	2.9619
l	0.2087	0.0293	0.5986
v	2.8914	0.2452	6.7678

(*continued*)

Table IV.

v	(0.5127)	(0.0631)	(0.4532)	
t-Value	(7.1682)	(1.5093)	(7.8068)	
Adjusted R^2	0.8859	0.8447	0.8968	
a(V5)	0.0051	0.0252	0.0228	
t-Value	1.2854	3.7071	5.3674	
b	1.0926	1.0060	0.8529	
t-Value	19.3406	11.0882	20.6825	
s	0.5422	0.7767	0.2246	
t-Value	6.9085	3.1109	2.9619	
l	0.2087	(0.4739)	0.5986	
t-Value	2.8914	(1.6678)	6.7678	
v	0.4873	0.9537	0.5468	
t-Value	6.8122	9.5960	9.4184	
Adjusted R^2	0.7970	0.5654	0.8346	

Panel C: portfolios framed using Independent sorting

	Brazil	India	South Africa	Indonesia
a(V3P1)	0.0198	0.0082	0.0277	0.0198
t-Value	3.9069	1.7119	2.8291	3.9069
b	0.7504	1.1913	0.2039	0.7504
t-Value	17.1885	17.3161	1.5580	17.1885
s	0.3975	0.5752	(0.0798)	0.3975
t-Value	3.9597	6.0181	(0.2216)	3.9597
l	(0.4339)	0.2382	0.4270	(0.4339)
t-Value	(3.6259)	2.7099	1.0419	(3.6259)
v	0.0463	0.6120	0.4188	0.0463
t-Value	0.8917	7.0258	2.9219	0.8917
Adjusted R^2	0.7000	0.7520	0.0469	0.7000
a(V1P3)	(0.0056)	0.0002	0.0090	(0.0056)
t-Value	(0.9311)	0.0435	1.0489	(0.9311)
b	1.0038	0.9851	0.2802	1.0038
t-Value	19.3778	12.3776	2.4553	19.3778
s	0.8798	0.5959	(0.3457)	0.8798
t-Value	7.3861	5.3893	(1.1009)	7.3861
l	0.4315	0.3434	0.3773	0.4315
t-Value	3.0385	3.3778	1.0559	3.0385
v	(0.1520)	(0.6197)	0.2024	(0.1520)
t-Value	(2.4647)	(6.1502)	1.6192	(2.4647)
Adjusted R^2	0.7789	0.7959	0.0334	0.7789

Panel D: portfolios framed using Conditional I sorting

	Brazil	India	South Africa	Indonesia
a(V3P1)	0.0187	0.0083	0.0418	0.0273
t-Value	3.5764	2.1174	3.1288	4.1633
b	0.7490	1.1258	1.1077	0.8753
t-Value	16.6304	19.9486	6.1952	13.7388
s	0.3902	0.5415	1.1253	0.3491
t-Value	3.7682	6.9063	2.2872	2.9791
l	(0.3871)	0.1676	(0.8296)	0.5125
t-Value	(3.1360)	2.3248	(1.4816)	3.7504
v	0.0366	0.5172	1.1287	0.2934
t-Value	0.6827	7.2381	5.7628	3.2713
Adjusted R^2	0.6850	0.8012	0.3055	0.6567
a(V1P3)	(0.0054)	0.0005	0.0025	(0.0102)

Table IV.

(*continued*)

t-Value	(0.9756)	0.0838	0.5933	(1.4574)
b	0.9760	1.0298	0.9812	1.2198
t-Value	20.7015	12.9330	17.3312	17.9148
s	0.7457	0.6126	(0.0817)	(0.0142)
t-Value	6.8785	5.5381	(0.5241)	(0.1136)
l	0.4856	0.3114	0.1906	0.6333
t-Value	3.7575	3.0617	1.0750	4.3364
v	(0.0974)	(0.5708)	0.0905	(0.4102)
t-Value	(1.7350)	(5.6617)	1.4591	(4.2788)
Adjusted R^2	0.7965	0.7982	0.7018	0.7666

Panel E: portfolios framed using Conditional II sorting

	Brazil	India	South Africa	Indonesia
a(P1V3)	0.0199	0.0079	0.0436	0.0301
t-Value	3.9072	1.7902	3.2252	4.6228
b	0.7722	1.1740	1.1590	0.8708
t-Value	17.6611	18.5383	6.4128	13.7872
s	0.3402	0.5209	1.2604	0.3908
t-Value	3.3841	5.9202	2.5343	3.3641
l	(0.3512)	0.1659	(0.8437)	0.6555
t-Value	(2.9309)	2.0504	(1.4906)	4.8388
v	0.0693	0.5388	1.1805	0.2787
t-Value	1.3318	6.7194	5.9625	3.1341
Adjusted R^2	0.7070	0.7725	0.3248	0.6719
a(P3V1)	(0.0041)	(0.0020)	0.0065	(0.0064)
t-Value	(0.7399)	(0.3613)	1.1966	(0.9354)
b	1.0086	1.0133	1.0237	1.2081
t-Value	21.0414	12.9340	14.1227	18.3301
s	0.6842	0.6243	(0.1496)	0.1328
t-Value	6.2075	5.7361	(0.7497)	1.0955
l	0.4211	0.3701	0.0256	0.5061
t-Value	3.2054	3.6980	0.1126	3.5799
v	(0.1127)	(0.5315)	0.1774	(0.3480)
t-Value	(1.9746)	(5.3578)	2.2347	(3.7508)
Adjusted R^2	0.7983	0.7988	0.5989	0.7637

(3) Fama-French Model augmented with both the factors

Panel A: price momentum sorted portfolios

	Brazil	India	South Africa
a(P1)	0.0085	0.0092	0.0115
t-Value	2.3023	2.3696	3.3380
b	0.9498	1.1730	0.9608
t-Value	29.1965	21.4553	21.3787
s	0.6958	0.5427	0.4856
t-Value	9.6422	7.1391	3.8830
l	(0.0046)	0.1065	0.1482
t-Value	(0.0533)	1.4785	1.0398
m	0.5218	0.3092	0.8661
t-Value	13.3302	6.5040	26.2595
v	0.0102	0.0577	0.3974
t-Value	0.2725	0.8333	8.0854
Adjusted R^2	0.8782	0.8589	0.9059
a(P5)	0.0085	0.0092	0.0115
t-Value	2.3023	2.3696	3.3380

(*continued*)

Table IV.

b	0.9498	1.1730	0.9608
t-Value	29.1965	21.4553	21.3787
s	0.6958	0.5427	0.4856
t-Value	9.6422	7.1391	3.8830
l	(0.0046)	0.1065	0.1482
t-Value	(0.0533)	1.4785	1.0398
m	(0.4782)	(0.6908)	(0.1339)
t-Value	(12.2147)	(14.5278)	(4.0613)
v	0.0102	0.0577	0.3974
t-Value	0.2725	0.8333	8.0854
Adjusted R^2	0.9145	0.8889	0.7801

Panel B: volume momentum sorted portfolios

	Indonesia
a(V1)	0.0033
t-Value	0.8239
b	1.1712
t-Value	30.0408
s	0.2922
t-Value	4.0825
l	0.8056
t-Value	8.6606
m	(0.2373)
t-Value	(4.6601)
v	(0.4369)
t-Value	(8.1276)
Adjusted R^2	0.9119
a(V5)	0.0254
t-Value	6.4090
b	0.8144
t-Value	20.8903
s	0.2922
t-Value	4.0825
l	0.8056
t-Value	8.6606
m	(0.2373)
t-Value	(4.6601)
v	0.5631
t-Value	10.4744
Adjusted R^2	0.8588

Panel C: portfolios framed using Independent sorting

	Brazil	South Africa	Indonesia
a(V3P1)	0.0167	0.0189	0.0266
t-Value	3.3721	1.9914	3.9727
b	0.7929	0.1727	0.8967
t-Value	18.1797	1.3916	13.6197
s	0.4311	(0.3046)	0.2938
t-Value	4.4556	(0.8823)	2.4310
l	(0.3727)	0.6947	0.3578
t-Value	(3.2101)	1.7656	2.2780
m	0.1825	0.3695	0.2902
t-Value	3.4775	4.0582	3.3746
v	0.0684	0.4099	0.2416

Table IV.

(*continued*)

t-Value	1.3617	3.0207	2.6613
Adjusted R^2	0.7241	0.1462	0.6586
a(V1P3)	0.0004	0.0104	(0.0020)
t-Value	0.0792	1.1811	(0.3197)
b	0.9220	0.2852	1.1144
t-Value	19.3959	2.4901	17.9708
s	0.8152	(0.3093)	0.2701
t-Value	7.7304	(0.9704)	2.3728
l	0.3137	0.3340	1.1381
t-Value	2.4791	0.9197	7.6925
m	(0.3511)	(0.0598)	(0.6619)
v	(6.1382)	(0.7118)	(8.1734)
v	(0.1945)	0.2038	(0.3783)
t-Value	(3.5510)	1.6275	(4.4244)
Adjusted R^2	0.8284	0.0298	0.8207
Panel D: portfolios framed using Conditional I sorting			
	Brazil	India	Indonesia
a(V3P1)	0.0155	0.0105	0.0249
t-Value	3.0334	2.4016	3.8465
b	0.7928	1.0587	0.9114
t-Value	17.6195	17.1906	14.3361
s	0.4249	0.4870	0.2856
t-Value	4.2563	5.6869	2.4477
l	(0.3240)	0.1154	0.3180
t-Value	(2.7053)	1.4224	2.0965
m	0.1882	(0.5608)	0.2229
t-Value	3.4752	(10.4702)	2.6851
v	0.0594	(0.5182)	0.2781
t-Value	1.1452	(6.6368)	3.1724
Adjusted R^2	0.7103	0.8793	0.6734
a(V1P3)	0.0009	0.0110	(0.0031)
t-Value	0.1890	2.5686	(0.5755)
b	0.8915	1.1055	1.1154
t-Value	21.5566	18.3053	20.8319
s	0.6789	0.5007	0.1691
t-Value	7.4007	5.9625	1.7200
l	0.3639	0.0770	1.1951
t-Value	3.3060	0.9679	9.3552
m	(0.3627)	(0.5766)	(0.6441)
t-Value	(7.2889)	(10.9778)	(9.2101)
v	(0.1413)	(0.4664)	(0.3659)
t-Value	(2.9648)	(6.0914)	(4.9560)
Adjusted R^2	0.8557	0.8854	0.8621
Panel E: portfolios framed using Conditional II sorting			
	Brazil	Indonesia	
a(P1V3)	0.0169	0.0272	
t-Value	3.3928	4.2954	
b	0.8120	0.9131	
t-Value	18.4806	14.6641	
s	0.3717	0.3165	
t-Value	3.8134	2.7686	
l	(0.2939)	0.4276	

(*continued*)

Table IV.

t-Value	(2.5126)	2.8782
m	0.1711	0.2613
t-Value	3.2356	3.2125
v	0.0900	0.2607
t-Value	1.7782	3.0367
Adjusted R^2	0.7273	0.6954
a(P3V1)	0.0019	0.0010
t-Value	0.3953	0.1995
b	0.9266	1.1000
t-Value	21.6305	22.4145
s	0.6195	0.3228
t-Value	6.5184	3.5829
l	0.3032	1.0884
t-Value	2.6588	9.2960
m	(0.3517)	(0.6676)
t-Value	(6.8233)	(10.4158)
v	(0.1552)	(0.3022)
t-Value	(3.1452)	(4.4657)
Adjusted R^2	0.8516	0.8748

Notes: Three versions of multifactor models are employed that augment Fama-French with: first, price momentum factor; second, volume momentum factor; finally, price and volume momentum factor

Table IV.

Shivakumar, 2002). The stock momentum factor may perhaps also be proxying for sector momentum, the risk argument for which has been provided by Liu and Zhang (2008).

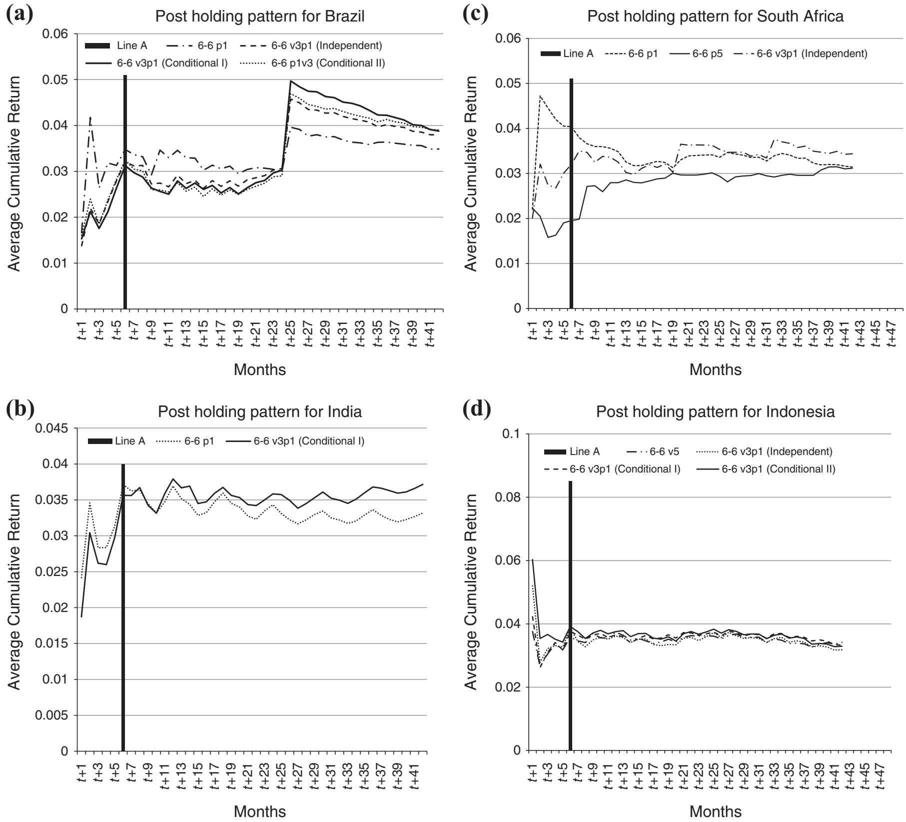
4.3 Some behavioral explanations

However, considering that some price/volume momentum sorted portfolios continue to outperform our multifactor asset pricing benchmarks, we need to explain their behavior. Investor irrationality, i.e., over or under reaction to past information may be the cause of these observable patterns. In the next section, we verify this by examining the post holding period pattern in returns for the sample portfolios that provide anomalous findings based on risk models.

Post holding pattern is analyzed for 20 unexplained portfolios, i.e., four for Brazil, two for India and seven each in case of Indonesia and South Africa. The average cumulative returns for these portfolios are depicted in Figure 1[3].

Under reaction is implied by a relatively flat return pattern in the post holding period. In a few cases momentum may continue for a few months beyond the holding period till all under reaction has been accounted for and stock prices return close to equilibrium values. On the other hand, overreaction is inferred by return reversals in the post holding period, i.e., there is a decline in returns after an initial rise in the holding period.

For Brazil, mild overreaction is observed for 6-6 price momentum winner, while under reaction seems to explain the behavior of 6-6 bivariate sorted portfolios that were unexplained by the risk models. In the Indian context, under reaction may account for the observable momentum for two unexplained portfolios; namely, 6-6 price momentum winner and 6-6 low-volume-winner (Conditional I portfolio).In case of Indonesia, under reaction hypothesis seems to work well for 6-6 unexplained portfolios, while overreaction hypothesis seems feasible for 12-12 unexplained portfolios. Thus, the Indonesian investors exhibit short-term under reaction and long-term overreaction. Finally in case of South Africa, the investors seem to over react and under react to short-term price information for momentum winners and losers,



Notes: Four graphs are drawn for four countries that have unexplained portfolios. Lines representing unrestricted excess return on sample portfolios which are not explained by our version of enhanced FF model for 6-6 strategies are drawn parallel to X-axis. Post holding pattern is analyzed after line A

Figure 1. Graphic display of post holding returns for sample portfolios whose returns are unexplained by our version of enhanced F-F Model

respectively. The return behavior of 12-12 price momentum winner and unexplained bivariate sorted portfolios seems to be an outcome of under reaction.

As stated earlier in the paper, momentum portfolios of China and South Korea do not pose challenge to risk models. Thus, investor behavior seems to be by and large rational in their case.

5. Summary and concluding observations

In this paper, we examine the profitability of trading strategies based on past price and volume data. We also attempt to find plausible explanation for these observable return patterns. Data are employed from January 1998 to December 2011 for six emerging markets, namely, Brazil, India, China, South Africa, South Korea and Indonesia. The starting month however, is different for each sample country owing to non-availability of sufficient data required to form moderately sized portfolios, which do not exhibit significant unsystematic risk.

Price momentum is observed for Brazil, India, South Africa, South Korea, while price reversals are reported for Indonesia and China. Higher price momentum profits are recorded for short-term (6-6) than long-term (12-12) strategies, except in case of Indonesia which provides contrarian profits. Further, low-volume stocks outperform high-volume stocks in all cases except China and Brazil (only in the short run). Long-term (12-12) trading strategies outperform short-term (6-6) trading strategies based on volume momentum. Bivariate trading strategies based on past price as well as volume data do a better job than univariate (price/volume) strategies in case of India, South Africa and South Korea. Further, it is observed that in India, price has additional significant information apart from information contained in volume. Whereas, reverse is true in case of South Africa where volume contains significant incremental information.

Next, we verify if these prior period patterns in returns can be explained by standard risk models.

The CAPM and the F-F Model do not do a good job in explaining these cross-sectional return patterns. Our enhanced F-F Model versions involving price or/and volume momentum factors are able to capture some of these return patterns as the number of unexplained portfolios drops down from 33 in case of F-F Model to 20 for our multifactor model versions.

The post holding return patterns for sample portfolios, which remained unexplained by the risk models, suggest that investor under or overreaction to past information may explain these price patterns. Thus, the sources of prior period patterns in stock returns seem to be partly risk based and partly behavioral.

6. Managerial implications

Our findings have important implications for global portfolio managers, policy makers, market regulators and the academic community.

From investors' and portfolio managers' perspective, the stock markets of Brazil, India, South Africa and Indonesia promise extra normal returns and hence an opportunity for global portfolio diversification. However, it is advisable to take market positions only from the long-side owing to higher cost of financing implied by performance of short-selling portfolio.

The policy makers as well as market regulators must understand the inherent informational inefficiency in their markets. More efforts are required in the future to improve market efficiency by strengthening corporate governance code encouraging better corporate disclosures reducing trading costs and taxing positions and widening investor base through a financial inclusion strategy including better financial education.

Also, our findings have important implications for academicians. Multifactor models seem to do better job in explaining cross section of stock returns that one factor CAPM. Our versions of enhanced F-F Model are a better performance benchmark as compared to CAPM and F-F Model. Profitability of portfolios based on past information seem to be partly driven by risk factors and partly by investor under/overreaction to information. Our findings are robust across a set of emerging markets with different geopolitical settings. In future, we expect the asset pricing models to be realigned in light of observed irrationality in investor behavior. More specifically, it may involve inclusion of an additional behavioral based factor in asset pricing models, one that proxies investor sentiment as suggested by Baker and Wurgler (2006).

The present study contributes to asset pricing and behavioral finance literature for emerging markets. Further research is required for a wide range of emerging markets and comparison needs to be drawn with evidence for mature markets before any general conclusions can be drawn relating to past information based pricing anomalies.

Notes

1. Tables containing results of only 6-6 strategies are reported. Tables with results of 12-12 strategies are not reported due to paucity of space and can be obtained on request.
2. Results are interpreted by observing the difference between price winners and losers within the low-volume portfolio for India, whereas for South Africa, the difference between low-volume and high-volume stocks is observed within the winner portfolio. These results are not reported due to paucity of space, and can be obtained on request.
3. The table containing values of average cumulative returns for portfolios whose returns are unexplained by our version of enhanced F-F models is not reported due to paucity of space. It can be obtained on request.

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About the authors

Sanjay Sehgal is a Professor of Finance at the Department of Financial Studies, South Campus, University of Delhi. He is PhD finance from Delhi School of Economics and post doctoral commonwealth research fellow from the London School of Economics, UK. He has completed five major research projects, one book and 123 research papers.

Vibhuti Vasishth is an Assistant Professor at the Kamala Nehru College, University of Delhi. She is pursuing PhD in finance from the Department of Financial Studies, South Campus, University of Delhi. Vibhuti Vasishth is the corresponding author and can be contacted at: vibhuti14@gmail.com