Conditional multifactor asset pricing model and market anomalies

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Abstract

Purpose – The purpose of this paper is to investigate the firm-specific anomaly effect and to identify market anomalies that account for the cross-sectional regularity in the Indian stock market. The paper also examines the cross-sectional return predictability of market anomalies after making the firm-specific raw return risk adjusted with respect to the systematic risk factors in the unconditional and conditional multifactor specifications.

Design/methodology/approach – The paper employs first step time series regression approach to drive the risk-adjusted return of individual firms. For examining the predictability of firm characteristics on the risk-adjusted return, the panel data estimation technique has been used.

Findings – There is a weak anomaly effect in the Indian stock market. The choice of a five-factor model (FFM) in its unconditional and conditional specifications is able to capture the book-to-market equity, liquidity and medium-term momentum effect. The size, market leverage and short-run momentum effect are found to be persistent in the Indian stock market even with the alternative conditional specifications of the FFM. The results also suggest that it is naï argue for disappearing size effect in the cross-sectional regularity.

Research limitations/implications – Constrained upon the data availability, certain market anomalies and conditioning variables cannot be included in the analysis.

Practical implications – Considering the practitioners' prospective, the results indicate that the profitable investment strategy with respect to the small size effect is still persistent and warrants close-ended mutual fund investment portfolio strategy for enhancing the long-term profitability. The short-run momentum effect can generate potential profits given a short-term investment horizon.

Originality/value – This paper provides the first-ever empirical evidence from an emerging stock market towards the use of alternative conditional multifactor models for the complete explanation of market anomalies. In an attempt to analyze the anomaly effect in the Indian stock market, this paper provides further evidence towards the long-short hedge portfolio return variations in terms of a wide set of market anomalies that have been documented in prior literature.

Keywords Liquidity, Conditional asset pricing model, Emerging stock market, Market anomaly, Multifactor model, Risk adjusted return

Paper type Research paper

1. Introduction

Since the appearance of book-to-market equity or value effect (Basu, 1977) and size effect (Banz, 1981), the apparent roles of several firm characteristics have proven to be

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important explanatory variables for the cross-sectional variation of expected stock returns. Over the past decades the list of variables to which cross-sectional regularity can be attributed includes: illiquidity (Amihud, 2002), price multipliers (Reinganum, 1981), leverage (Bhandari, 1988), momentum (Jegadeesh and Titman, 1993), sales growth (Lakonishok *et al.*, 1994), accounting accruals (Sloan, 1996), firm's intangible investment to sales ratio (Chan *et al.*, 2001), capital expenditure (Titman *et al.*, 2004), and asset growth (Cooper *et al.*, 2008). As the cross-sectional regularities of the identified firm characteristics are not in agreement with the theoretical strand of traditional asset pricing literature (Lintner, 1965; Merton, 1973; Ross, 1976; Sharpe, 1964), these firm characteristics are often termed market anomalies. Available literature also suggests that patterns of cross-sectional return predictability with respect to such firm characteristics initially identified in the US market often exist in other developed and emerging stock markets (Artmann *et al.*, 2012; Chen *et al.*, 2010; Rouwenhorst, 1998, 1999).

In common, the existence of return predictability of such firm characteristics is considered either as the resultant of profit opportunities pertinent to market inefficiency or as proxies for the riskiness of the firm and therefore, serve as the better determinants of cross-section of expected stock return (Fama and French, 1992). Motivated by such risk-based argument, and the fact that empirical examination of several mainstream asset pricing models fails to give conclusive evidence of return predictability, recent literature advocates the applicability of several alternative multifactor models (Fama and French, 1993; Carhart, 1997; Pastor and Stambaugh, 2003). The fundamental approach in this regard is to incorporate additional factors formed on the basis of the excess return on traded portfolios of underlying firm characteristics and then reexamine the intercept of newly introduced asset pricing model indistinguishable from zero (MacKinlay, 1995). In this regard, this approach conjectures for the test of a joint null hypothesis. First, the additional risk factors constructed on trade portfolios are the sufficient explanation for the missing risk factors in the traditional asset pricing models. Second, if such empirically motivated risk factors are able to explain the characteristic-based portfolio return variation, then the underlying firm characteristics that motivate such factors are indeed priced source of systematic risk. If the joint hypothesis fails to be rejected, then it is evident that the earlier identified fundamental firm characteristics are a proxy for systematic risk, and they simply are not priced because of the mispricing pertinent to an inefficient market.

More specifically, empirical investigations to test such a hypothesis give convincing evidence to believe that the suggested multifactor models incorporating systematic risk factors with respect to market, size, book-to-market equity, momentum and liquidity give better explanations for the cross-section of stock return variation (Fama and French, 1996, 2012; Dash and Mahakud, 2012; Her *et al.*, 2004; Lischewski and Voronkova, 2012). Evidently, the multifactor specification in terms of the FFM that includes all the relevant systematic risk factors with respect to market, size, book-to-market equity, momentum and liquidity performs much better than the three factor (Fama and French, 1993) or four factor (Carhart, 1997) model specifications (Keene and Peterson, 2007; Lam and Tam, 2011; Dash and Mahakud, 2012). In recent years, following the time varying risk premia argument (Cochrane, 2001; Ferson and Harvey, 1998), the conditional specifications of such multifactor models perform even better in cross-sectional tests as compared to their unconditional specifications (Drobetz *et al.*, 2002; Iqbal *et al.*, 2010; Lettau and Ludvigson, 2001; Schrimpf *et al.*, 2007).

Although the empirical evidence gives a reason to believe that factor models are better predictors of stock returns, the existing literature never gives a conclusive observation that the factor models are sole determinants of stock returns (Avramov and Chordia, 2006; Brennan *et al.*, 1998). To put it differently, whether the risk factors suggested by multifactor asset pricing models are sufficient to account for both cross-sectional and time series variations in stock return or there is still scope for the consideration of firm characteristics or commonly known market anomalies. Intuitively, as the systematic factors are empirically motivated by the firm characteristics, so it is apparent to expect that the raw stock returns once risk adjusted for the systematic risk factors should never leave any scope for the predictability of firm characteristics or the commonly known market anomalies, at least in the statistical sense. A set of recent literature investigated this complete explanation hypothesis in several developed markets. Brennan *et al.* (1998), Avramov and Chordia (2006) and Chou *et al.* (2010) lead the way in the US stock market and find evidence that size and value effects are captured with the conditional specification of the Fama and French (1993) three factor model. However, the authors find that momentum and liquidity effects are still persistent. In contrast to the findings in the US stock market, in the European market Bauer *et al.* (2010) find that three factor model (Fama and French, 1993) fails to eliminate the size, value, liquidity and momentum effect completely. Narayan and Zheng (2010) in the Chinese stock market find that Carhart's (1997) four factor model augmented with the liquidity factor is able to explain the liquidity, size and value effect but not the momentum effect. To briefly sum up, the empirical evidence across the different markets is inconclusive and the factor model that apparently performs better in one market to explain certain market anomalies fails to hold in other markets. Nevertheless, the asset pricing literature still fails to suggest a multifactor model specification that can answer the long-standing intriguing question: what explains expected returns, risk factors, or firm characteristics that are commonly perceived to be financial market anomalies (Avramov and Chordia, 2006, pp. 1002-1004).

This question remains unresolved in the asset pricing literature and still gives conspicuous scope to test such a hypothesis in other markets apart from the market to which most of the market anomalies trace their origin. Additionally, the complete explanation argument is more challenging for an emerging stock market given the characteristics like high stock price synchronicity or low price informativeness (Morck *et al.*, 2000; Chana and Hameed, 2006) and thus a lower chance to find a profitable trading strategy with respect to the cross-sectional regularity of firm characteristics. In this regard, the present paper aims to revisit the complete explanation debate in the context of an emerging stock market like India to provide further insights on such a well debated persuasive issue with two specific questions. First, which market anomalies account for the cross-sectional regularity in the Indian stock market? Second, do firm-specific risk characteristics continue to predict expected stock returns regardless of the presence of systematic risk factors in the unconditional and conditional multifactor specifications?

In particular, we contribute to the available literature in three major ways. First, with special reference to the Indian stock market, this paper gives further evidence for the cross-sectional regularity of some of the major market anomalies. Previous studies on the predictability of Indian stock returns focus on a small set of firm characteristics or market anomalies as the predictive variables (Kumar and Sehgal, 2004; Mohanty, 2002; Singh, 2008a, b; Sehgal and Subramaniam, 2012; Sehgal and Balakrishnan, 2002) and thus are not able to provide significant insight on several other market anomalies that have been documented in prior literature. In the present analysis we specifically identify 18 firm-specific variables, known to be predictors of cross-sectional stock returns in the US market. In this regard, our analysis on a wide range of market anomalies attempts to broaden the understanding of market anomaly behavior in the Indian stock market. Second, in the context of emerging stock markets and so also for the Indian stock market, our findings give the first ever evidence with respect to the applicability of conditional specification of liquidity augmented FFM to capture the predictability of market anomalies. To our knowledge, none of the existing studies in emerging stock markets have made an attempt to examine the applicability of multifactor model in its conditional specification. One of the existing studies which is close to our analysis is by Narayan and Zheng (2010) in the context of the Chinese stock market; however, the study is focused only on the unconditional multifactor models. Though with different implications, the first and second observations make a complementary stand from the practitioners' prospective. From the real world investment scenario it helps to generalize the idea about the firm characteristics or market anomalies that can be perused upon as profitable investment strategies and to what extent the multifactor model in its alternative specifications can be able to capture the market anomalies. Third, this out-of-sample evidence from an emerging stock market is arguably more important given the sample selection bias and data-snooping bias (Lo and MacKinlay, 1995) observed in the developed market like the USA to which almost all the asset pricing anomalies trace their origin.

The remainder of this paper is organized as follows. Section 2 elaborates the model specifications and methodology. Section 3 discusses the variables that have been used for this analysis. Section 4 presents the empirical findings and discusses results. Section 5 offers summary and conclusions.

2. Model specification and methodology

Assuming that asset returns are generated by a L-factor asset pricing model, the excess return of security of an asset can be specified as:

$$R_t - r_{ft} = \theta_t + \sum_{l=1}^{L} \beta_t F_t + \varepsilon_t, \quad t > 0, \tag{1}$$

where, R_t is the $\mathrm{N} \times 1$ vector of excess returns in the month t of N firms ($j = 1, \ldots, \mathrm{N}$), r_{ft} is the risk free interest rate, β_t is a $L \times 1$ vector of common factors, β_t is an $\mathrm{N} \times L$ matrix of factor loadings, ε_t is an $\mathrm{N} \times 1$ vector of residuals. Following equation specification (1), the FFM that augments Carhart (1997) four factor model with a liquidity factor can be specified as:

$$R_{jt} - r_{ft} = \theta_t + \sum_{l=1}^{4} \beta_1 CFFM + \beta_2 LMHL_t + \varepsilon_{jt}, \quad \forall j, t > 0, \tag{2}$$

where, R_{jt} and r_{ft} indicate the gross raw return on security j and risk free interest rate, respectively. *CFFM* is a vector containing Carhart (1997) four factors (market return in excess of risk free rate, i.e. *MRKT*), size factor (small minus big, i.e. *SMB*) and book-to-market factor (high minus low, i.e. *HML*) and momentum factor (winner minus loser, i.e. *WML*). *LMHL* (low minus high liquid) is the liquidity factor as in Lam and Tam (2011). Extending equation (2) we have:

$$R_{jt} - r_{ft} = \theta_t + \beta_{MRKT} MRKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{WML} WML_t + \beta_{LMHL} LMHL_t + \varepsilon_{jt}, \tag{3}$$

For deriving the risk adjusted return of security j at time t (R^*_{jt}) in first part time series regression, we follow the approach of Brennan *et al.* (1998) and Avramov and Chordia (2006). Considering the L factor asset pricing model of equation specification (1) and following the approach of Brennan *et al.* (1998) and Avramov and Chordia (2006, p. 1008), the estimated risk adjusted return from the first pass time series regression on each security j for the month t can be specified as:

$$R^*_{jt} = R_{jt} - r_{ft} - \sum_{l=1}^{L} \widehat{\beta}_{jl} F_{lt}, \tag{4}$$

where, $\widehat{\beta}_{jl}$ is the beta estimated by a first pass time series regression over the entire sample period, R^*_{jt} is the estimated risk adjusted return on stock j at time t from the first pass time series regression. Following the equation specification (4), the risk adjusted returns for security j in terms of the FFM specified in equation (3) can be given as $\theta_j + \varepsilon < AsSETInferior > jt$. The risk adjusted return derived in the first pass time series regression will be the ideal candidate for testing the explanatory power of market anomalies in the second step.

Apart from the unconditional specification of FFM as in equation (3), we also consider the conditional specification of the FFM for deriving the risk adjusted returns. For the conditional specification following the scaled factor methodology of Cochrane (2001), the risk factors are allowed to vary with time as per the available conditioning information set (I). Following the approach of Cochrane (2001) in a linear single factor asset pricing model, the conditional specification of the factor beta (β_{jt-1}) of security j can be expressed as a function of the conditioning information set z_{t-1} ($z_{t-1} \in I$) in the following form:

$$\beta_{jt-1} = \beta_{j1} + \beta_{j2} z_{t-1}, \quad \forall j, t > 0, Z_{t-1} \in I_{t-1} \tag{5}$$

Considering the conditional specification of the equation (5), the first pass time series regression of conditional five factor based model of the equations (2) and (3) can be specified as:

$$R_{jt} - r_{ft} = \theta_{jt} + \sum_{l=1}^{4} \beta_1 CFFM + \sum_{l=1}^{4} \beta_2^Z CFFM Z_{t-1} + \beta_3 LMHL_t + \beta_3^Z LMHL_t \; Z_{t-1} + \varepsilon_{jt}, \tag{6}$$

$$
\begin{aligned}
R_{jt} - r_{ft} = \theta_j &+ \beta_{MRKT} MRKT_t + \beta^{Z}_{MRKT} MRKT_t \; Z_{t-1} + \beta_{SMB} SMB \\
&+ \beta^{Z}_{SMB} SMB_t \; Z_{t-1} + \beta_{HML} HML_t \\
&+ \beta^{Z}_{HML} HML_t \; Z_{t-1} + \beta_{WML} WML_t + \beta^{Z}_{WML} WML_t \; Z_{t-1} \\
&+ \beta_{LMHL} LMHL_t + \beta^{Z}_{LMHL} LMHL_t \; Z_{t-1} + \varepsilon_{jt},
\end{aligned} \tag{7}
$$

where, $R_{jt} - r_{ft}$ is the excess return of security j over the risk free rate. The risk adjusted return R^*_{jt} on stock j at time t to be used in the second step is equal to $\theta_j + \varepsilon_{jt}$. The derived risk adjusted return in equations (3) and (7) becomes the ideal candidate for testing the unique impact of market anomalies on stock returns left unexplained by the risk adjustment process of alternative pricing models. Given that the asset pricing models are sufficient to describe the pervasive firm characteristics in both conditional and unconditional specifications, the unique impact of the market anomalies is expected to be ruled out completely.

The argument for testing the importance of market anomalies (i.e. $m = 1, \ldots, M$) for explaining the risk adjusted return can be specified as:

$$
R^*_{jt} = \alpha + \sum_{m=1}^{M} \mu_m \varphi_{mjt-1} + \varepsilon_{jt}, \tag{8}
$$

where, φ_{jt-1} is the vector of market anomalies and μ_{jt} is a vector of characteristics rewards with respect to the market anomalies. Under the null of exact pricing or expected excess return on security j is determined solely by the loadings of the security's return on the L-factors, and the coefficients of non-risk market anomalies will be equal to zero. We extend the equation (8) to a panel data model specification as follows:

$$
R^*_{jt} = \alpha_j + (\mu_m \varphi_{mt-1} + \cdots + \mu_M \varphi_{Mt-1}) + \varepsilon_{jt}, \tag{9}
$$

where, R^*_{jt} is the risk adjusted return of regressors at time t. The regressors namely $m, \ldots, M$ are the firm specific explanatory variables. α_j is the individual effect, which is assumed as constant over time and varies across the individual cross-sectional unit (firm). ε_{jt} is a stochastic error term assumed to have mean zero and constant variance. equations (3) and (7) have been estimated using first pass time series regression approach of Brennan *et al.* (1998) and Avramov and Chordia (2006). For the equation (9), in order to test the risk adjusted return predictability of firm characteristics or market anomalies, we use panel data estimation technique. Our motivation to use panel estimation technique follows from two arguments. First, Goyal (2012) suggests that the popularity of Fama and MacBeth's approach in portfolio-based and firm-specific studies helps to accommodate unbalanced panels by providing a flexibility to use returns on only those stocks which exist at time t. Since in an active and operational stock exchange companies come, operate and continue to operate or delist in the due course of time, therefore, in a state of delisting of firms, the flexibility of the use of panel estimation technique is limited as it turns out to be an unbalanced panel. In a state of delisting of firms, the use of Fama and MacBeth's approach helps the risk premium estimation results not to be influenced due to the appearance and delisting of stocks in the exchange as it considers the available stocks at time t (Goyal, 2012). As our individual stock sample focuses on the continuously traded stocks (see for detail discussion Section 3), we therefore explore a different approach as compared to Avramov and Chordia (2006) by using panel data models. With continuously traded stocks, our panel is a balanced panel having the advantage to explore panel data models. Moreover, as an alternative to the commonly used Fama and MacBeth's (1973) two-pass cross-sectional regression approach, the use panel data estimation approach helps to avoid the errors-in-variables problem (Shanken, 1992) associated with Fama and MacBeth's approach. Second, panel data sets for economic research possess several major advantages over conventional cross-sectional or time-series data sets. Panel data set by using information on the intertemporal dynamics and the individualities of entities helps to control in a more natural way for the effects of missing or unobserved variables (Hsiao, 1986). In the empirical analysis, likelihood ratio (LR) test (Gourieroux *et al.*, 1982) has been carried out to identify the existence of individual firm-specific effects in the data set. Lagrange Multiplier (LM) test (Breusch and Pagan, 1980) has been used to test the acceptability of panel data models over the classical regression models. The Hausman (1978) test has been used to determine the preferred model (i.e. fixed effect model or random effect model).

3. Data and variables

The basic data consists of monthly returns and other firm-specific characteristics of National Stock Exchange (NSE) of India listed non-financial companies for the period September 1995 to March 2011 (187 months). Controlling for various stock selection criteria as discussed in Fama and French (1992) and omitting the firms with negative book-to-market equity value, we have considered 582 continuously traded individual stocks for the whole sample period. In order to avoid data snooping bias and survivorship bias, for our analysis we consider only those stocks which have been continuously traded in NSE since December 1994. However, for the selection of our sample period we exclude an initial one-year period in 1994, as the initial stage of NSE operation may have a high volatile return pattern for the listed stocks. Consistent with the approach of Avramov and Chordia (2006) unlike the popular portfolio-based approach in asset pricing literature, we focus on the use of individual stocks as it helps to avoid the under rejection bias (Roll, 1977) and data snooping bias (Lo and MacKinlay, 1990) observed with the portfolio-based approach. Restricting ourselves to the continuously traded firms also helps us to have a balanced panel with 1,08,834 firm-month observations. The S&P CNX Nifty has been taken as the market proxy. The 91-days Treasury bill rate is considered as the proxy for risk free rate. The required data on stocks return and other firm-specific information has been collected from the Centre for Monitoring Indian Economy (CMIE) PROWESS database, risk free rate data and other conditioning variables have been collected from the Reserve Bank of India (RBI) web site.

3.1 Variables

This subsection has been categorized into four parts. In the first part we discuss our approach for testing the cross-sectional regularity of firm characteristics and measures of firm characteristics. The second part briefly elaborates the construction of five market-wide risk factors. The third part presents the several conditioning information variables that have been used for conditional specification of FFM. The fourth part discusses the relevant measures of selected market anomalies for the cross-sectional return predictability.

3.1.1 Identification and measures of firm characteristics or market anomalies. Available literature on the relation between firm-specific characteristics and the cross-section of expected stock return is vast. The selection of a specific characteristic or a group of such characteristics as potential return predictors poses a distinctive challenge. In this regard Subrahmanyam (2010, p. 28) observes that:

> [. . .] our learning about the cross-section is hampered when so many predictive variables accumulate without any understanding of the correlation structure between the variables, and our collective inability or unwillingness to adequately control for a comprehensive set of variables.

In order to circumvent such a selection problem, following the related literature, we identify 18 variables which have been subject to empirical tests in other markets apart from the US stock market (Artmann *et al.*, 2012; Chen *et al.*, 2010). Following Chen *et al.* (2010), we group these variables into the following categories:

- two return predictors that are related to relative profitability and growth: size (SZ), and book-to-market equity (BM);
- three typical value indicators: earnings-to-price ratio (EP), cash flow-to-price ratio (CP), dividend yield (DIVY) or dividend-to-price ratio and sales growth (SG);
- one measure for earnings quality: accounting accruals (ACC);
- two measures related to firm's past returns: short run momentum (MM) and long-term reversal (LngR);
- two measures of firm's intangible investment: research and development intensity (R&Dint) and advertising intensity (ADVint);
- stock liquidity measure (LQ);
- two proxies related to the leverage risk: book leverage (Bliv) and market leverage (Mliv); and
- four proxies that summarize firm's profitability, tangibility and investment opportunity: return on asset (ROA), capital expenditure (CAPEX), asset growth (AG) and investment-to-assets ratio (INVST).

Following Fama and French (1992, 1993), Chen *et al.* (2010), Artmann *et al.* (2012) and Jegadeesh and Titman (1993), the above mentioned firm characteristics are measured as follows: SZ is the natural logarithm of market capitalization (stock prices times outstanding shares) at the end of August of year *y*. BM in year *y* is the ratio between book equity for the fiscal year ending in calendar year *y* by the market value of equity at the end of August in calendar year *y*. EP is the ratio of net earnings (profit after tax) for the fiscal year end March to the market capitalization at the end of the August of year *y*, but only when the net earnings are positive. Our motivation for not considering companies with negative earnings is based on the argument of related literature which suggest that EP as a measure of risk (Ball, 1978) does not stand to justify the theoretical argument of high risk (i.e. high EP) and high expected return relationship for firms with negative earnings (Artmann *et al.*, 2012; Fama and French, 1992). DIVY is the ratio of dividend paid by the firm for the fiscal year end March to the market capitalization at the end of the August of year *y*. CP is the sum of earnings before extraordinary items and depreciation over the firm's market capitalization at the fiscal year-end of year *y*. SG is the ratio of sales revenue for the March in the year *y* over the sales revenue from the March of year $y-1$. Excise duty paid has been deducted from the total sale. MM is the cumulative return of a stock in month $t-12$ through month $t-2$ preceding August of year y. We skip one month between portfolio formation and holding period to avoid the effects of bid-ask spread, price pressure, and any lagged reaction. LngR of a stock in month t is measured each month by sorting stocks on past returns from month $t-36$ through $t-7$.

Following Sloan (1996), we estimate ACC as the change in noncash current assets less the change in current liabilities (excluding debt in current liabilities and income tax payable) less depreciation, during the fiscal year ending in year $y-1$, scaled by the average total assets at the beginning and end of that fiscal year in the calendar year y. Following Chan *et al.* (2001), R&Dint and ADVint is the ratio of R&D expenditure and advertising expenditure for the fiscal year ending in calendar year y over market capitalization at the end of August of calendar year y. Following Keene and Peterson (2007), LQ is measured at the end of August of calendar year y as the annual average of monthly turnover ratio, i.e. number of shares traded to the number of shares outstanding. Following Titman *et al.* (2004), CAPEX is the capital expenditure of the firm for the fiscal year ending March in calendar year y over the average total assets at the beginning and end of that fiscal year in calendar year $y-1$ and y. Following Cooper *et al.* (2008), AG is measured as the percentage change in total assets from the fiscal year ending in calendar year $y-2$ to the fiscal year ending in calendar year $y-1$. Following Artmann *et al.* (2012), ROA of a firm is measured as the net earnings (profit after tax) divided by total assets for the fiscal year end March in the calendar year y. Following Chen and Zhang (2010), INVST is measured as the annual change in gross fixed assets plus annual change in inventories at the fiscal year ending in year y divided by book value of total assets of the fiscal year ending in year $y-1$. Following Fama and French (1992), Bliv is measured as total assets divided by book equity of the fiscal year ending in year y and Mliv is computed as total assets in the fiscal year ending in year y divided by market value of equity at the end of August of year y.

In order to specifically identify firm characteristics that are persistent in the Indian stock market for the cross-sectional variation in average stock returns, we follow the approach of Chen *et al.* (2010) and Artmann *et al.* (2012) for using equally weighted one dimensional short. In other words, we form equally weighted decile portfolios for all the 18 firm characteristics to find which firm-specific variables are able to explain the cross-sectional variation in subsequent one-year return. To calculate monthly portfolio returns, we apply an equal weighting. Consistent with prior literature, we apply an equal weighting since our objective is to capture the cross-sectional pattern in average returns with respect to each specific characteristic and not to highlight the role of investability (Artmann *et al.*, 2012; Chen *et al.*, 2010). For each firm characteristic at the beginning of September of year y we form ten portfolios based on the decile breakpoints. The conservative five months lag is imposed to ensure that the required accounting data of the financial year end March of calendar year y must be made available to the investors. The portfolios are held constant during the following 12 months, and portfolios are reformed every year at the beginning of September of year y. Portfolios formed on technical firm characteristics like short run momentum and LngR are rearranged every month.

Table I reports the average returns for portfolios sorted on all the 18 stock return predictors. Table I suggests that in the one-dimensional sorts SZ, BM, Mliv, MM and LQ lead to significant average hedge portfolio returns. Long-short-strategies of buying

Table I.
Average returns for portfolios sorted on firm characteristics

Stock return predictors	Mean return on decile portfolios										Hedge portfolio return	
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	10-5	10-1
EP	2.11	1.76	1.42	0.89	1.24	1.36	1.82	2.19	2.03	2.38	1.14 (1.53)	0.27 (0.49)
DIVY	2.69	2.38	2.46	2.64	2.39	2.19	2.42	2.08	2.14	2.21	−0.18 (−0.36)	−0.48 (−0.38)
SZ	3.34	1.98	1.96	1.78	1.85	1.66	1.91	1.60	1.47	1.03	−0.85*** (−1.68)	−2.31*** (−1.78)
BM	0.81	1.21	1.80	1.92	2.28	1.99	1.69	2.09	2.59	3.46	1.18*** (1.97)	2.66** (2.36)
LngR	3.07	2.65	2.98	3.11	3.15	2.81	2.86	2.68	3.09	4.09	0.94 (0.96)	1.02 (0.67)
Mliv	1.79	1.61	1.84	1.85	2.18	2.58	2.62	2.89	2.91	3.09	0.91*** (1.68)	1.30*** (1.72)
Bliv	0.31	0.37	0.45	0.42	0.61	0.67	0.72	0.52	0.78	1.08	0.47 (0.75)	0.77 (0.46)
MM	1.25	1.70	1.33	2.15	1.33	1.52	1.17	1.73	2.17	4.31	2.98** (2.74)	3.06** (2.35)
SG	3.09	2.72	2.67	2.45	2.40	2.53	2.42	2.43	2.37	2.29	−0.11 (−0.33)	−0.80 (−0.17)
CP	1.09	1.21	1.32	1.67	1.50	1.89	1.85	2.19	2.08	2.45	0.95 (1.33)	1.37 (0.42)
ACC	2.02	2.01	2.09	2.31	2.03	1.71	1.58	2.31	2.25	2.37	0.34 (0.58)	0.35 (0.30)
R&Dint	2.95	2.67	2.61	2.81	2.39	2.34	1.62	1.96	2.43	2.63	0.24 (0.19)	−0.32 (−0.24)
ADVint	2.65	2.59	2.56	2.29	2.34	2.31	2.36	2.54	2.42	2.87	0.53 (0.43)	0.22 (0.17)
LQ	2.33	1.78	1.73	1.49	1.51	1.45	1.33	1.29	1.11	1.05	−0.46 (−1.41)	−1.28* (−3.19)
CAPEX	2.67	2.52	2.74	2.78	2.48	2.39	2.47	2.09	2.04	2.23	−0.25 (−0.20)	−0.44 (−0.33)
AG	4.34	3.52	2.79	2.81	2.61	2.65	2.96	2.52	2.62	2.41	−0.20 (−0.16)	−1.93 (−1.50)
ROA	2.12	2.38	2.56	2.96	2.87	2.91	2.41	2.22	2.09	1.96	−0.91 (−0.11)	−0.16 (−0.28)
INVST	1.45	0.78	0.87	0.85	0.67	0.60	0.72	1.22	0.97	0.39	−0.28 (−0.51)	−1.06 (−0.24)

Notes: Statistical significant at: *1, **5 and ***10 percent; this table reports mean monthly return for each decile portfolios on 18 stock return predictors; D10 represents the highest decile of the stock return predictor, and D1 is the lowest; the average monthly hedge portfolio return obtained from a long-short position in deciles D10 and D5, D10 and D1, respectively; corresponding *t*-statistics are in parenthesis; except for LngR sample period is from September 1995 to March 2011 (187 months); for LngR the sample period is from September 1997 to March 2011; the 18 predictors are defined in Section 5.3; the accounting data is from fiscal year end March 1995 to March 2010 and stock return data is from September 1995 to March 2011; except for LngR and momentum stocks are allocated to ten portfolios at the end of August of each year *y* (1995-2011); monthly equal-weighted returns on the portfolios are calculated from September to the following August. The portfolios formed on momentum and reversal is rearranged every month stocks with the high BM, Mliv, MM and selling stocks with low BM, Mliv, MM generate significant monthly average returns of 2.66, 1.30, 3.06 percentages, respectively. Furthermore, the average return spread between the small SZ and low LQ stocks and large SZ and high LQ stocks are 2.31 and 1.28 percentage, respectively. Jegadeesh and Titman's (1993) momentum anomaly is clearly evident in our sample. The LngR anomaly fails to generate a statistically significant return spread on the hedge portfolios. Our finding is also consistent with the findings of Sehgal and Balakrishnan (2002) which suggest a weak reversal pattern in the long-term returns and a strong continuation pattern in short-term returns for the Indian market. Additionally, from Table I one-dimensional sorts for all the 18 firm characteristics, it is evident that except for SZ, BM, Mliv, MM and LQ no other firm characteristics are able to provide statistically significant cross-sectional return variations in the Indian stock market. However, for the whole sample period, all the proposed return predictors predict the direction of subsequent one-year stock returns in a way consistent with their predictive patterns in the US market. This indicates that there is weaker anomaly effect in the Indian stock market as compared to the US market. Our results are consistent with the findings of Chen *et al.* (2010) for the Chinese stock market. Chen *et al.* (2010) suggest that there can be two possible reasons for the existence of a smaller number of firm characteristics that are attributable for the statistically significant cross-sectional return variation in an emerging stock market. First, return predictors in an emerging stock market are less heterogeneously distributed as compared to other developed markets. Since risk levels of firms differ according to firm-specific characteristics, if there is not much cross-sectional dispersion in a return-predictive variable or more homogeneity in the firm-specific characteristics examined, the cross-sectional dispersion in stock returns associated with such a variable will also be small (Chen *et al.*, 2010). Second, perhaps the stock prices are less informative in an emerging stock market like India given the argument of high stock market synchronicity or low price informativeness observed in such markets (Morck *et al.*, 2000). Our observation is close to the findings of Chen *et al.* (2010) as it is based on a very recent sample period (July 1995 to June 2007) and gives a comparative stand with respect to the cross-sectional regularity of firm characteristics in the context of developed and emerging stock markets. With special reference to small size effect, our result is consistent with the recent findings of Moor and Sercu (2013) for the persistent size effect in the other international stock markets including the Indian stock market.

3.1.2 Construction of market risk factors. The systematic market factor (MRKT) is measured as market excess return in excess of risk-free rate of interest. The measures of SZ, BM, MM and LQ for the construction of risk factors are similar to the measures mentioned in Section 3.1.1 for the construction of decile portfolios. The six value-weighted portfolios used for SMB and HML construction are small-low, small-medium, small-high, big-low, big-medium and big-high from the intersection of two SZ and three BM groups. Following Fama and French (1993), SMB is measured each month as the equal-weight average of the returns on the three small stock portfolios minus the returns on the three big stock portfolios. HML measured each month as the equal-weight average of the returns on two high BM portfolios minus returns on the two low BM portfolios. Following Keene and Peterson (2007) for the LMHL construction four value weighted portfolios formed with the intersection of two SZ-based and two LQ-based portfolios, i.e. small-high liquid, small-low liquid, big-high liquid, big-low liquid. LMHL is the difference between the simple average of returns from the two low liquid portfolios and the simple average of returns from the two high liquid portfolios. In order to measure WML, we follow Carhart (1997) and Her *et al.* (2004) for constructing six value-weight portfolios with the intersection of two size and three return momentum groups are small-winner, small-neutral, small-looser, big-winner, big-neutral and big-looser. WML is the equal-weight average of the returns on the two winner stock portfolios minus the returns on the two loser stock portfolios.

Table II reports the descriptive statistics for market risk factors. Table II shows mean positive return for all the risk factors except the market factor. The high level of standard deviation observed for the HML and WML warrants the caution for following such investible strategies. Table II confirms the presence of the SZ, BM, LQ and MM premiums on the Indian stock market. Except for the market excess return, monthly mean returns reported in Table II with respect to SMB, HML and WML are found to be higher than the mean returns observed by Fama and French (2012) for the global, North America, Europe, Japan and Asia Pacific markets. Consistent with the findings of Rouwenhorst (1999), our results suggest that market risk factors in emerging markets are qualitatively similar to those documented for many developed markets. In Table II except for MRKT the positive but small correlation between LMHL and other factors indicates that liquidity factor in addition to the well documented four factors captures another dimension of systematic risk. The positive correlation observed within SMB and LMHL may be because of the apparent relationship between market equity and liquidity. Amihud (2002) and Keene and Peterson (2007) suggest that the negative (positive) relationship of large size (small size) stocks with return can be considered as an alternative proxy for liquidity (illiquidity) measure of stocks.

3.1.3 The conditioning information variables. Literature on conditional asset pricing models suggests that the selected conditioning information variables should capture investors' expectations about future market return or business cycle conditions. In principle, since the information set of the investors at the time t is inherently unobservable (Cochrane, 2001), the lagged instrumental variables (Z_{t-1}) have been selected with respect to certain macroeconomic variables which validate the time series predictability of stock return and future economic conditions. Consistent with the conditional asset pricing literature (Fama and French, 1988; Ferson and Harvey, 1998, 1999; Iqbal *et al.*, 2010; Schrimpf *et al.*, 2007), we consider four conditioning information variables namely: term spread (TS), dividend yield (DY), SIR, and interest rate differential (IRD). TS is measured as the difference between ten-year Government bond yields and 91-days Treasury bill rate. DY is computed by summing monthly dividends on the value weighted S&P CNX Nifty

Table II.
Descriptive statistics and correlation matrix of risk factors

	Descriptive statistics		Correlation matrix of risk factors				
Risk factors	Mean	SD	MRKT	SMB	HML	LMHL	WML
MRKT	−5.81	7.48	1.00				
SMB	0.30	9.97	0.26	1.00			
HML	1.55	11.12	−0.25	0.29	1.00		
LMHL	0.48	3.50	−0.13	0.06	0.05	1.00	
WML	1.09	10.35	−0.02	0.02	−0.10	0.04	1.00

Note: Sample period consists of 187 monthly observations from September 1995 to March 2011 index portfolio for the year preceding t and dividing by the value of the portfolio at t. SIR is measured as the monthly weighted average call money rate. In order to access the relevance of global risk factors, we consider IRD measured as the difference between Mumbai Interbank Offered Rate (MIBOR) and London Interbank Offered Rate (LIBOR) as the fourth conditioning information variable.

Table III reports the descriptive statistics of the four conditioning variables. The observed negative correlation between TS and DY indicates the apparent opposite relationship of both the variables with the business cycle and expected returns (Fama and French, 1988). The positive correlation between the SIR and IRD in Table III is evident because of the common interest rate component among the two variables. However, as the two conditioning variables will be used in different alternative specifications, we are not running the risk of multicollinearity problem.

3.1.4 Measures of firm characteristics for cross-sectional return predictability. Motivated by the cross-sectional regularities observed for SZ, BM, Mliv, MM and LQ (Table I of Section 3.1.1), we will restrict ourselves to these five characteristics for examining the explanatory power of such characteristics on the risk adjusted returns derived for each security (j). The risk adjusted return for each security (R_j^*) has been calculated by employing unconditional and alternative conditional specification of FFM following the approach of Avramov and Chordia (2006). In our subsequent analysis all these five firm-specific characteristics are lagged by one month with respect to the stock return for each firm j. Since our subsequent analysis will examine the cross-sectional return predictability of firm characteristics as compared to the time series returns variation observed in portfolio-based approach (Table I), we mention the aforementioned selected five market anomalies (SZ, BM, Mliv, MM and LQ) for the subsequent cross-sectional analysis as S*z*, B*m*, M*liv*, M*m* and L*q*. Such distinction in terms of the symbolic representation has been made for the purpose of clarity in understanding as the selected five anomalies need to be measured in a different way for the cross-sectional tests. Such symbolic distinction helps to make the distinction in terms of the empirical measure of such variable without distorting their theoretical and economic relevance.

Table III. Descriptive statistics of conditioning information variables

Panel (A) summary statistics of the conditioning information variables				
Variables	*Mean*	*SD*	*Minimum*	*Maximum*
TS	2.13	1.57	−0.35	9.17
DY	1.49	0.49	0.65	3.08
SIR	7.08	3.98	0.73	34.83
IRD	3.49	3.58	−4.59	28.80
Panel (B) correlation matrix of the conditioning information variables				
	TS	*DY*	*SIR*	*IRD*
TS	1			
DY	−0.27	1		
SIR	−0.21	−0.28	1	
IRD	−0.37	0.01	0.84	1

Notes: Sample period consists of 187 monthly observations from September 1995 to March 2011; required data for conditioning variables (TS, SIR) have been collected from *Hand Book of Statistics of Indian Economy* published by Reserve Bank of India; DY data have been collected from NSE web site; for IRD calculation LIBOR and MIBOR data have been collected from official web sites of Bank of England, United Kingdom and National Stock Exchange of India

Consistent with related literature, for each stock the following variables were calculated each month as follows: S*z* of the firm is measured as the natural logarithm of the market value of the equity at the end as of the end of the second to last month. B*m* is the ratio of book value of equity at the financial year end in the calendar year *y* to the market value of equity at the end of the month $t - 1$ in the calendar year *y*. L*q* is measured as the annual average of monthly turnover ratio, i.e. number of shares traded to the number of shares outstanding. The values have been considered from the end of second to last month. To account for the momentum effect (M*m*) in short-run and long-run, we consider three sets of lagged return variables (M*m*2-3, M*m*4-6, and M*m*7-12). The two sets of lagged return variables namely M*m*2-3, M*m*4-6 given the importance of the short run momentum strategy documented in the context of the Indian stock market (Ansari and Khan, 2012). M*m*2-3 is the cumulative return over the two months ending at the beginning of the previous month. M*m*4-6 is the cumulative return over the three months ending three months previously. M*m*7-12 is the cumulative return over the six months ending six months previously. Consistent with Brennan *et al.* (1998), the lagged return variables were constructed to exclude the return during the immediate prior month in order to avoid any spurious association between the prior month return and the current month return caused by thin trading or bid-ask spread effects. Each month Mliv is computed as the ratio of total assets in the fiscal year ending March in the calendar year *y* to the market value of equity at the end of the month t-2 in the calendar year *y*.

Table IV reports summary statistics and correlation matrix for the risk characteristics of our interest. Results of Table IV show the time series averages of the cross-sectional means and standard deviations of security characteristics. Consistent with Table I the mean values of all the risk characteristic variables representing the short and long-term executable momentum strategies show a positive value. This indicates the momentum strategy both short and long and more specifically the long strategies can have a chance to generate positive momentum profits. The high value of standard deviation in the case of all momentum or return characteristics may be the result of the highly volatile nature of emerging stock markets. However, the standard deviation is relatively lower for short-term momentum (M*m*2-3) strategy. The correlation

	Descriptive statistics		Correlation matrix of firm characteristics						
	Mean	SD	S*z*	B*m*	L*q*	M*liv*	M*m*2-3	M*m*4-6	M*m*7-12
S*z*	20.62	1.97	1.00						
B*m*	4.86	12.25	−0.28	1.00					
L*q*	2.22	13.41	0.12	−0.03	1.00				
M*liv*	4.92	6.72	−0.35	0.01	−0.06	1.00			
M*m*2-3	4.94	23.36	0.03	−0.01	0.07	−0.09	1.00		
M*m*4-6	7.43	28.65	0.03	−0.02	0.04	−0.10	−0.02	1.00	
M*m*7-12	14.30	41.18	0.04	−0.02	0.05	−0.13	0.04	0.03	1.00

Notes: This table reports the descriptive statistics of firm characteristics and risk factors; sample period consists of 187 monthly observations of 582 firms from September 1995 to March 2011; for firm characteristics the descriptive statistics is computed as the time series average of cross-sectional mean standard deviation value; for firm characteristics the correlation matrix is computed from the time series of monthly cross-sectional correlations

Table IV. Descriptive statistics and correlation matrix of selected firm characteristics matrix shows a very low level of correlation structure among the selected firm characteristics.

4. Discussion of results

The Appendix reports the cross-sectional average slope coefficients of systematic risk factors for the first step time series regression specifications in equations (3) and (7) for deriving the risk adjusted returns of individual firms. For the purpose of brevity, we only report the cross-sectional average slope coefficients and *t*-statistics of risk factors (MRKT, SMB, HML, LMHL and WML) used in the alternative asset pricing models for deriving the risk adjusted returns in first step. The insignificant intercepts across all the alternative asset pricing models suggest that the systematic risk factors are able to explain the return behavior of individual firms.

Table V shows the estimation results of the equation (3) for the unconditional FFM. Columns 1-3 of Table V indicate the estimation results with respect to the three different momentum characteristics (M*m*2-3, M*m*4-6, M*m*7-12). The LR-test results for all the four different specifications show that the firm-specific effects are present in the dataset. For all the four different specifications, the reported LM test statistics indicate that either the fixed effect or random effect panel data models are to be preferred to the classical linear regression model. Hausman test results for all the alternative specifications in Table V reject the use of the random effect model. Therefore, our results are based on the fixed effect estimators. The reported results under columns 1-3 suggest that unconditional FFM fails to capture the importance of S*z*, M*liv* and M*m*

Coefficients and test statistics	(1)	(2)	(3)
S*z*	−0.78* (−17.67)	−0.76* (−17.24)	−0.77* (−17.06)
B*m*	0.01 (0.16)	0.08 (0.45)	0.28 (1.01)
L*q*	−0.12 (−0.65)	−0.10 (−0.63)	−0.10 (−0.64)
M*liv*	0.05* (7.06)	0.07* (7.39)	0.06* (7.41)
M*m*2-3	0.02* (6.55)	–	–
M*m*4-6	–	0.17 (1.12)	–
R*m*7-12	–	–	0.16** (2.59)
LR-test [x^2(581)]	630.54 {0.00}	626.66 {0.00}	623.44 {0.00}
LM test [x^2(1)]	451.07 {0.00}	482.10 {0.00}	477.52 {0.00}
Hausman test [x^2(5)]	1,417.98 {0.00}	1,728.06 {0.00}	1,607.66 {0.00}
R^2	0.0039	0.0035	0.0035
D-W stat.	2.13	2.21	2.19
F-test	81.61 {0.00}	73.26 {0.00}	73.40 {0.00}

Notes: Statistical significant at: *1, **5 and ***10 percent; the three different columns under each asset pricing models indicate the estimation results with respect to the three different momentum characteristics such as RET-2-3, RET-4-6 and RET 7-12 along with other firm characteristics; sample period consists of 187 monthly observations of 582 firms from September 1995 to March 2011; LR-test (Gourieroux *et al.*, 1982) carried out to identify the existence of individual firm specific effects in the data set; Lagrange Multiplier (LM) test (Breusch and Pagan, 1980) has been used to test the acceptability of panel data models over the classical regression models; the Hausman (1978) specification test is performed on each system to determine which estimation method is most appropriate; *t*-statistics are in parenthesis; figures in the curly brackets represent corresponding *p*-values of model specification test statistics

Table V. Fixed effect model estimates of equation (9) for unconditional FFMs characteristics. Even though the firm specific value effect is well captured for the Indian stock market, the model fails to account for the size effect completely. The reported results for unconditional FFM show that the model has reasonably captured the medium-term momentum characteristic (M*m*4-6) along with the L*q* and B*m* characteristics.

The persistent effect of S*z* characteristic in Table V seems to be inconsistent with the argument of Fama and French (1993) for the market-wide size and value effect explanation through the proposed three factor model. Since the risk adjustment process in the first step includes size and value factors (SMB and HML) along with other factors, it is reasonable to expect that the firm characteristics coefficients should be insignificant while explaining the risk adjusted returns in the second step. In common, the reported results of Table V give an indication of the special nature of S*z* and M*liv* characteristics, as the two are found to be indifferent for the risk adjustment process using several systematic risk factors in the multifactor specification. Although the available literature raises concern about the apparent relationship between S*z* and L*q* (Amihud, 2002; Keene and Peterson, 2007), findings in Table V for the FFM give no additional information for the insignificant size effect even in the presence of systematic liquidity risk factor.

Table VI shows the estimation results of the equation (9) for different conditional specifications of FFM. Columns 1-3 of Table VI show the estimated results for conditional FFM specification with the TS as the conditioning information. Columns 4-6 show the estimated results for conditional FFM specification with the DY as the conditioning information. Columns 7-9 of Table VI show the estimated results for conditional FFM with the SIR as the conditioning information and columns 10-12 present the estimated results for conditional FFM with IRD as the conditioning information, respectively. For all the alternative conditional specifications of FFM in Table VI, the reported model specification test statistics of LR-test and Hausman test negate the use of random effect model and give an indication for the use of fixed effect model estimation.

The reported results in Table VI suggest that the FFM in its several conditional specifications give similar results for the complete explanation of B*m* and L*q* effects as compared to its unconditional specification. In particular, the model fails to capture the momentum effects in its several conditional specifications. Regardless of the alternative conditioning information, the characteristic based pricing evidence is observed with respect to the S*z*, M*liv*, M*m*2-3 and M*m*7-12. The time varying conditional specification is only able to explain the presence of medium-term momentum (M*m*4-6) strategy. The use of DY conditioning information is not even able to explain the L*q* characteristic completely. Inconsistent with the findings of Ho and Hung (2009), Narayan and Zheng (2010) and Bauer *et al.* (2010), we do not observe any significant improvement of the liquidity augmented multifactor model for capturing the cross-sectional regularities associated with firm characteristics. With special reference to the L*q* characteristics, our results are also inconsistent with the concern raised by the related literature in developed markets. For instance, Avramov and Chordia (2006) raise concern over alternative conditional and unconditional asset pricing models' failure to capture the impact of L*q* effect. A similar line of concern is also raised by Ho and Hung (2009) for the failure of unconditional liquidity augmented models to capture the importance of L*q* pricing evidence.

Table VI. Fixed effect model estimates of equation (9) for conditional FFM

	Term spread (TS)			Dividend yield (DY)				SIR		Interest rate differential (IRD)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
S*z*	−1.35*	−1.34*	−1.32*	−0.98*	−0.99*	−0.97*	−0.85*	−0.84*	−0.87*	−0.76*	−0.75*	−0.73*
	(−28.51)	(−28.16)	(−27.59)	(−19.24)	(−19.14)	(−18.81)	(−15.91)	(−15.69)	(−16.21)	(−15.87)	(−15.59)	(−15.15)
B*m*	0.02	0.03	0.02	0.05	0.06	0.07	0.02	0.02	0.03	0.02	0.02	0.01
	(0.85)	(0.97)	(0.12)	(0.90)	(1.08)	(1.30)	(0.50)	(0.58)	(0.49)	(0.58)	(0.68)	(0.78)
L*q*	−0.03	−0.03	−0.02	−0.54*	−0.52*	−0.51*	−0.03	−0.02	−0.02	−0.01	−0.04	−0.01
	(−0.65)	(−0.65)	(−0.66)	(−6.94)	(−6.69)	(−6.60)	(−1.41)	(−1.41)	(−1.44)	(−0.85)	(−0.85)	(−0.85)
M*liv*	0.09*	0.10*	0.10*	0.06*	0.07*	0.07*	0.07*	0.08*	0.02*	0.11*	0.10*	0.11*
	(11.24)	(11.52)	(11.82)	(7.21)	(7.70)	(8.21)	(7.07)	(7.29)	(9.34)	(12.02)	(12.23)	(12.41)
M*m*2-3	0.03*	–	–	0.02*	–	–	0.03*	–	–	0.02*	–	–
	(11.05)			(4.83)			(13.73)			(6.88)		
M*m* 4-6	–	0.05*	–	–	0.02*	–	–	0.02*	–	–	0.02	–
		(3.43)			(2.04)			(6.95)			(1.22)	
M*m*7-12	–	–	0.02**	–	–	0.08*	–	–	0.01*	–	–	0.02**
			(2.08)			(7.44)			(9.34)			(2.43)
LR-test [$x^2(581)$]	625.35	620.89	635.40	631.07	622.10	637.52	617.19	622.74	627.64	633.29	638.35	630.54
	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}
LM test [$x^2(1)$]	37.52	43.02	49.77	166.96	184.93	210.16	22.76	20.11	23.63	17.81	21.49	27.11
	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}
Hausman test [$x^2(5)$]	2,791.32	1,385.19	1,043.99	2,950.34	2,047.77	1,220.23	362.67	371.17	368.13	977.10	836.23	735.07
	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}	{0.00}
R^2	0.0092	0.0082	0.0081	0.0061	0.0059	0.0065	0.0041	0.0028	0.0032	0.0034	0.0029	0.0030
D-W stat.	2.59	2.60	2.59	2.47	2.47	2.46	2.43	2.46	2.47	2.39	2.40	2.39
F-test	195.21	172.96	171.55	102.13	98.27	108.56	87.33	59.24	67.16	70.55	61.36	62.12

Notes: Statistical significant at: *1, **5 and ***10 percent; the three different columns under each asset pricing models indicate the estimation results with respect to the three different momentum characteristics such as RET-2-3, RET-4-6 and RET 7-12 along with other firm characteristics. RET-2-3, RET-4-6 and RET 7-12 are measured as the cumulative returns over the two months ending at the beginning of the previous month, three months ending three months previously, and six months ending six months previously, respectively; sample period consists of 187 monthly observations of 582 firms from September 1995 to March 2011; LR-test (Gourieroux *et al.*, 1982) carried out to identify the existence of individual firm specific effects in the data set; Lagrange Multiplier (LM) test (Breusch and Pagan, 1980) has been used to test the acceptability of panel data models over the classical regression models; the Hausman (1978) specification test is performed on each system to determine which estimation method is most appropriate; *t*-statistics are in parenthesis; figures in the curly brackets represent corresponding *p*-values of model Specification test statistics

The findings in other emerging markets that advocate similar conclusions of unconditional multifactor models' complete explanation evidence of L*q* effect are associated with Narayan and Zheng (2010). The authors find that even the alterative multifactor model specifications that do not account for the additional liquidity factor are able to explain S*z*, B*m* and L*q* effects. Suggesting a possible explanation, the authors argue that this may be attributable to the special nature of order driven market structure. Following such empirical evidence in the context of emerging stock markets and considering the order driven market structure of the Indian stock market (Dash and Mahakud, 2012), we also expect that the special nature of an order driven market structure may be a the possible reason for the complete explanation of L*q* effect among most of the asset pricing models that we consider in our analysis. This argument is more intuitive given the theoretical argument of market microstructure literature. For instance, Brockman and Chung (2002) suggest that order driven market system generates liquidity demand and supply schedules that are consistent with the equilibrium under perfect competition. In this regard, one possible explanation for the complete explanation evidence of L*q* characteristic in several alternative models may be attributable to the order driven market structure of the Indian stock market. However, regardless of the alternative asset pricing models that we consider and irrespective of their different conditional specifications, the S*z*, M*liv* and short run momentum characteristics retain their significance as the potential source of cross-sectional regularity in the Indian stock market.

5. Summary and conclusions

Since the early eighties, the asset pricing literature has attracted considerable empirical research over the cross-sectional regularity observed with respect to certain firm characteristics commonly called market anomalies. However, the continuing debate over the complete explanation of firm characteristics through the risk adjustment process of systematic risk factors is a new phenomenon. The available literature in the developed countries is inconsistent and inconclusive with respect to finding a benchmark asset pricing model that can probably explain all or some of the market anomalies. Moreover, with the paucity of research in the context of emerging stock markets, this continuing debate even limits our understanding with respect to the emerging stock market. In this regard, the present paper makes an attempt to revisit the complete explanation debate in the context of an emerging stock market like India. This paper essentially attempts to access the cross-sectional stock return regularity of several well debated market anomalies. Based on statistical significance of the cross-sectional regularity of certain market anomalies, we further investigate the complete explanation debate using a comprehensive FFM in its unconditional and alternative conditional specifications.

Results suggest that, for the whole sample period, all the proposed return predictors predict the direction of subsequent one-year stock returns consistent with their respective theoretical arguments. We observe weaker anomaly effect in the Indian stock market as only five return predictors (size, book-to-market equity, liquidity, market leverage and momentum) appear to be statistically significant. This may be because of high stock price synchronicity or more firm specific homogeneity nature of an emerging stock market like India (Chan *et al.*, 2001; Morck *et al.*, 2000). It has been observed that considering liquidity augmented FFM in its unconditional specification, the impact of book-to-market equity and liquidity is explained by the market risk factors completely.

However, the unconditional specification fails to capture size, market leverage and short and long-term momentum effects. Considering alternative conditional specifications of the FFM and allowing for the fact that risk factors vary over time with respect to business cycle and macroeconomic conditioning information, the models behave in a similar way for capturing the impact of book-to-market equity, liquidity and short-run momentum on stock returns. The conditional models fail to subsume the size effect and short-run momentum effect. Our finding with respect to the significant size effect is consistent with the findings of Moor and Sercu (2013) in the context of international stock markets and casts doubt on the empirical strand of related literature that suggests the disappearing size effect (Dichev, 1998). The common argument for the disappearing size effect is that the size anomaly disappeared around the time of its discovery because practitioners began to use investment vehicles that tried to exploit the anomaly (van Dijk, 2011; Schwert, 2003). However, our results suggest significant size effect in the Indian stock market.

Considering the practitioners' perspective, our results indicate that the profitable investment strategy with respect to the small size warrants close ended mutual fund investment portfolio strategy for enhancing the long-term profitability. The close ended fund strategy is advisable given the low liquidity associated with such stocks. The associated significant cross-sectional regularity of the other firm characteristics and more specifically the short-run momentum effect can generate profit keeping a short-term investment scenario.

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Appendix

Table AI. Cross-sectional average of slope coefficients for risk factors

Panel (A) unconditional FFM

Model	θ	β_{MRKT}	β_{SMB}	β_{HML}	β_{WML}	β_{LMHL}	*Adj.* R^2
FFM	0.02	0.68	0.80	0.56	−0.12	0.79	0.26
	(1.56)	(4.28)	(2.75)	(2.38)	(−0.92)	(2.19)	

Panel (B) FFM scaled by term spread (TS)

Model	θ	β_{MRKT}	β_{SMB}	β_{HML}	β_{WML}	β_{LMHL}	β^{TS}_{MRKT}	β^{TS}_{SMB}	β^{TS}_{HML}	β^{TS}_{WML}	β^{TS}_{LMHL}	*Adj.* R^2
FFM	1.22	0.31	0.40	0.19	−0.38	0.18	−0.16	−0.09	−0.11	0.06	0.13	0.31
	(0.80)	(3.28)	(2.11)	(1.38)	(−1.32)	(1.78)	(−1.36)	(−0.66)	(−0.36)	(0.37)	(1.21)	

Panel (C) FFM scaled by dividend yield (DY)

Model	θ	β_{MRKT}	β_{SMB}	β_{HML}	β_{WML}	β_{LMHL}	β^{DY}_{MRKT}	β^{DY}_{SMB}	β^{DY}_{HML}	β^{DY}_{WML}	β^{DY}_{LMHL}	*Adj.* R^2
FFM	0.36	1.73	1.14	0.04	−0.19	0.65	−0.18	0.94	−0.01	−0.07	0.24	0.34
	(0.71)	(1.86)	(2.13)	(0.56)	(−0.32)	(2.16)	(−1.53)	(0.98)	(−0.62)	(−0.42)	(1.01)	

Panel (D) FFM scaled by SIR

Model	θ	β_{MRKT}	β_{SMB}	β_{HML}	β_{WML}	β_{LMHL}	β^{SIR}_{MRKT}	β^{SIR}_{SMB}	β^{SIR}_{HML}	β^{SIR}_{WML}	β^{SIR}_{LMHL}	*Adj.* R^2
FFM	0.18	0.71	0.29	0.46	−0.53	0.29	−0.92	−0.88	−0.54	0.71	0.18	0.29
	(0.20)	(2.69)	(2.08)	(2.11)	(−1.39)	(2.10)	(−1.01)	(−0.98)	(−0.61)	(0.69)	(1.53)	

Panel (E) FFM scaled by IRD

Model	θ	β_{MRKT}	β_{SMB}	β_{HML}	β_{WML}	β_{LMHL}	β^{IRD}_{MRKT}	β^{IRD}_{SMB}	β^{IRD}_{HML}	β^{IRD}_{WML}	β^{IRD}_{LMHL}	*Adj.* R^2
FFM	0.96	0.63	1.44	0.18	−0.10	0.07	−0.30	−0.23	−0.02	0.19	0.09	0.32
	(1.41)	(2.43)	(2.39)	(1.78)	(−0.82)	(1.68)	(−0.31)	(−0.31)	(−0.47)	(0.26)	(0.68)	

Notes: This table reports the cross-sectional average of slope coefficients estimated in the first step time series regression for calculating the risk adjusted return of individual firms; the estimation for the time series regression of different alternative conditional models follows the specified equations (4) and (7); cross-sectional average *t*-statistics are in parenthesis

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