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Market anomalies, asset pricing models, and stock returns: evidence from the Indian stock market
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Abstract

Purpose – *This paper aims to investigate whether the use of conditional and unconditional Fama and French (1993) three-factor and Carhart (1997) four-factor asset pricing models (APMs) captures the role of asset pricing anomalies in the context of emerging stock market like India.*

Design/methodology/approach – *The first step time series regression approach has been used to drive the risk-adjusted returns of individual securities. For examining the predictability of firm characteristics or asset pricing anomalies on the risk-adjusted returns of individual securities, the panel data estimation technique has been used.*

Findings – *Fama and French (1993) three-factor and Carhart (1997) four-factor model in their unconditional specifications capture the impact of book-to-market price and liquidity effects completely. When alternative APMs in their conditional specifications are tested, the importance of medium- and long-term momentum effects has been captured to a greater extent. The size, market leverage and short-term momentum effects still persist even in the case of alternative unconditional and conditional APMs.*

Research limitations/implications – *The empirical analysis does not extend for different market scenarios like high and low volatile market or good and bad macroeconomic environment. Because of the constraint of data availability, the authors could not include certain important anomalies like net operating assets, change in gross profit margin, external equity and debt financing and idiosyncratic risk.*

Practical implications – *Although the active investment approach in stock market shares a common ground of semi-strong form of market efficiency hypothesis which also supports the presence of asset pricing anomalies, less empirical evidence has been explored in this regard to support or repute such belief of practitioners. Our empirical findings make an attempt in this regard to suggest certain anomaly-based trading strategy that can be followed for active portfolio management.*

Originality/value – *From an emerging market perspective, this paper provides out-of-sample empirical evidence toward the use of conditional Fama and French three-factor and Carhart four-factor APMs for the complete explanation of market anomalies. This approach retains its importance with respect to the comprehensiveness of analysis considering alternative APMs for capturing unique effects of market anomalies.*

Keywords *Market anomaly, Emerging market, Stock return, Momentum, Asset pricing model, Risk factor*

Paper type *Research paper*

1. Introduction

Identification and empirical validation of factors which explain the cross-sectional variation of expected stock returns has been one of the key issues in the investment management research. Over the past two decades, there has been considerable research to support that the predictable component of stock returns can be associated with several firm characteristics or commonly perceived market anomalies. The existence of anomaly effect as cross-sectional determinants of stock returns negates the cross-sectional relation between average stock returns and systematic risk measured by alternative asset pricing models (APMs hereafter). Interpretation of such empirical evidences across developed and

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emerging markets around the world is, of course, strongly debated. The present paper attempts to shed more light on this debate by investigating whether cross-section of expected stock returns is better explained by risk factors suggested by alternative APMs, or market anomalies. More importantly, we seek to examine the use of Fama and French (1993) three-factor and Carhart (1997) four-factor APMs in their alternative specification for the complete explanation of market anomalies.

The role of firm characteristics or financial market anomalies for the determination of cross-section of stock returns behavior (Amihud, 2002; Banz, 1981; Jegadeesh and Titman, 1993; Stattman, 1980) has long been recognized as a challenge to the central paradigm of the traditional asset pricing literature. In common, related literature suggests two competing arguments on the cross-sectional regularity of such anomalies. First, the apparent role of firm characteristics is the resultant of market inefficiency or profit opportunities, and they are mere chance results that often seem to disappear after documented in the academic literature (Dimson and Marsh, 1999). Second, the documented firm characteristics serve as proxies for the riskiness of firms and, therefore, serve as the better determinant of cross-section of stock returns behavior (Fama and French, 1992; Chan and Chen, 1991). However, the debate between the two competing arguments is still open and has drawn considerable attention in the investment management research.

Following the risk-based argument of market anomalies, the available literature conjecture that the identification and empirical validation of financial market anomalies have been indeed a joint hypothesis test of informational efficiency of the market and predictability of APMs (Schwert, 2003; MacKinlay, 1995). Rejection of the tests suggest that either the market examined is not efficient, i.e. market anomalies are mere chance results (Schwert, 2003) appeared due to methodological illusions (Fama, 1998), or the equilibrium APMs fail to properly describe stock returns behavior due to its inappropriateness, i.e. bad model problem (Fama, 1998; MacKinlay, 1995). However, if the joint hypothesis is rejected, it still fails to give a conclusive stand to attribute such rejection to either any one of the aforementioned hypotheses. For instance, testing a three-factor model (Fama and French, 1993) for explaining the cross-sectional regularity of firm size (MC) and book-to-market price (BP) ratio may lead to a situation where the proposed three-factor model may not be able to capture the MC or BP effects, even though the proposed three-factor model contains risk factors (small minus big, i.e. SMB, and high minus low, i.e. HML) that are empirically motivated from the risk-based argument of MC and BP. In such a scenario, it will be unconventional to argue that persistence of MC and BP effects are mere chance results or methodological illusions (Schwert, 2003; Fama, 1998), and premature to discard the claim that the systematic risk factors involved in the three-factor model (Fama and French, 1993) are inappropriate and subject to the bad model problem (Fama, 1998). Similar line of argument can also be advocated with respect to the four-factor model (Carhart, 1997), which augments the three-factor model with the momentum (MOM) risk factor. Given the case of an opposite scenario, i.e. if the factor models are able to explain the market anomalies, then also it will be premature to discard the propositions, e.g. stock market is efficient (anomalies are resultant of market inefficiency) or anomalies are mere chance results with no systematic risk attributes. We mention such an attempt as premature because this will discard the theoretical argument of systematic risk-based explanation for such firm characteristics, which motivates the development of alternative multifactor APMs (Carhart, 1997; Fama and French, 1993; Pastor and Stambaugh, 2003).

To circumvent such issues, in recent finance literature, attention has been gradually shifted from mere identification of market anomalies and testing their empirical cross-sectional regularities to a more fundamental question, i.e. what explains expected returns, risk factors or firm characteristics that are commonly perceived to be market anomalies. It has been argued that if the empirically motivated risk factors of alternative multifactor APMs (Fama and French, 1993; Carhart, 1997) represent market wide systematic risk, then after making the stock raw returns risk adjusted using such systematic risk factors, the incremental explanatory power of the market anomalies for the risk-adjusted returns should be statistically insignificant (Avramov and Chordia, 2006 pp. 1002-1004). In recent years, following Avramov and Chordia (2006) argument that several studies in the context of developed markets examine the complete explanation debate (Antoniou *et al.*, 2007; Bauer *et al.*, 2010; Chou *et al.*, 2010). However, the universal validation of a particular APM is still inconclusive. Moreover, the available literature on this issue is quite minimal in the context of emerging stock markets. Given the far less universal dominance of any single APM, either in its unconditional or conditional specifications for capturing the market anomalies, it is imperative to assess the complete explanation debate in other emerging markets due to their different market structure (Biscarri and Espinosa, 2008; Drobetz *et al.*, 2002; Iqbal *et al.*, 2010; Jun *et al.*, 2003; Lim and Brooks, 2010; Morck *et al.*, 2000) and importance as a special case of international portfolio diversification.

Drawing motivation on such arguments, the present paper attempts to revisit the complete explanation debate, i.e. the applicability of alternative factor models for the complete explanation of market anomalies, in the context of an emerging stock market like India. To be more specific, the present paper seeks to answer two complementary research questions. First, whether the alternative APMs in their conditional and unconditional specifications are able to capture the unique importance of market anomalies. Second, do the market anomalies retain their cross-sectional return predictability potential once the raw return of individual securities are risk adjusted using the alternative unconditional and conditional APMs.

Our approach in this regard extends the asset pricing literature in two ways. First, given the distinctive nature of emerging stock markets, it helps to broaden our understanding in terms of the applicability of alternative factor models for the complete explanation of market anomalies. Over the years, asset pricing research in the context of emerging markets have attracted considerable attention because of the growth in market size, liquidity, liberalization of their markets and demand for international portfolio diversification. However, to our knowledge, none of the existing literature in the contest of emerging stock market has tested the applicability of such wide range of alternative multifactor APMs in unconditional and conditional specifications for the complete explanation of market anomalies. With special reference to the Indian stock market, this study retains its importance because of the stock market's unique nature in terms of the ownership structure, investor participation and the decade-long institutional reform process for enhancing the market efficiency. Second, it provides an out-of-sample evidence for the applicability of factor models to explain the anomaly effect for stock returns behavior. Such out-of-sample evidence from an emerging market is empirically more intuitive, as it is not highly correlated with the data used in previous research and free from the data-snooping biases (Lo and MacKinlay, 1990) associated with the developed markets.

Our results for alternative APMs specifications revel that, as compared to unconditional APMs, conditional models perform better to capture the market anomalies. Results reveal that considering several alternative APMs in their unconditional specifications, the BP and liquidity (LIQ) effects can be explained by the market risk factors completely. When the risk factors of alternative APMs are allowed to vary over time employing business cycle conditioning information, the importance of medium-term and long-term momentum effect have been captured to a greater extent. Although the active investment approach in stock market shares a common ground of semi-strong form of market efficiency hypothesis, which also supports the presence of market anomalies, less empirical evidence has been explored in this regard to support or repute such belief of practitioners. Our empirical findings make an attempt in this regard to suggest certain anomaly-based trading strategy that can be followed for active portfolio management.

This paper is organized into seven sections. Section 2 provides a brief review of related literature and elaborates the motivation behind this study. Section 3 outlines empirical approach. Section 4 describes the data and variables. Section 5 presents empirical results. Section 6 documents some robustness tests, and Section 7 concludes the paper.

2. Related literature and motivation

Following the seminal work of Brennan *et al.* (1998), attention in the recent finance literature has been gradually shifted from mere identification of market anomalies and testing their cross-sectional regularity, toward the applicability of existing factor models for capturing the effects of such anomalies. Put it differently, whether the factor models are sufficient enough to subsume the return predictability of asset market anomalies, or still the anomalies retain their unique importance for the cross-sectional return predictability (Avramov and Chordia, 2006). In this section, we attempt to review a set of related literature that investigates the complete explanation debate in several developed and emerging stock markets. While presenting the respective studies in this area, we tried to emphasize in terms of the use of alternative APMs and their significance to capture the anomaly effect.

Brennan *et al.* (1998) lead the way in the US stock market by using unconditional Fama and French (1993) three-factor model find evidence that MC and BP effects are attenuated, while the MOM and LIQ effects persist. Further evidence to the debate on the application of factor models to capture the effect of market anomalies is provided by Avramov and Chordia (2006). In essence, Avramov and Chordia (2006) using US individual stock return data for the sample period July 1964 through December 2001 and employing six alternative APM attempt to find best APM for this debate. Avramov and Chordia (2006) find evidence that capital asset pricing model (CAPM) (Lintner, 1965; Sharpe, 1964), Fama and French (1993) three-factor model and Carhart (1997) four-factor model are not able to capture the MC, BP, MOM and LIQ effects in their unconditional specifications. In the European stock market, Bauer *et al.* (2010) find that unconditional three-factor model (Fama and French, 1993) fails to eliminate the size, value, liquidity and momentum effect completely.

Motivated with the success of conditional APMs, which accounts for time-varying nature of systematic risk premia (Jagannathan and Wang, 1996), recent literature also explores the complete explanation hypothesis using alternative conditional APMs. Using alternative conditional APMs tests, Avramov and Chordia (2006) show that conditional specification of Fama and French (1993) three-factor model is able to capture the MOM effect; however, it fails to capture the LIQ effect. Ho and Hung (2009) and Ho (2012) using US stock market data for the sample period July 1964 to December 2005 observe that conditional model specifications outperform the unconditional models in terms of capturing anomalies. Specifically, Fama and French three-factor model in its conditional specification is able to capture the impact of MC and BP effects on returns. Ho and Hung (2009) also find evidence to support the applicability of momentum augmented four-factor model to capture the effect of MOM and LIQ effect. Chou *et al.* (2010) for the US stock market find evidence that MC and BP effects are captured with the conditional Fama and French (1993) three-factor model, whereas MOM and LIQ effects are still persistent. In contrast to Avramov and Chordia's (2006) findings in the US stock market, Antoniou *et al.* (2007) and Bauer *et al.* (2010) for the European stock market observe strong MOM effect even after using the conditional multifactor APMs for deriving risk-adjusted returns of individual securities. To briefly sum up, the related literature across different developed markets suggest that the effects of market anomalies are not consistently captured through alternative APMs either in their unconditional or conditional specifications. Furthermore, the unconditional specification of APMs are less effective to capture the anomaly effect as compared to their conditional specifications (Antoniou *et al.*, 2007; Avramov and Chordia, 2006; Bauer *et al.*, 2010; Chou *et al.*, 2010; Ho and Hung, 2009; Ho, 2012). Most of the empirical research concerning this complete explanation debate has been focused on the developed markets, and limited attention has been paid to the emerging stock markets. Extending the available literature for the Japan stock market, Chang *et al.* (2010) observed strong liquidity effect even after making the raw return risk adjusted using alternative multifactor models. Narayan and Zheng (2010) in the context of Chinese stock market find that five-factor model or Carhart (1997) four-factor model augmented with the liquidity factor is able to explain the LIQ, MC and BP effects but not the MOM effect. Using similar argument, Dash and Mahakud (2013) in the context of Indian stock market observe that five-factor model, i.e. Carhart (1997) four-factor model augmented with the liquidity factor helps to explain BM and LIQ effects, but not the SZ and MOM effect. Apart from the aforementioned two studies, the existing literature remains silent about the applicability of such research hypothesis in the context of any other emerging markets. Table I summarizes the related literature in this area and presents the anomaly explanation evidence across different markets.

In this paper, we attempt to revisit the complete explanation debate in the context of Indian stock market employing unconditional and conditional specification of CAPM, Fama and French three-factor model and Carhart four-factor model. Apart from the limited attention caveat in the context of emerging stock markets to test the complete explanation debate, another significant limitation of the existing literature is the use of only unconditional multifactor APMs in the context of emerging stock market. The existing study that closely resembles ours is Dash and Mahakud (2013). Our study employs same set of anomalies and conditioning information variable from the Indian stock market, as in Dash and Mahakud (2013), and extends the sample period till March 2012. However, the unique distinction of our paper from Dash and Mahakud (2013) is its focus on several alternative APMs. In this paper, we explore Fama and French (1993) three-factor and Carhart (1997) four-factor APMs which are never been considered by Dash and Mahakud (2013). In essence, our study provides a more microscopic approach to this debate by focusing each APM as a unique representation of systematic risk factors. As there is no empirical consensus with respect to any particular APM that is having a universal dominance, so it is perceptible to test them all together. To find a comparative benchmark, our motivation to examine several APMs in alternative specifications follows Jagannathan and Wang (1996 p. 36), who suggest that:

> [. . .] we have to keep in mind that any APMs is only an approximation of reality. Hence, it would be rather surprising if it turns out to be 100 per cent accurate. The interesting question is not whether a particular asset-pricing model can be rejected by the data. The question is how inaccurate is the model?

Table I Correlation matrix of conditioning information variables and risk factors

Variables	*MRKT*	*SMB*	*HML*	*WML*	*TS*	*DY*	*IR*	*IRD*
MRKT	1							
SMB	0.27	1						
HML	−0.23	0.29	1					
WML	−0.03	0.02	−0.09	1				
TS	0.04	0.01	−0.04	−0.08	1			
DY	0.26	0.14	−0.02	0.16	−0.27	1		
IR	−0.30	−0.21	0.11	−0.02	−0.21	−0.28	1	
IRD	−0.16	−0.15	0.06	−0.03	−0.37	0.01	0.84	1

Notes: Sample period consists of 199 monthly observations from September 1995 to March 2012; following Fama and French (1993), SMB is measured each month as the equal-weighted average of the returns on the three small stock portfolios minus the returns on the three big stock portfolios; similarly, HML is measured each month as the equal-weighted average of the returns on two high BP portfolios minus returns on the two low BP portfolios; following Carhart (1997), WML is the equal-weighted average of the returns on the two winner stock portfolios minus the returns on the two loser stock portfolios; for the construction of size factor or SMB, firm size is measured as natural logarithm of market capitalization (stock prices times outstanding shares) at the end of August of year *y*; for value factor or HML, BP has been measured as the ratio between book price for the fiscal year ending in calendar year *y* by the market value of equity at the end of August in year *y*; for momentum factor WML, we measure momentum as the cumulative return of a stock in month *t*-12 through month *t*-2 preceding August of the 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; conditioning variables are lagged by one month to the risk factors

Our approach to test alternative APMs for explaining anomaly effect follows the similar argument. Therefore, we attempt to accommodate alternative APMs in our analysis to observe their individual anomaly explanation capacity.

Our motivation to test the complete explanation debate in the context of an emerging market retains its importance because of two complementary arguments. First, it has been argued in the prior literature that the cross-sectional return predictability associated with large number of firm characteristics or market anomalies in the context of developed markets may not be applicable in the context of emerging stock markets (Chen *et al.*, 2010). It could be due to the fact that emerging markets have been characterized with high stock price synchronicity or low price informativeness (Chana and Hameed, 2006; Morck *et al.*, 2000), and with such characteristics, it is reasonable and practical to anticipate that there is little scope for the diffusion of more firm-specific information to the stock prices and, thus, a lower chance to find a profitable trading strategy using market anomalies. Therefore, minimal presence of market anomalies in the context of emerging markets no way validates the claim that market is efficient; rather, it is the lower price informativeness of stock prices that hinders the significant role of market anomalies. Second, emerging stock markets are distinguished by certain unique characteristics like unstable macroeconomic condition (Drobetz *et al.*, 2002; Iqbal *et al.*, 2010), gradual liberalization and volatile market, thin trading and low liquidity (Jun *et al.*, 2003) and accounting information heterogeneity because of accounting regulation effects (Biscarri and Espinosa, 2008). Pertinent to such unique characteristics, it has also been argued that "emerging markets have long posed a challenge for finance. Standard models are often ill suited to deal with the specific circumstances arising in these markets" (Bekaert *et al.*, 2003). Therefore, the factor models that account for the explanation of certain market anomalies in the context of developed market can never be generalized in the context of emerging markets because of its distinctive nature. If market structures of emerging stock markets hinder the price informativeness negatively and so also the early detection of anomalies, and the special characteristics of emerging market provide a notion that the performance of APMs in such markets cannot be generalized with the developed markets, then, which APMs performs better in such kind of market scenario to capture the effects of market anomalies becomes an important empirical issue to investigate.

3. Empirical approach

Our methodology closely follows the empirical approach developed by Brennan *et al.* (1998) and Avramov and Chordia (2006). Assuming that returns of security *j* at time *t* are generated by an L-factor approximate factor model:

$$\widetilde{R_{jt}} = E_{t-1}(\widetilde{R_{jt}}) + \sum_{l=1}^{L} \beta_{jlt-1}\tilde{f}_{lt} + \widetilde{\varepsilon_{jt}}, \ \forall j, \ t > 0, \tag{1}$$

where: E_{t-1} is the conditional expectation operator; $\widetilde{R_{jt}}$ is the return on security *j* at time t; β_{jlt-1} is the factor loading of the security's return on factor *l*; $\tilde{f}_{lt}$ is the return on factor *l* at time t; and $\widetilde{\varepsilon_{jt}}$ is the error term. To derive the risk-adjusted return of each security *j* for the month *t*, we follow the first step time series regression approach of Brennan *et al.* (1998) (for a detail discussion, see also Avramov and Chordia, 2006) with the following specifications:

$$R^{*}_{jt} \equiv R_{jt} - R_{Ft} - \sum_{l=1}^{L} \hat{\beta}_{jl}F_{lt}, \tag{2}$$

where: $F_{lt} \equiv f_{lt} + \lambda_{lt}$ is the sum of the factor realization and its corresponding risk premium. $\hat{\beta}_{jl}$ is the beta estimated by a first pass time series regression over the entire sample period, and R^{*}_{jt} is the estimated risk-adjusted return on stock *j* at time *t* from the first pass time series regression. The suggested risk adjustment procedure imposes the assumption that the zero beta equals the risk-free rate, and that the *L*-factor premium is equal to the excess return on the factor (Avramov and Chordia, 2006).

For the deriving risk-adjusted returns of individual securities, we consider three alternative linear factor models in their conditional and unconditional specifications: single-factor CAPMs (Lintner, 1965; Sharpe, 1964), Fama and French (1993) three-factor model and Carhart (1997) four-factor model. In our multifactor specifications, we restrict ourselves for the three-factor and four-factor model (Carhart, 1997; Fama and French, 1993), following the recent findings of Maio and Santa-Clara (2012), which suggest that the Fama and French (1993) and Carhart (1997) multifactor models perform the best on time series and cross-sectional behavior of state variables and factors. For all the three aforementioned linear factor models, we also estimate their conditional specifications using four conditional information variables. From the conditional asset pricing literature, we consider four conditioning information variables, namely, term spread (TS), dividend yield (DY), short-term interest rates (IRs) and interest rate differential (IRD) (detail discussion in Section 4). The alternative unconditional and conditional APMs then used to derive risk-adjusted returns of each security using the first step time series regression approach of equation (2). The conditional specifications of the alternative APMs follow the scaled factor methodology of Cochrane (1996), in which coefficients of the factors vary with the available conditioning information set.

The derived risk-adjusted return in equation (2) 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. Assuming that the APMs are sufficient enough to describe the pervasive firm characteristics in both conditional and unconditional specifications, the unique impact of the asset pricing anomalies to explain the risk-adjusted returns is expected to be ruled out completely. The argument for testing the importance of market anomalies (i.e. $c = 1$ [. . .] [. . .] C) for explaining the risk-adjusted return can be specified as follows:

$$R^{*}_{jt} = \alpha + \sum_{c=1}^{C} \mu_c \psi_{cjt-1} + \varepsilon_{jt}, \tag{3}$$

where: ψ_{jt-1} is the vector of financial 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 (μ_c) of market anomalies will be equal to zero. Assuming both firm and time effects in the data set, we extend the equation (3) to a two-way panel data model specification as follows:

$$R^{*}_{jt} = \alpha_0 + \alpha_j + (\mu_c \psi_{ct-1} + \ldots\ldots\ldots + \mu_C \psi_{Ct-1}) + \Gamma_t + \varepsilon_{jt}, \tag{4}$$

where, R^{*}_{jt} is the risk-adjusted return of regressors at time t. The regressors, namely, c [. . .] [. . .] C are the firm-specific explanatory variables. α_0 is the overall constant. α_j is the individual effect, which is assumed as constant over time and varies across the individual cross-sectional unit (firm). Γ_t is the time-specific effect which varies across the time, but constant across the firms. ε_{jt} is a stochastic error term assumed to have mean zero and constant variance. For the estimation of equation (4), we use panel data estimation technique to examine the predictability of firm characteristics for the risk-adjusted returns derived from the first step. As an alternative to the Fama and MacBeth's (1973) two-pass cross-sectional regression approach, the use of panel data estimation helps to avoid the errors-in-variables problem (Shanken, 1992) associated with Fama and MacBeth approach. Moreover, panel dataset 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). As an alternative to the Fama and MacBeth approach, the use of panel estimation for the data property that conjectures a balanced panel with continuously traded stocks has also been highlighted by Goyal (2012). More specifically, Goyal (2012) suggests that the popularity of Fama and MacBeth approach in the asset pricing literature is attributable to the fact that the risk premium estimation results not to be influenced because of the appearance and delisting of stocks in the exchange, as it considers the available stocks at given point of time. 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 to be an unbalanced panel. As our data set comprised continuously traded stocks, our empirical analysis is not susceptible to missing observation and unbalanced panel.

4. Data and variables

Our sample consists of monthly returns of continuously traded non-financial common stocks listed on the National Stock Exchange (NSE) of India from September 1995 to March 2012 (199 months). We obtain monthly data for individual securities from the PROWESS database compiled by the Centre for Monitoring Indian Economy. To include a stock in the sample for a given month, we select stocks based on the following criteria: its return in the current month and in 24 of the previous 60 months had to be available in the PROWESS database; must have sufficient data to calculate the market capitalization, the book-to-market ratio, the price and other firm-specific information to calculate firm-specific characteristics; to reduce delisting or backfilling biases, the stock must be a continuously traded stocks. The selection of continuously traded individual stocks helps us to construct a balanced panel, and to avoid missing observation, data-snooping bias and under rejection bias that have been subject of considerable debate in prior asset pricing literature. Considering the continuously traded stocks since the inception of NSE in 1994 and avoiding the stocks that have negative BP values, we restrict our sample for 582 stocks. To avoid excess volatility-induced return variation during the initial days of the NSE, we consider monthly return observations since September 1995. For the risk-free rate proxy, we use 91-days Treasury bill rate collected from the Reserve Bank of India official Web site. The systematic market factor (MRKT) is measured as market return in excess of the risk-free rate of interest. Our approach for the construction of these risk factors like SMB, HML and WML (winners minus losers) closely follows the approach of Fama and French (1993) and Carhart (1997). For the construction of SMB, HML and WML, consistent with the related literature, we consider one-year holding period, and in September of each year, portfolios are rebalanced to calculate value weighted returns from the beginning of September of year y till August y+1.

Available literature on the performance of conditional APMs suggests that the selected conditioning information variables should capture investors' expectations about future market return or business cycle conditions. Consistent with the conditional asset pricing literature (Cochrane, 1996; Drobetz *et al.*, 2002; Iqbal *et al.*, 2010), the four conditioning information variables have been measured as follows. Following Dash and Mahakud (2013), TS is measured as the difference between 10-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 index portfolio for the year preceding *t* and divided by the value of the portfolio at *t*. IR is measured as the weighted average of call money rate reported by the Reserve Bank of India on monthly basis. To assess the relevance of global risk factors, we consider IRD measured as the difference between Mumbai Interbank Offered Rate (MIBOR) or the Indian money market benchmark rate and London Interbank Offered Rate (LIBOR) as fourth conditioning information variable. For IRD calculation, LIBOR and MIBOR data have been collected from official Web sites of Bank of England and NSE.

Table I reports the correlation matrix of systematic risk factors and the conditioning information variables. Observed negative correlation between TS and DY indicates the apparent opposite relationship of both the variables with the business cycle and expected returns (Fama, 1990). The positive correlation between TS and MRKT suggests that high (low) values of TS reflects trough (peak) of business cycle fluctuation and, thus, higher (lower) expected return (Fama and French, 1988). The positive correlation between DY and MRKT suggests that when stock prices are low relative to dividends (high DY), the expected returns are high (Fama, 1990). The positive correlation between the IR and IRD in Table I is because of the common IR component among the two variables. Observed negative (positive) correlation of IR and IRD with SMB (HML) is consistent with the argument of investor expectation hypothesis and superior size and value premium during expansive monetary periods (Jensen and Mercer, 2002). The relationships between WML and the conditioning information variables are consistent with the suggested systematic link between macroeconomic effects and premiums associated with such risk factors in the related literature (Chordia and Shivakumar, 2002).

4.1 Identification of firm characteristics or anomalies having cross-sectional regularity

For identifying firm characteristics or anomalies that are significantly associated with the cross-section of stock return variation in the Indian stock market, we use the similar analysis of Dash and Mahakud (2013). The only difference between the analysis of Dash and Mahakud (2013) and ours is the extension of sample period. As suggested by Subrahmanyam (2010), although the number of cross-sectional return predictors may be as large as 50, to make a comparative stand, we have tried to focus on those market anomalies which have been analyzed in earlier study in the context of Indian stock market. Such approach is also consistent with related literature in the context of other emerging and developed markets (Artmann *et al.*, 2012; Chen *et al.*, 2010; Haugen and Baker, 1996) and minimizes the data or sample selection biases (Kothari *et al.*, 1995; Lo and MacKinlay, 1990). Similar to the Dash and Mahakud (2013) study, we have considered the following return predictors: MC, BP, earnings-to-price ratio (E/P), cash flow-to-price ratio (C/P), dividend-to-price ratio (D/P), sales growth (SLG), accounting accruals (AC), 12 months stock return momentum (MOM), past three years long-term reversal (LR), research and development intensity (RDint), advertising intensity (AVint), stock liquidity (LIQ), book leverage (Bliv), market leverage (Mliv), return on asset (ROA), capital expenditure (CAP), asset growth (AG) and investment-to-assets ratio (INVT). Appendix provides a detail description on the measurement of aforementioned firm characteristics or market anomalies and the reference from which we derive their measurement motivation. If the selected firm characteristics or market anomalies are able to explain the cross-sectional variation in subsequent one-year returns, then, we must experience a statistically significant return spread in the hedge portfolio that has been constructed using the return difference of P10-P1 (large minus small). We calculate equal weighted portfolio returns of each decile portfolios for making the return spread comparison tests. This approach also helps to judge the return variation with respect to each anomaly without being influenced by firm market capitalization.

With the extension of sample period and repeating the same test, we do not find any significant difference in results (reported in Appendix) as compared to Dash and Mahakud's (2013) findings. The figures are qualitatively similar with statistical significance associated with MC, BP, MOM, LIQ and Mliv. With the extension of sample period, this further validates the weak anomaly effect in the Indian stock market. Similar to the observation made by Dash and Mahakud (2013), we propose that the weak anomaly effect may be partially because of more homogeneity of return predictors distribution with lower dispersion of firm-level risk (Chen *et al.*, 2010) or low price informativeness (Chen *et al.*, 2010; Morck *et al.*, 2000). Our finding toward strong MC effects in the Indian stock market is consistent with the findings of Mohanty (2002), Sehgal and Tripathy (2005), Moor and Sercu (2013) and Dash and Mahakud (2013). For the significant MOM effect in the Indian stock market, our finding is consistent with Sehgal and Jain (2011).

Motivated from the cross-sectional regularities observed for MC, BP, MOM, LIQ and Mliv, we will restrict ourselves to these five risk characteristics for examining the explanatory power of these market anomalies on the risk-adjusted returns of individual securities. Our measurement of the five market anomalies closely follows the approach of Dash and Mahakud (2013) and extends the sample period for further validation. In other words, if the firm characteristics or market anomalies are found to be significantly explaining the risk-adjusted returns derived from the alternative APMs, then it can be set for the conclusion that anomalies retain their unique effects irrespective of the use of alternative APMs. In other words, APMs fail to explain the anomalies, and the use of trading strategies based on such anomalies still retains their unique importance.

Consistent with Brennan *et al.* (1998), Avramov and Chordia (2006), Dash and Mahakud (2013) in our subsequent risk-adjusted return predictability tests, we measure the aforementioned five anomalies differently. For each security and for each moth, firm characteristics or market anomalies are calculated as follows: MC of the firm in month *t* is measured as the natural logarithm of the market value of the equity at the end of the second to last month. Monthly BP is the ratio of book value of equity at the financial year end in the calendar year *y* to the market price of equity at the end of the month *t*-1 in the calendar year *y*. LIQ is measured each month as the annual average of monthly turnover ratio, i.e. number of shares traded to the number of shares outstanding. The liquidity values have been considered from the end of second to last month. 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*. To account for the short-, medium- and long-term MOM effects, we consider SRM (the cumulative returns over the second through third months, before the month of measurement), MRM (the cumulative returns over the fourth through sixth months, before the month of measurement *t*) and LRM (is the cumulative returns over the seventh through twelfth months before the month of measurement). Consistent with Brennan *et al.* (1998), the lagged return variables were constructed to exclude the return during the immediate prior month to avoid any spurious association between the prior month return and the current month return caused by thin trading or bid-ask spread effects. As the variables are measured for individual firms, the descriptive statistics and the correlation matrix of these variables can be calculated as the time series averages of monthly cross-sectional mean and correlations. We explicitly do not go further to analyze any inference from these figures and, hence, not reported for the purpose of brevity. Moreover, as the calculated figures will be time series averages of monthly cross-sectional values, any statistical significance level cannot be associated with such figures. In terms of the direction of correlation, we have found negative correlation between BP with all the three momentum variables. Consistent with the findings of Asness (1997) and Asness *et al.* (2009), it indicates that measures of MOM and BP values are negatively correlated across stocks. Observed positive correlation between MC-MOM and LIQ-MOM suggests that stock momentum increases (decreases) with the increase (decrease) of firm market capitalization and liquidity. This indicates that in the context of Indian stock market, momentum strategy can be better implemented with the large and liquid stocks (Dash and Mahakud, 2013). Although available literature in the area of firm characteristics effects on the predictability of stock return behavior focuses on the portfolio-based approach (Artmann *et al.*, 2012; Chen *et al.*, 2010; Hart *et al.*, 2003 among others), the present study uses individual securities data. This approach helps us to control for under rejection bias and data-snooping bias (Lo and MacKinlay, 1990) observed with the portfolio-based approach.

5. Discussion of results

This section has been divided into four subsections. We discuss results for each APM that has been employed for deriving the risk-adjusted returns of individual securities. The first subsection presents results for the test of firm characteristics effects to explain the risk-adjusted returns derived using unconditional APMs. The second, third and fourth subsections focus on the explanatory power of firm characteristics for the risk-adjusted return derived by the conditional specifications of CAPM, three-factor model and Carhart four-factor model, respectively. In all the sections, we estimate panel data model specified in equation (4), using the risk-adjusted returns derived through alternative conditional and unconditional APM specifications as the dependent variable. For all the subsections, reported model specification test statistics such as likelihood ratio (LR) test, Lagrange multiplier (LM) test and Hausman test statistics suggest that the firm-specific and time-specific effects are present in the dataset, and the two-way fixed-effect model (fixed-effect firm and time model) is more suitable for the estimation of equation (4).

5.1 Alternative unconditional APMs

Table II shows estimation results of the equation (4) for four alternative unconditional APMs. The three different columns under each APMs indicate the estimation results with respect to the three different momentum characteristics (RET 2-3, RET 4-6, RET7-12). Reported results for unconditional CAPM (Columns 1, 2 and 3) fail to capture the importance of MC, Mliv and MOM effects. MOM characteristics of three different forms have been statistically significant in explaining the risk-adjusted return of individual stocks. Similar to the results of unconditional CAPM, the unconditional three-factor model (Columns 4, 5 and 6) also fails to give a complete explanation for MC, Mliv and MOM effects. The explanatory powers of these characteristics are still persistent, given the inclusion of size (SMB) and value (HML) factors in the three-factor model for deriving risk-adjusted returns of individual stocks in the first step. This result reveal that even in the presence of systematic risk factors in the unconditional specification of three-factor model, the role of market anomalies for the predicting stock returns behavior cannot be ruled out completely. Similar results with respect to the significant MC, Mliv and MOM effects are also evident for the risk-adjusted return derived by using Carhart four-factor model (Columns 7, 8 and 9). These results are intuitively more appealing with respect to the behavior of three momentum characteristics. As the Carhart four-factor model augments the three-factor model with the momentum factor (WML), from the theoretical stand of the multifactor models, the MOM characteristics are expected to be insignificant in the second step. In common, the reported results in Table II give an indication toward the special nature of MC, Mliv and MOM effects as the three found to be indifferent toward the inclusion of additional risk factors in alternative multifactor specifications.

Reported results in Table II for all the alternative APMs show a distinctive behavior for explaining the LIQ effect. All the APMs even in their unconditional specifications are able to explain the LIQ completely. This is different as compared to the related literature in the context of developed stock market. For instance, Avramov and Chordia (2006) using US stock market data observe strong LIQ effect irrespective of the use of alternative APMs. However, our result in Table IV shows consistency with the findings of Narayan and Zheng (2010) in the context of emerging stock market. Using unconditional multifactor models, Narayan and Zheng (2010) observe that LIQ effect losses its impact in the case of Chinese stock market. This difference in behavior of LIQ effect in the context of emerging stock markets may be attributable to the special order-driven market structure which is different from the quote-driven market structure of developed market structure of the developed markets. The special nature of order-driven market supports several unique characteristics, as it generates liquidity demand, supply schedules and price discovery that are consistent with equilibrium under perfect condition (Brockman and Chung, 2002). Perhaps because of such characteristics, the LIQ effect do not possess unique characteristics for explaining the risk-adjusted returns, as the risk factors in the APMs are able to subsume its importance completely.

5.2 Conditional capital APMs

Table III shows the estimation results of equation (4) for different conditional specifications of CAPM. Reported results in Table III (Columns 1, 2 and 3) suggest that conditional CAPM with TS as the conditioning information fails to rule out the importance of MC, Mliv and MOM characteristics. Results for DY as the conditioning information (Columns 4, 5 and 6) even fail to explain LIQ effect along with the earlier persistent MC, Mliv and MOM effects. In the case of IR conditioning information (Columns 7, 8 and 9) and IRD conditioning information (Columns 10, 11 and 12), the models still fail to rule out the persistent effect of MC, Mliv and MOM characteristics. Overall, the reported results of conditional CAPM never seem to be

Table II Fixed-effect firm and time model estimates for unconditional APMs

		CAPMs			*Fama and French three-factor model*			*Carhart four factor model*	
Coefficients	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
MC	−0.93* (−21.27)	−0.91* (−21.25)	−1.03* (−21.1)	−0.89* (−19.13)	−0.83* (−18.41)	−0.85* (−18.62)	−0.81* (−18.29)	−0.85* (−18.05)	−0.81* (−18.57)
BP	0.17 (0.29)	0.21 (0.39)	0.49 (0.69)	0.22 (0.86)	0.11 (0.23)	0.48 (0.09)	0.08 (0.14)	0.11 (0.18)	0.17 (0.31)
LIQ	−0.21 (−0.79)	−0.21 (−0.71)	−0.01 (−0.16)	−0.11 (−0.69)	−0.17 (0.73)	−0.11 (−0.68)	−0.29 (−0.67)	−0.05 (−0.79)	−0.19 (−0.73)
SRM	0.02* (5.61)	–	–	0.03* (5.17)	–	–	0.14* (6.11)	–	–
MRM	–	0.02* (5.37)	–	–	0.05* (3.47)	–	–	0.03* (5.86)	–
LRM	–	–	0.16* (11.6)	–	–	0.21*** (1.93)	–	–	0.17** (2.59)
Mliv	0.03** (2.25)	0.05** (2.26)	0.01** (1.89)	0.07* (7.51)	0.09* (8.01)	0.07* (7.89)	0.05* (7.86)	0.09* (8.37)	0.07* (8.31)
LR test									
[x^2 (780)]	831.27 (0.00)	825.89 (0.00)	811.65 (0.00)	829.63 (0.00)	809.55 (0.00)	819.28 (0.00)	831.63 (0.00)	806.00 (0.00)	825.47 (0.00)
LM test [x^2 (2)]	437.19 (0.00)	452.76 (0.00)	368.77 (0.00)	497.87 (0.00)	541.37 (0.00)	501.49 (0.00)	519.26 (0.00)	567.65 (0.00)	529.71 (0.00)
Hausman test									
[x^2 (5)]	831.11 (0.00)	1,301.67 (0.00)	652.19 (0.00)	1,103.01 (0.00)	1,206.53 (0.00)	1,704.84 (0.00)	2,580.55 (0.00)	2,861.51 (0.00)	1,383.73 (0.00)
R^2	0.0049	0.0057	0.0063	0.0045	0.0043	0.0043	0.0047	0.0049	0.0043
D-W statistic	2.22	2.29	2.31	2.35	2.33	2.37	2.32	2.38	2.39
F-test	117.22 (0.00)	126.67 (0.00)	129.03 (0.00)	91.37 (0.00)	89.57 (0.00)	93.79 (0.00)	101.07 (0.00)	94.21 (0.00)	93.57 (0.00)

Notes: The three different columns under each APMs indicate the estimation results with respect to the three different momentum characteristics such as SRM, MRM and LRM along with other firm characteristics; for each stock and for each month, SRM, MRM and LRM are the cumulative returns over the second through third, fourth through sixth and seventh through twelfth months before the month of analysis; MC is the natural logarithm of the market value of the equity at the end of the second to last month; BP is the ratio of book value of equity at the financial year end in the calendar year *y* to the market price of equity at the end of the month *t*-1 in the calendar year *y*; LIQ is the annual average of monthly turnover ratio, i.e. number of shares traded to the number of shares outstanding; the liquidity values have been considered from the end of second to last month; Mliv is 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*; sample period consists of monthly observations of 582 continuously traded firms from September 1995 to March 2012; LR test (Gourieroux *et al.*, 1982) carried out to identify the existence of individual firm-specific effects in the data set; 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; *; **; ***represent statistical significance at 1, 5 and 10%, respectively

Table III Fixed-effect firm and time model estimates for conditional CAPMs

		Term spread			*Dividend yield*			*Interest rate*			*Interest rate differential*	
Coefficients	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
MC	−1.47** (−3.15)	−1.48** (−3.22)	−1.48** (−3.61)	−1.67* (−9.48)	−1.66* (−9.39)	−1.68* (−9.27)	−0.82* (−7.41)	−0.85* (−7.37)	−0.88* (−7.43)	−1.07* (−9.72)	−0.99* (−9.51)	−1.08** (−2.09)
BP	0.03 (0.81)	0.02 (0.83)	0.03 (0.96)	0.04 (0.61)	0.02 (0.56)	0.02 (0.45)	0.02 (0.58)	0.02 (0.66)	0.04 (0.59)	0.02 (0.12)	0.03 (0.16)	0.02 (0.11)
SRM	0.02* (9.85)	–	–	0.02*** (1.89)	–	–	0.04* (12.08)	–	–	0.01* (6.88)	–	–
MRM	–	0.11* (5.09)	–	–	0.03** (2.56)	–	–	0.02* (6.64)	–	–	0.02** (2.89)	–
LRM	–	–	0.06* (5.59)	–	–	0.05* (3.62)	–	–	0.02* (8.69)	–	–	0.01* (6.90)
LIQ	−0.05 (−1.27)	−0.05 (−1.41)	−0.03 (−1.12)	−0.61* (−6.59)	−0.61* (−6.07)	−0.61* (−6.89)	−0.02 (−1.25)	−0.02 (−1.25)	−0.01 (−1.28)	−0.08 (−0.37)	−0.06 (−0.42)	−0.07 (−0.37)
Mliv	0.12* (9.08)	0.11* (9.88)	0.14* (4.21)	0.11* (9.39)	0.10* (9.11)	0.09* (8.91)	0.11* (8.17)	0.09* (8.17)	0.08* (8.61)	0.11* (9.53)	0.09* (9.53)	0.10* (9.53)
LR test												
[χ^2 (780)]	888.51 (0.00)	879.36 (0.00)	819.21 (0.00)	891.36 (0.00)	871.35 (0.00)	839.78 (0.00)	856.19 (0.00)	889.25 (0.00)	853.21 (0.00)	836.29 (0.00)	821.81 (0.00)	829.45 (0.00)
LM Test [χ^2 (2)]	11.93 (0.00)	12.51 (0.00)	14.69 (0.00)	195.31 (0.00)	184.27 (0.00)	166.49 (0.00)	50.22 (0.00)	48.29 (0.00)	55.78 (0.00)	37.15 (0.00)	31.29 (0.00)	35.11 (0.00)
Hausman Test												
[χ^2 (5)]	1,539.27 (0.00)	1,009.1 (0.00)	818.72 (0.00)	2,325.3 (0.00)	3,216.53 (0.00)	1,412.7 (0.00)	368.41 (0.00)	383.63 (0.00)	385.51 (0.00)	717.11 (0.00)	675.29 (0.00)	607.79 (0.00)
R^2	0.0115	0.0307	0.0131	0.0483	0.0129	0.0127	0.0044	0.0037	0.0038	0.0045	0.0041	0.0045
DW statistic	2.39	2.33	2.57	2.41	2.42	2.44	2.43	2.43	2.45	2.41	2.42	2.42
F-test	201.21 (0.00)	186.59 (0.00)	191.21 (0.00)	207.33 (0.00)	209.43 (0.00)	204.18 (0.00)	89.27 (0.00)	71.36 (0.00)	72.09 (0.00)	91.22 (0.00)	85.27 (0.00)	90.81 (0.00)

Notes: Same as Table II; *; **; ***represent statistical significance at 1, 5 and 10%, respectively encouraging for capturing the anomaly effect; moreover, in its conditional specification, the CAPM performs similar to its unconditional specification.

5.3 Conditional Fama and French three-factor model

Table IV shows the estimation results of equation (4) for different conditional specifications of Fama and French (1993) three-factor model. Reported results in Table V suggest that the performance of three-factor model in the alternative conditional specifications have never been satisfactory to capture MC and Mliv effects. The effects of MC and Mliv for the firm-specific risk-adjusted return explanation retain their significance irrespective of the use of different conditioning information variables. Significance of MC effect for explaining risk-adjusted returns of individual securities derived using conditional three-factor model is inconsistent with the findings of asset pricing literature in the context of emerging stock markets. For instance, Schrimf *et al.* (2007) and Iqbal *et al.* (2010) support the applicability of conditional three-factor model as the better benchmark APMs for describing the cross-sectional variation of expected stock returns in the context of emerging markets. Considering the argument of Schrimf *et al.* (2007) and Iqbal *et al.* (2010), it can be expected to have less number of significant anomaly effects for explaining the risk-adjusted returns. However, on the contrary to such propositions, our results suggest that anomalies like MC, Mliv and SRM retain their significance for explaining stock returns behavior. Persistence of MC effect is also inconsistent with the findings of Avramov and Chordia (2006), which suggest that conditional three-factor model specification with business cycle conditioning information helps to capture the cross-sectional regularity related to MC characteristic.

In the case of TS and IRD conditioning information variable, the conditional three-factor model is able to capture MRM and LRM effects. Across all the four different conditional specifications of three-factor model, the SRM effect is found to be persistent. To the extent of MRM and LRM complete explanation, our findings are consistent with the related literature that attributes the macroeconomic or business cycle conditions as the sources of momentum strategy pay-off (Chordia and Shivakumar, 2002). In a related strand, Avramov and Chordia (2006) argue that conditional APMs specification (i.e. making factor loadings time varying with respect to business cycle variables) is suitable to explain profitability of MOM strategies. The conditional three-factor model specifications with the use of DY and IR conditioning information variables, however, are not able to capture any of the MOM effects.

5.4 Conditional Carhart four-factor model

Table VI presents estimation results of equation (4) for different conditional specifications of Carhart (1997) four-factor model. Reported results in Table VII suggest that the alternative conditional Carhart four-factor model specifications fail to give a complete explanation evidence for MC, SRM2-3, MRM4-6, LRM7-12 and Mliv effects. The MC and Mliv effects are able to maintain their statistical significance as the determinants of cross-sectional return variation. The coefficients are qualitatively similar to the conditional three-factor model. For the TS and IRD conditional specifications, the relative importance of MRM4-6 and LRM7-12 effects loses their significance. However, SRM2-3 which indicates short-run momentum effect still retains its importance for the cross-sectional returns variation irrespective of the conditional specification of Carhart four-factor model.

Consistent with the findings of Avramov and Chordia (2006) for the US stock market and Dash and Mahakud (2013) for Indian stock market, our results in Table VI reveal that MRM and LRM momentum effects in the case of TS and IRD conditional specifications suggest that medium- and long-term momentum profits are attributable to the asset pricing misspecification that varies with the business cycle. In common, reported results in Tables IV and VI also give an insight that conditional three-factor model and Carhart four-factor model offer similar set of evidences irrespective of the presence of additional momentum factor in the Carhart four-factor model specification.

Table IV Fixed-effect firm and time model estimates for conditional three-factor model

Coefficients	*(1)*	*Term spread* *(2)*	*(3)*	*(4)*	*Dividend yield* *(5)*	*(6)*	*(7)*	*Interest rate* *(8)*	*(9)*	*(10)*	*Interest rate differential* *(11)*	*(12)*
MC	−1.45* (−9.87)	−1.42* (−9.32)	−1.43* (−9.53)	−1.02* (−9.31)	−1.01* (−8.75)	−1.01* (−8.86)	−0.84* (−5.41)	−0.81* (−5.01)	−0.82* (−5.60)	−0.96* (−9.79)	−0.97* (−9.35)	−0.98* (−9.41)
BP	0.02 (0.96)	0.03 (0.12)	0.02 (0.14)	0.06 (0.98)	0.09 (1.19)	0.07 (−1.25)	0.02 (0.28)	0.06 (0.28)	0.02 (1.27)	0.04 (0.28)	0.02 (0.39)	0.05 (0.32)
SRM	0.03* (10.57)	–	–	0.09* (3.51)	–	–	0.03* (12.94)	–	–	0.05* (7.07)	–	–
MRM	–	0.01 (0.86)	–	–	0.02* (4.02)	–	–	0.02* (6.61)	–	–	0.01 (0.99)	–
LRM	–	–	0.05 (0.61)	–	–	0.01* (5.26)	–	–	0.07* (9.34)	–	–	0.05* (3.66)
LIQ	−0.10 (−0.56)	−0.06 (−0.57)	−0.02 (−0.58)	−0.62* (−8.01)	−0.59* (−7.19)	−0.61* (−7.11)	−0.02 (−1.39)	−0.16 (−1.61)	−0.01 (−1.42)	−0.09 (−0.51)	−0.08 (−0.50)	−0.09 (−0.49)
Mliv	0.11* (11.41)	0.14* (12.01)	0.11* (11.78)	0.07* (7.42)	0.08* (8.37)	0.09* (8.13)	0.09* (7.56)	0.73* (7.51)	0.08* (7.49)	0.15* (13.59)	0.12* (13.58)	0.12* (13.41)
LR test [x^2 (780)]	828.31 (0.00)	821.16 (0.00)	825.39 (0.00)	804.41 (0.00)	809.02 (0.00)	821.31 (0.00)	834.58 (0.00)	827.53 (0.00)	831.38 (0.00)	871.49 (0.00)	838.26 (0.00)	835.21 (0.00)
LM test [x^2 (2)]	18.79 (0.00)	24.05 (0.00)	25.29 (0.00)	179.0.85 (0.00)	203.47 (0.00)	209.53 (0.00)	65.31 (0.00)	59.57 (0.00)	65.29 (0.00)	21.75 (0.00)	26.83 (0.00)	19.53 (0.00)
Hausman Test x^2 (5)	1963.7 (0.00)	1227.1 (0.00)	970.87 (0.00)	1314.7 (0.00)	2425.6 (0.00)	1296.1 (0.00)	301.7 (0.00)	320.6 (0.00)	325.8 (0.00)	1203.2 (0.00)	970.9 (0.00)	799.7 (0.00)
R^2	0.0099	0.0088	0.0088	0.0067	0.0064	0.0045	0.0038	0.0029	0.0032	0.0037	0.0047	0.0049
D-W statistic	2.61	2.62	2.63	2.47	2.43	2.47	2.43	2.47	2.47	2.43	2.48	2.45
F-test	211.38 (0.00)	181.27 (0.00)	189.85 (0.00)	107.41 (0.00)	105.21 (0.00)	109.47 (0.00)	81.25 (0.00)	59.93 (0.00)	64.81 (0.00)	101.27 (0.00)	95.67 (0.00)	94.91 (0.00)

Notes: Same as Table II; *; **; ***represent statistical significance at 1, 5 and 10%, respectively

Table V Fama–MacBeth regression estimates for three-factor and four-factor model

	Fama and French three-factor model			Carhart four-factor model		
		Term spread			Term spread	
Coefficients	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Intercept	0.61 (0.27) [0.43]	0.24 (0.34) [0.22]	0.73 (0.32) [0.17]	0.37 (0.82) [0.64]	0.39 (0.45) [0.17]	0.35 (0.17) [0.11]
MC	−4.83 (−2.17) [−1.94]	−3.27 (−5.70) [−2.01]	−5.20 (−2.58) [−1.84]	−3.55 (−2.01) [−1.82]	−4.10 (−2.62) [−2.08]	−4.61 (−3.29) [−1.93]
BP	1.55 (1.02) [0.83]	1.17 (0.63) [0.21]	0.57 (0.39) [0.16]	1.83 (1.49) [0.60]	1.40 (1.16) [0.43]	1.22 (1.37) [1.21]
LIQ	−0.22 (−0.11) [−0.03]	−1.24 (−0.83) [−0.27]	−1.52 (−1.20) [−0.87]	−2.71 (−2.47) [−1.73]	−1.66 (−0.22) [−0.16]	−1.63 (−0.38) [−0.20]
SRM	0.39 (0.12) [1.23]	–	–	1.28 (0.92) [1.21]	–	–
MRM	–	1.39 (1.11) [0.72]	–	–	1.46 (0.61) [0.22]	–
LRM	–	–	1.42 (1.83) [1.24]	–	–	0.83 (1.76) [1.33]
Mliv	5.13 (3.06) [2.78]	3.24 (2.09) [1.98]	5.29 (2.62) [2.02]	3.91 (2.06) [1.91]	3.52 (2.38) [1.82]	3.08 (2.41) [1.87]
R^2 (%)	3.29	2.86	3.42	3.73	2.62	2.85

Notes: This table presents the time series averages of individual stock cross-sectional ordinary least squares (OLS) regression coefficient estimates using the Fama–MacBeth approach; R^2 is the time series average of the monthly adjusted R^2; the OLS *t*-statistics are presented under the coefficient estimates, *t*-statistics in parenthesis use standard errors as per Shanken (1990)

Table VI Fixed-effect firm and time model estimates for conditional Carhart four-factor model

Coefficients	(1)	Term spread (2)	(3)	(4)	Dividend yield (5)	(6)	(7)	Interest rate (8)	(9)	(10)	Interest rate differential (11)	(12)
MC	−1.44* (−9.61)	−1.41* (−8.97)	−1.39* (−8.58)	−1.07* (−9.37)	−1.03* (−9.37)	−1.01* (−19.4)	−0.86* (−5.91)	−0.85* (−5.69)	−0.86* (−6.21)	−0.96* (−9.57)	−0.94* (−9.21)	−0.94* (−9.41)
BP	0.02 (0.98)	0.02 (0.15)	0.06 (0.17)	0.07 (1.14)	0.07 (1.16)	0.07 (1.37)	0.02 (0.47)	0.04 (0.56)	0.02 (0.48)	0.03 (0.25)	0.02 (0.37)	0.02 (0.29)
LIQ	−0.11 (−0.60)	−0.12 (−0.61)	−0.16 (−0.61)	−0.63* (−7.81)	−0.65* (−7.71)	−0.63* (−7.47)	−0.03 (−1.41)	−0.03 (−1.39)	−0.02 (−1.44)	−0.02 (−0.57)	−0.02 (−0.57)	−0.03 (−0.58)
SRM	0.03* (10.7)	–	–	0.09* (4.1)	–	–	0.04* (12.8)	–	–	0.03* (7.2)	–	–
MRM	–	0.01 (1.15)	–	–	0.08* (4.18)	–	–	0.02* (6.47)	–	–	0.02 (0.94)	–
LRM	–	–	0.05 (0.45)	–	–	0.02 (1.26)	–	–	0.03 (1.73)	–	–	0.04 (1.11)
Mliv	1.12* (11.1)	0.14* (11.9)	0.12* (12.6)	0.09* (7.6)	0.06* (7.8)	0.08* (8.6)	0.08* (7.3)	0.07* (7.7)	0.07* (7.9)	0.14* (12.9)	0.15* (12.7)	0.14* (11.9)
LR test [x^2 (780)]	809.21 (0.00)	862.01 (0.00)	810.26 (0.00)	814.24 (0.00)	822.11 (0.00)	819.36 (0.00)	829.34 (0.00)	827.15 (0.00)	821.19 (0.00)	828.53 (0.00)	821.37 (0.00)	819.27 (0.00)
LM test [x^2 (2)]	39.01 (0.00)	38.78 (0.00)	38.57 (0.00)	175.02 (0.00)	199.61 (0.00)	201.77 (0.00)	47.33 (0.00)	45.79 (0.00)	48.27 (0.00)	17.19 (0.00)	21.29 (0.00)	17.51 (0.00)
Hausman test [x^2 (5)]	2,797.1 (0.00)	1,369.0 (0.00)	1,025.2 (0.00)	2,791.7 (0.00)	2,021.3 (0.00)	1,119.5 (0.00)	325.1 (0.00)	339.7 (0.00)	343.2 (0.00)	1,085.5 (0.00)	902.1 (0.00)	755.7 (0.00)
R^2	0.0099	0.0080	0.0089	0.0062	0.0062	0.0063	0.0045	0.0028	0.0031	0.0048	0.0041	0.0044
D-W statistic	2.36	2.31	2.36	2.41	2.44	2.45	2.44	2.47	2.48	2.47	2.46	2.48
F-test	231.11 (0.00)	192.05 (0.00)	188.67 (0.00)	111.47 (0.00)	117.36 (0.00)	121.31 (0.00)	91.83 (0.00)	65.27 (0.00)	71.49 (0.00)	98.43 (0.00)	90.83 (0.00)	91.29 (0.00)

Notes: Same as Table II; *; **; ***represent statistical significance at 1, 5 and 10%, respectively

To briefly sum up, results across all the alternative APMs specifications suggest that, as compared to unconditional APMs, conditional models perform better to capture the asset pricing anomalies. APMs in their unconditional specification are able to explain only the LIQ and BP effects completely. Among the conditional APMs, conditional CAPM performs poorly to capture asset pricing anomaly effects as compared to the other conditional multifactor models like three-factor model and Carhart four-factor model. Among the conditional three-factor model and Carhart four-factor model, we observe that both the models scaled with the TS conditioning information variable perform better by explaining BP, LIQ, MRM and LRM anomaly effects. It is, however, interesting and appealing to note that none of the APMs either in their unconditional or conditional specifications are able to capture the MC, Mliv or SRM effects. The reported strong presence of short-term momentum effect, i.e. SRM in the context of Indian stock market, is qualitatively similar to the related literature in the context of emerging markets. Griffin *et al.* (2003) suggest that the differential profit associated with the momentum strategy shows weak evidence in the emerging markets as compared to the developed markets. For instance, as compared to Rouwenhorst's (1998) findings of significant momentum profit (on average 0.91 per cent per month) in 11 of the 12 European markets and Jegadeesh and Titman's (1993) average 0.95 per cent per month for the US market, Rouwenhorst (1999) found that only 6 of the 20 emerging markets exhibit momentum profits (average 0.39 per cent per month). Although our empirical approach is very different as compared to the aforementioned studies, the strong presence of short-term momentum, i.e. SRM2-3, and not the long-term momentum, i.e. LRM7-12, gives an indication that the lower momentum profit observed by Rouwenhorst (1999) using long-term momentum scenario with one-year holding period may be due to the special nature of emerging markets. The significant cross-sectional regularity observed with respect to size and momentum is also consistent with the findings of Rouwenhorst (1998), Hart *et al.* (2003) and Lischewski and Voronkova (2012), in other emerging international stock markets. However, inconsistent with Asness *et al.*'s (2009) proposition of "value and momentum everywhere" in the context of international stock markets, we find strong evidence of size and short run momentum effect. Over all, the results reveal that in emerging stock markets, the applicability of APMs and the anomaly effect behavior cannot be generalized completely with that of the developed markets because of the very different market structure.

6. Robustness tests

Among the aforementioned alternative conditional APM specifications, we observe that Fama and French three-factor model (Table IV) and Carhart four-factor model (Table VI) specification with TS conditioning information is able to explain more anomalies. To be specific, results reveal that BM, LQ, SRM and LRM anomaly effects are completely explained by the two conditional APM. However, it may be argued that our results may be because of the methodology that has been adopted. As our empirical approach is different, the results warrant robustness tests. In this section, we specify a robustness test for the two APMs using the Fama–MacBeth regression approach of Avramov and Chordia (2006). Our interest is to reexamine our data using the Fama–MacBeth regression approach to see whether our results show any deviation in terms of the observed anomaly effect.

Our robustness test results in Table V reveal that using alternative approach the anomaly effect is only persistent in MC and Mliv. In both, the three-factor model and Carhart four-factor model scaled with TS as conditioning variable is able to explain all other anomaly effect. The use of conditional Carhart four-factor model is able to explain the SRM2-3 effect, which was persistent in our earlier tests of Carhart four-factor model. In case of other anomaly effects, like BM, LIQ, MRM and LRM, results are qualitatively similar to fixed-effect firm and time model estimates.

7. Conclusions

This paper investigates whether the alternative unconditional and conditional APMs capture the role of market anomalies in the context of emerging stock market like India. Results reveal that considering three alternative APMs in their unconditional specifications, the BP and liquidity effects can be explained by the market risk factors completely. However, conditional factor models' do not outperform their unconditional counterparts always. When the risk factors of alternative APMs are allowed to vary over time employing business cycle conditioning information like TS, the importance of medium- and long-term momentum effect have been captured to a greater extent. Results are robust to the use of alternative approach. Our finding related to the presence of significant size effect is inconsistent with asset pricing literature that argues for the disappearing size effect in the developed stock markets because practitioners use it as an investment strategy and tried to exploit the anomaly (van Dijk, 2011). Consistent with recent findings by Moor and Sercu (2013) and Dash and Mahakud (2013) for strong size effect in the Indian stock market, our findings suggest that size effect retains its importance as a profitable investment strategy. For enhancing the performance of long-term investment portfolios, the observed pattern of small size effect warrants close-ended mutual fund investment strategy. We recommend a close-ended mutual fund strategy related to size effect because small size stocks are generally attributed with illiquidity and high transaction cost characteristics. Considering a short-term investment scenario, the investment managers can look forward to the large size stocks. We expect that large size stocks with high liquidity may be better suitable for the momentum strategy implementation because of the lower risk of illiquidity. However, the high transaction costs because of frequent portfolio rebalancing in a short horizon investment window warrants due attention under such momentum investment strategy.

The results also reveal that market leverage effect is still persistent in the Indian stock market. This warrants further research in this direction by using the approach of Chou *et al.* (2010) and Muradoglu and Sivaprasad (2013) for testing the applicability of leverage risk factor in an augmented three-factor or four-factor model. Recent findings by Avramov *et al.* (2013) also intuitive to test distress risk evidence in the context of Indian stock market and implications of financial distress for the profitability of anomaly-based trading strategies. The findings can be used for further research by incorporating some of the market anomalies which have been excluded from our sample. This will bring better understanding for the presence of market anomalies in the Indian stock market. One of the reasons of limited anomaly effect related to stock price synchronicity also gives an intuitive opportunity to test the relationship between stock price synchronicity and cross-section of stock returns behavior.

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Appendix

Table AI Detail description of firm characteristics or anomalies measurement and hedge portfolio returns

Symbol	*Firm characteristics or anomalies measurement and hedge portfolio return difference (HPRD)*
MC (Banz, 1981)	Natural logarithm of market capitalization (stock prices times outstanding shares) at the end of August of year *y*. *(HPRD* = −*2.02)*
BP (Stattman, 1980)	Ratio between book price for the fiscal year ending in calendar year *y* by the market value of equity at the end of August in year *y*. *(HPRD* = *3.21)*
E/P (Basu, 1977)	Ratio of net profit for the fiscal year end March to the market capitalization at the end of the August of year *y*. *(HPRD* = 1.53)
C/P(Lakonishok *et al.*, 1994)	Sum of earnings before extraordinary items and depreciation over the firm's market capitalization at the fiscal year-end March of year *y*. (*HPRD* = 1.59)
D/P (Fama and French, 1988)	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*. (*HPRD* = −0.47)
SG (Lakonishok *et al.*, 1994)	Ratio of net sales revenue for the March in the year *y* over the sales revenue from the March of the year *y*-1. (*HPRD* = −1.72)
AC (Sloan, 1996)	Change in noncash current assets less the change in current liabilities 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*. (*HPRD* = 0.84)
MOM (Jegadeesh and Titman, 1993)	Cumulative return of a stock in month *t*-12 through month *t*-2 preceding August of the 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. (*HPRD* = 3.06)
LR (De Bondt and Thaler, 1985)	LR of a stock in the month t is measured each month by sorting stocks on past returns from month *t* -36 through *t* -7. For the LR, the portfolio return has been constructed from September 1997 to March 2011, given the 36 month lag. (*HPRD* = *1.01*)
RDint (Chan *et al.*, 2001)	Ratio of research and development expenditure for the fiscal year ending in calendar year *y* to market capitalization at the end of August of year *y*. (*HPRD*=−0.42)
AVint (Chan *et al.*, 2001)	Ratio of advertising expenditure for the fiscal year ending in calendar year *y* over market capitalization at the end of August of calendar year *y*. (*HPRD* = 0.82)
LIQ (Amihud, 2002)	Annual average of monthly turnover ratio i.e. number of shares traded to the number of shares outstanding at the end of August of calendar year *y*. (*HPRD* = −0.73)
Bliv (Artmann *et al.*, 2012)	Total assets divided by book equity of the fiscal year ending in year *y*. (*HPRD* = 1.61)
Mliv (Artmann *et al.*, 2012)	Total assets in the fiscal year ending in year y divided by market value of equity at the end of August of the year *y*. (*HPRD* = 1.43)
ROA (Artmann *et al.*, 2012)	Net earnings divided by total assets for the fiscal year end March in the calendar year *y*. (*HPRD* =−*0.27*)
CAP (Chen *et al.*, 2010)	Capital expenditure for the fiscal year ending 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*. (*HPRD* = −*0.59*)
AG (Cooper *et al.*, 2008)	Percentage change in total assets from the fiscal year ending March in calendar year *y*-2 to the fiscal year ending in calendar year *y*-1. (*HPRD* = −*1.52*)
INVT (Titman *et al.*, 2004)	Annual change in gross fixed assets plus annual change in inventories in the fiscal year ending March in year y divided by book value of total assets of the fiscal year ending in year *y*-1. (*HPRD* = −1.51)

Notes: This table reports the detail description on the measurement of the firm characteristics and the hedge portfolio return variation of decile portfolios shorted on the firm characteristics; the measurement of firm characteristics closely follows the approach of Artmann *et al.* (2012), Chen *et al.* (2010) and Dash and Mahakud (2013); for the purpose of brevity, we only report the HPRDs; *HPRD* is the difference between tenth decile (i.e. largest) and first decile (i.e. smallest) of the portfolio; sample period except for long-term reversal (LR) is from September 1995 to March 2012; since NSE started its operation in 1994, sample period for LR is from September 1997 to March 2012; except for long-term reversal and momentum stocks are allocated to ten portfolios at the end of August of each year *y* (1995-2012); the portfolios formed on momentum (long-term reversal) are rearranged every month; monthly equal-weighted returns on the portfolios are calculated from September to the following August; to avoid the look ahead bias, five months gap has been provided to match the accounting data available at the end of financial year end March in calendar year *y* to the stock price data at the beginning of September in the calendar year *y*

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