



Review of Behavioral Finance

Does investor sentiment as conditioning information help to explain stock returns behaviour? A test of alternative asset pricing models

Saumya Ranjan Dash

Article information:

To cite this document:

Saumya Ranjan Dash , (2016), "Does investor sentiment as conditioning information help to explain stock returns behaviour? A test of alternative asset pricing models", Review of Behavioral Finance, Vol. 8 Iss 2 pp. -

Permanent link to this document:

<http://dx.doi.org/10.1108/RBF-03-2014-0022>

Downloaded on: 19 October 2016, At: 08:51 (PT)

References: this document contains references to 0 other documents.

To copy this document: permissions@emeraldinsight.com

The fulltext of this document has been downloaded 28 times since 2016*

Users who downloaded this article also downloaded:

(2016), "Asset price formation and behavioral biases", Review of Behavioural Finance, Vol. 8 Iss 2 pp. -

(2016), "Analysis of default behavior of borrowers under Islamic versus conventional banking", Review of Behavioural Finance, Vol. 8 Iss 2 pp. -

Access to this document was granted through an Emerald subscription provided by emerald-srm:333301 []

For Authors

If you would like to write for this, or any other Emerald publication, then please use our Emerald for Authors service information about how to choose which publication to write for and submission guidelines are available for all. Please visit www.emeraldinsight.com/authors for more information.

About Emerald www.emeraldinsight.com

Emerald is a global publisher linking research and practice to the benefit of society. The company manages a portfolio of more than 290 journals and over 2,350 books and book series volumes, as well as providing an extensive range of online products and additional customer resources and services.

Emerald is both COUNTER 4 and TRANSFER compliant. The organization is a partner of the Committee on Publication Ethics (COPE) and also works with Portico and the LOCKSS initiative for digital archive preservation.

*Related content and download information correct at time of download.

Does Investor Sentiment as Conditioning Information Help to Explain Stock Returns Behaviour? A Test of Alternative Asset Pricing Models

1. Introduction

Apart from the systematic risk factors, a possible impact of investor sentiment on stock returns has been a subject of considerable interest in the finance literature, and a question of long-standing concern to both economists and practitioners. The behavioral equity pricing literature defines Investor sentiment (hereafter, IS) as the systematic error or biases in investors' belief about future cash flows and investment risks that are inconsistent with the fundamental facts (Baker and Wurgler, 2006). The related literature argues that, since all investors fail to hold rational beliefs about the correct price of a stock due to inherent behavioral bias (Barberis et al., 1998; Barberies and Thaler, 2003), the demand shifts induced by irrational speculation in a state of limited arbitrage opportunity and short sale constraint (Shleifer and Vishny, 1997) generates systematic sentiment risk (Shefrin, 2005). The conventional, behavioral equity pricing literature supports a positive (negative) relationship between IS and contemporaneous (expected) stock returns, because of the overvaluation (undervaluation) in the stock prices (for e.g., Baker and Wurgler, 2006; Baker et al., 2011; Berger and Turtle, 2012; Brown and Cliff, 2004; Chuang et al., 2010; Chi et al., 2012; Dasgupta and Chattopadhyay, 2014; Finter et al., 2011). The present paper attempts to revisit the role of IS in explaining the cross-section of stock returns behaviour with a different perspective. This paper uses IS as a conditioning information variable for the cross-sectional return predictability tests of alternative asset pricing models (hereafter, APMs) in the Indian stock market. To be more precise, the present paper assesses whether incorporating IS as conditioning information in APMs return predictability tests helps to explain the cross-sectional variation of expected stock returns. Putting it differently, assuming sentiment risk to be pervasive and reflected in aggregate investors' expectations about the current state and future prospects of financial markets (Ho and Hung, 2009; Ho, 2012), does IS qualify to be considered as a conditioning information variable in the conditional specification of alternative APMs?

Recent empirical evidence from two related strands of literature motivates the argument mentioned above. Existing research on the asset pricing and cross-sectional tests of APMs across different markets is increasingly coming to the consensus that conditional APMs explain the stock returns behavior significantly in comparison to the unconditional specifications (see Drobtez et al., 2002; Iqbal et al., 2010; Jagannathan and Wang, 1996; Schrimpf et al., 2007). Such results are apparently found to be consistent across different markets and time periods (Goyal, 2012). For instance, in the context of the Indian stock market, Das (2015) find supportive evidence for the suitability of conditional versions of APMs and hence, investors use the prior belief of conditioning

macroeconomic variables to determine equity returns. In recent years, using IS as conditioning information, Ho and Hung (2009) and Ho (2012) argue that, since IS variable reflects investors' expectations about the current state and future prospects of financial markets or business-cycle conditions, it is, therefore, intuitive to use IS as conditioning information in the conditional specification of APMs. Motivated by the success of the conditional asset pricing literature, Ho and Hung (2009), Xu (2010) and Ho (2012) provide intuitive arguments for the use of IS as a conditioning information variable for evaluating the performance of alternative APMs. For instance, Xu (2010) finds that sentiment conditionally affects the loadings of risk factors in the conventional Fama and French (1993) three-factor model. The present paper builds on the empirical success of the conditional asset pricing literature and the argument of Ho and Hung (2009), and Ho (2012) to use IS as a conditioning information variable.

This paper contributes to an emerging literature in the following areas. First, using IS as the conditioning information variable, this study extends the available literature in the context of both developed and emerging stock markets for the cross-sectional tests of conditional APMs. Perhaps, the study most closely related to the present paper is that of Ho and Hung (2009), who argue that incorporating IS as conditioning information in pricing models helps capture the impact of market anomaly effects on the cross-section of risk-adjusted stock returns. Motivated by similar arguments, this paper attempts to examine whether conditional asset-pricing models that incorporate IS as conditioning information explain cross-sectional variation in expected stock returns. Existing literature on the validation of conditional APMs and sentiment influenced stock return behaviour is prominently focussed on the developed markets and limited attention has been paid to the emerging stock markets. In this regard an emerging stock market like India, which has witnessed increasing importance for international portfolio diversification can be considered as an ideal ground for providing out-of-sample evidence on the cross-sectional tests of APMs with specific focus on IS.

Second, the investment management decision application of IS as conditioning information variable may have practical feasibility. The sentiment conditioned APMs may be helpful for the fundamental value determination of certain category of hard to value and difficult to arbitrage (Baker and Wurgler, 2006) stocks when market sentiment is high. Such argument is motivated by the fact that due to the market-wide variations in IS, overpricing can occur for many stocks during periods of high sentiment and mispricing is more likely during boom periods in the stock market (Stambaugh et al., 2012). A similar line of concern can also be observed from the expressions of finance professionals. Investment managers often describe the uninformed demand and supply shocks in the market as investor herding, market rally, market sentiment, irrational exuberance, emotional traps, and market mood in the popular financial press. Such connotations are mere reflections that, due to the market-wide variations in IS the overvaluation of stock prices at certain

instances is hard to find any justification in the fundamental facts. For example, in mid-November 2013, commenting on the unprecedented optimism about the Indian stock market an investment analyst observed that “the rise in stock market without fundamental support puts a big question mark on the current rally. When Sensex touched 21000 first time before 2008 global crisis, our GDP growth was around 8%. Today it is 3% down at 5% and still we are at the higher level on both Sensex and Nifty as compared to 2008. How one should view these developments?”¹ During the last two decades, the Indian stock market has witnessed several examples of speculative boom and bust cycles. At a fundamental level, the return predictability of such overvalued stocks during a high market sentiment or boom period is an important factual issue, not only because of the apparent negative wealth effect on individual investors’ portfolio but also because of the aggregate market instability risk.

In principle, the stock market as a leading indicator of economic activity reflects the investors’ expectation about forecast economic trends. In recent years, by allowing the decomposition of stock price movements, researchers in the developed economies observed the weakening link between stock returns and real economic activity during the stock market boom in the 1990s (Laopodis, 2011). Given the decade-long economic liberalization and financial sector reforms in the emerging markets, the focus of policy priorities has been gradually shifted from the development of financial markets to financial market stability. To put it differently, the focus has been shifted from achieving a higher market capitalization to GDP ratio as a measure of the stock market development to questioning, whether the high value of the ratio is because of the excessive overvaluation of the numerator or because of the inconsistency of the denominator value to support the numerator. Apart from the negative wealth effect on investor portfolios the sentiment driven mispricing can also generate aggregate resource misallocation in the economy. Daniel et al. (2002), for example, suggest that systematic mispricing in the market because of the investors’ psychological biases causes substantial resource misallocation in the economy due to the erroneous beliefs about discount rates and its subsequent effect on the approximation of the cost of capital. A reasonable response to these concerns is to test the return predictability of well-accepted APMs using IS information. If, IS reflects investors’ expectations about the current state and future prospects of the financial market (Ho and Hung, 2009) and during high sentiment periods a firm’s stock price can reflect the views of investors who are too optimistic (Stambaugh et al., 2012), then, it is important to test the return predictability of APMs using IS as a conditioning information variable.

Third, although the sentiment index construction approach detailed in this paper follows the related literature, it introduces a new implicit proxy to measure IS. The new implicit sentiment

proxy is measured as the difference between the average price-to-earnings ratio (PE) of high liquidity and low liquidity stocks. As a growth opportunity proxy (Bekaert et al., 2007) the PE ratio shows investor's confidence about the firm's future performance and the willingness to pay for each rupee of firm's earnings. Given the typical price component in both the measures, such an underlying implication of the PE ratio information can also be inferred from the liquidity position of a stock. Highly liquid stocks experience high price increases (low return) because of the overvaluation by investors (Baker and Stein, 2004). Therefore, the associated high PE multiplier for such shares indicates the relative demand for such stocks. The resulting high (low) value of the difference between the average PE ratio of high liquid and low liquid stocks suggests positive (negative) sentiment in the market. Measured in a similar spirit to the dividend premium proxy of Baker and Wurgler (2006), this new implicit sentiment proxy may be useful in some of the markets where dividends are uncommon and thus, have lower signalling importance within local investors' investment information (Baker et al., 2011).

The empirical approach focusses on the scaled factor model approach of Cochrane (1996, 2001) to estimate the conditional specifications of alternative APMs. The available literature on conditional APMs suggests that the selected conditioning information variables should capture investors' expectations about future market returns or business cycle conditions (Jagannathan and Wang, 2002). However, validation of a conditional asset pricing model in a particular market can be subjective, because, the choice of instrumental variables for conditioning information is arbitrary and there can be many conditional models according to the combination of instrumental variables (Kim et al., 2012). Since, the comparison of conditioning information proxies is beyond the scope of this paper, the empirical approach focuses on a single IS conditioning information variable. The sentiment index construction method follows Baker and Wurgler (2006). For the cross-sectional tests of APMs, the Fama and Macbeth (1973) approach for linear beta representation and Generalized Method of Moments (Hansen, 1982; Shanken and Zhou, 2007) estimation technique for the stochastic discount factor specification has been used. Cross-sectional test results show that IS as a conditioning information variable contains significant information for making the discount factors time varying. Model comparison test statistics suggests that the five-factor model that augments Carhart (1997) four-factor model with a liquidity factor performs better.

The rest of the paper is organized as follows. Section 2 discusses the methodology. Section 3 presents the data and variables. Section 4 reports the cross-sectional test results and investigates the robustness of outcomes. Section 5 concludes the paper.

2. Model Specification and Methodology

This section attempts to develop a formal approach to test the time-variant relations between the cross-section of expected stock returns, systematic risks and IS by incorporating IS as

conditioning information. The empirical approach focuses on the dynamic or conditional specifications of alternative APMs. Assuming a zero arbitrage condition, the positive stochastic discount factor (SDF) or pricing kernel M_{t+1} that prices all payoffs for all test assets i ($i = 1 \dots N$) in the economy, the Euler equation of necessary condition can be expressed as:

$$E_t(M_{t+1}R_{it+1}) = E(M_{t+1}R_{it+1} | I_t) = 1 \dots \dots \dots (1)$$

Where, R_i denotes a gross raw return of asset i at time $t+1$ and I_t is the available information set at time t . By considering excess return (r_{t+1}) of a risky asset from time t to $t+1$ and following the law of iterated expectations equation specification (1) can be represented as:

$$E_t(M_{t+1}r_{it+1}) = 0, \quad \forall i, t > 0, \dots \dots \dots (2)$$

Consistent with the general linear factor model, a model in which the discount factor is linear in factors f can be specified as:

$$\tilde{M}_{t+1} = \alpha_t + \beta_t' f_{t+1} \dots \dots \dots (3)$$

Where \tilde{M}_{t+1} is an approximation of the true SDF (M_{t+1}) such that, $\forall \tilde{M}_{t+1} \in M_{t+1} \cdot f_{t+1}$ is a L -dimensional vector of factors. Equation (3) indicates a conditional linear factor model since the parameters α_t and β_t' are time varying. Several empirical studies on the time series predictability of excess stock return over business cycle horizons suggest that these risk premia are time-varying (Jagannathan and Wang, 1996, 2002). However, following the approach of Jagannathan and Wang (1996) taking the conditional expectation of the equation (1) may encounter the problem of equating the conditional mean-variance efficiency with the unconditional mean-variance efficiency i.e., $[E(M_{t+1}R_{it+1} | I_t) = 1] \neq [E_t(M_{t+1}R_{it+1}) = 1]$. To overcome this issue, following the scaled factor model approach of Cochrane (1996, 2001) the parameters of the SDF α_t and β_t' depend linearly on the time t information set Z_t ($\forall Z_t \in I_t$) and can be specified as:

$$\alpha_t = \alpha' z_t, \beta_t = \beta' z_t \dots \dots \dots (4)$$

In the case when Z_t is a scalar, the SDF of the scaled factor model is given by,

$$\tilde{M}_{t+1} = (\alpha_0 + \beta_1 Z_t) + (\beta_2 + \beta_3 Z_t)' f_{t+1} = \alpha_0 + \beta_1 Z_t + \beta_2' f_{t+1} + \beta_3' (f_{t+1} Z_t) \dots \dots \dots (5)$$

In this approach apart from the fundamental factors f_{t+1} , the scaled model also contains the lagged conditioning variables as well as the interaction term between the fundamental factors and the lagged conditioning variable i.e., Z_t . Hence the scaled factor model in equation (4) is effectively an unconditional multifactor model, where factors f'_{t+1} are given by $f'_{t+1} = [Z_t, f_{t+1}, f'_{t+1} Z_t]'$ and

the coefficients are now constant. Incorporating investor sentiment (IS) as conditioning information ($IS_t \in I_t$) specification (5) can be rewritten as:

$$\tilde{M}_{t+1} = (\alpha_0 + \beta_1 IS_t) + (\beta_2 + \beta_3 IS_t)' f_{t+1} = \alpha_0 + \beta_1 IS_t + \beta_2' f_{t+1} + \beta_3' (f_{t+1} IS_t) \dots \dots \dots (6)$$

Extending the equation (6) for the different linear factor models that are intended to be tested can be specified as follows: Single market factor based CAPM,

$$\tilde{M}_{t+1} = \alpha_0 + \beta IS_t + \beta_{MRKT_{t+1}} MRKT_{t+1} + \beta_{MRKT_{t+1}}^{IS} (IS_t MRKT_{t+1}) \dots \dots \dots (7)$$

Fama and French (1993) three-factor model (TFM),

$$\tilde{M}_{t+1} = \alpha_0 + \beta IS_t + \beta_{MRKT_{t+1}} MRKT_{t+1} + \beta_{SMB_{t+1}} SMB_{t+1} + \beta_{HML_{t+1}} HML_{t+1} + \beta_{MRKT_{t+1}}^{IS} (IS_t MRKT_{t+1}) + \beta_{SMB_{t+1}}^{IS} (IS_t SMB_{t+1}) + \beta_{HML_{t+1}}^{IS} (IS_t HML_{t+1}) \dots \dots \dots (8)$$

Carhart (1997) four-factor model (CFFM),

$$\tilde{M}_{t+1} = \alpha_0 + \beta IS_t + \beta_{MRKT_{t+1}} MRKT_{t+1} + \beta_{SMB_{t+1}} SMB_{t+1} + \beta_{HML_{t+1}} HML_{t+1} + \beta_{WML_{t+1}} WML_{t+1} + \beta_{MRKT_{t+1}}^{IS} (IS_t MRKT_{t+1}) + \beta_{SMB_{t+1}}^{IS} (IS_t SMB_{t+1}) + \beta_{HML_{t+1}}^{IS} (IS_t HML_{t+1}) + \beta_{WML_{t+1}}^{IS} (IS_t WML_{t+1}) \dots \dots \dots (9)$$

Five-factor Model (FFM),

$$\tilde{M}_{t+1} = \alpha_0 + \beta IS_t + \beta_{MRKT_{t+1}} MRKT_{t+1} + \beta_{SMB_{t+1}} SMB_{t+1} + \beta_{HML_{t+1}} HML_{t+1} + \beta_{WML_{t+1}} WML_{t+1} + \beta_{LMHL_{t+1}} LMHL_{t+1} + \beta_{MRKT_{t+1}}^{IS} (IS_t MRKT_{t+1}) + \beta_{SMB_{t+1}}^{IS} (IS_t SMB_{t+1}) + \beta_{HML_{t+1}}^{IS} (IS_t HML_{t+1}) + \beta_{WML_{t+1}}^{IS} (IS_t WML_{t+1}) + \beta_{LMHL_{t+1}}^{IS} (IS_t LMHL_{t+1}) \dots \dots \dots (10)$$

Where, $\beta_{MRKT_{t+1}}, \beta_{SMB_{t+1}}, \beta_{HML_{t+1}}, \beta_{WML_{t+1}}, \beta_{LMHL_{t+1}}$ represents the factor loading on the systematic risk factors, namely MRKT (market return in excess of the risk-free rate), SMB (small minus big), HML (high minus low), WML (winner minus lower) and LMHL (low minus high liquidity). $\beta_{MRKT_{t+1}}^{IS}, \beta_{SMB_{t+1}}^{IS}, \beta_{HML_{t+1}}^{IS}, \beta_{WML_{t+1}}^{IS}, \beta_{LMHL_{t+1}}^{IS}$ represents the factor loading on the systematic risk factors scaled with the IS conditioning information variable. It is also perceptible to analyze if a particular factor that considered as a determinant of the pricing kernel carries a significant risk premium, referred as λ_i . In other words, λ_i indicates the factor risk price.

Combining equation (1) and (2) the conditional expected return beta representation can be stated as:

$$E_t(R'_{t+1}) = \lambda_0 + \lambda_i' \beta_i \dots \dots \dots (11)$$

Where, $\beta_i = Cov(f_{t+1}, f'_{t+1})^{-1} Cov(f_{t+1}, R'_{t+1})$ are the conditional betas of test asset i , the elements of $\lambda_i = -\lambda_0 Cov_t(f_{t+1}, f'_{t+1}) \beta_i'$ are known as the conditional factor risk premia and $\lambda_0 = 1 / E_t(\tilde{M}_{t+1})$ is the conditional zero-beta rate. For instance, following the specification (12) the risk premium for the pricing kernel of single market factor based CAPM, can be specified as:

$$E_t(R'_{t+1}) = \lambda_0 + \lambda_{MRKT_{t+1}} MRKT_{t+1} + \lambda_{MRKT_{t+1}}^{IS} (IS_t MRKT_{t+1}) \dots \dots \dots (12)$$

The other three alternative conditional APMs specified in equations (8), (9) and (10) follows a similar specification of the equation (12). In the asset pricing literature the two methods that have received wide attention for addressing the aforementioned fundamental questions can be categorized as; the stochastic discount factor (SDF) method and the classical beta representation method. The empirical link and relative merits of the discount factor approach and the beta representation approach have been discussed extensively by many authors (Cochrane, 2001; Jagannathan and Wang, 2002). However, the specification test based on the SDF method is as powerful as the one based on the linear beta approach (Jagannathan and Wang, 2002). In this regard, the present paper uses the Fama and MacBeth (1973) two-step estimation approach for linear beta specification and the generalized method of moments (GMM) (Hansen, 1982) estimation approach for SDF specification. For model specification tests, while estimating SDF parameters in equation (7), (8), (9) and (10) JT-statistics (Hansen, 1982) have been used for the over-identification of restrictions, and the Wald test to check whether the coefficients corresponding to the particular risk factors are cross-sectionally equal to zero. The Hansen and Jagannathan (1997) distance (*HJ-Dist*) measure has been used to compare and evaluate alternative APMs. The Sup-*LM* test formulated by Andrews (1993) has been used to test the structural stability of the SDF parameters.

3. Data and Variables

The sample period spans over 98 monthly observations from February 2003 till March 2011 and focuses primarily on the National Stock Exchange (NSE) listed nonfinancial companies. Selection of the sample period is constrained by the availability of data for constructing the IS variable. The S&P CNX Nifty value-weighted index return is used as a proxy for the market return. 91 days T-bill yields collected from the Reserve Bank of India are used as the risk-free rate proxy. The Centre for Monitoring Indian Economy (CMIE) PROWESS database has been used to obtain the required data on monthly stock returns and other firm-specific information. Required data for the market related implicit sentiment proxies have been obtained from the official websites of the NSE, Association of Mutual Funds in India, Securities and Exchange Board of India, Bombay Stock Exchange and World Federation of Exchanges (WFE). Accounting data for the financial year ending March of year y have been compared with the stock returns from September of year y to August of year $y+1$. This five months lag approach to match financial statement information with the stock return information, helps for the disclosure and availability of accounting information to market participants. All the test asset portfolios with the one-year holding period are formed and rebalanced at the beginning of September of year y .

3.1 Construction of Risk Factors and Test Asset Portfolios

Five systematic risk factors, namely: market factor (MRKT), size factor (SMB), value factor (HML), momentum factor (WML), and liquidity factor (LMHL) are constructed following Fama and French

(1993), Carhart (1997), Knee and Peterson (2007). For the construction of systematic risk factors, firm size (SZ) is measured as the natural logarithm of market capitalization (stock prices times number of outstanding shares) at the end of August of year y (Fama and French, 1993). Book-to-market equity (BM) is the ratio between book equity for the fiscal year ending in calendar year y to the market value of equity at the end of August in the year y (Fama and French, 1993). Momentum (MM) is the cumulative return of a stock in month $t-12$ through month $t-1$ preceding August of year y . The annual average of the monthly turnover ratio (the value of shares traded to the value of shares outstanding at the end of August in the year y) considered for the Liquidity (LQ) proxy. In unreported results, except for the excess market return all the other risk factors show positive mean returns.

Table 1 Description of the 36 Test Asset Portfolios

36 Test Asset Portfolios			Assigned Portfolio Numbers of the Test Asset Portfolios		
Size Sorts	Liquidity Sorts	Book-to-Market Sorts	Momentum		
			Winner (W)	Neutral (N)	Loser (L)
Small SZ	Low LQ	Low BM	P-1 {24}	P-2 {22}	P-3 {19}
		High BM	P-4 {24}	P-5 {21}	P-6 {19}
	High LQ	Low BM	P-7 {22}	P-8 {20}	P-9 {17}
		High BM	P-10 {22}	P-11 {19}	P-12 {18}
Medium SZ	Low LQ	Low BM	P-13 {20}	P-14 {18}	P-15 {20}
		High BM	P-16 {18}	P-17 {18}	P-18 {21}
	High LQ	Low BM	P-19 {21}	P-20 {18}	P-21 {19}
		High BM	P-22 {20}	P-23 {18}	P-24 {18}
Large SZ	Low LQ	Low BM	P-25 {18}	P-26 {19}	P-27 {17}
		High BM	P-28 {16}	P-29 {19}	P-30 {15}
	High LQ	Low BM	P-31 {18}	P-32 {14}	P-33 {17}
		High BM	P-34 {18}	P-35 {18}	P-36 {19}

Notes: Sample period consists of 98 monthly observations from February 2003 till March 2011. The 36 SZ-LQ-BM-MM test asset portfolios are formed using three SZ groups, two LQ groups, two BM groups, and three MM groups. Figures in the curly bracket represent number of stocks in each portfolio.

The measures mentioned above for four firm characteristics have been used to construct 36 SZ-LQ-BM-MM test assets portfolios by using three SZ groups, two LQ groups, two BM groups and three MM groups (3x2x2x3). For the purpose of brevity, the 36 portfolios are reported with assigned numbers of P-1...P-36. The restriction has been imposed on the four firm characteristics (SZ, LQ, BM, MM) because these four characteristics are found to be persistent in explaining a cross section of the stock return variation in both developed and emerging equity markets (Lam and Tam, 2011; Lischewski and Voronkova, 2012). For the three SZ groups, the market capitalization break points of National Stock Exchange of India have been used. Table 1 reports the average annual number of stocks in each test asset portfolio. Value weighted returns of 36 portfolios for the sample period becomes the test asset portfolio returns.

3.2 Measure of Investor Sentiment (IS) Variable

The construction of the investor sentiment (IS) variable closely follows the index

construction approach of Baker and Wurgler (2006). The present paper focuses on the common variation in 12 market related implicit sentiment proxies (MRISPs) that have been identified in the related literature. Two market liquidity related MRISPs; turnover volatility ratio (TVR) motivated from Jun et al. (2003), share turnover velocity (STV) collected from the WFE. Following Brown and Cliff (2004) five selected MRISPs are advance decline ratio (ADR), change in margin borrowing (CMB), the put-call ratio (PCR), fund flow (FF) and cash to total assets (CTA). Following Baker and Wurgler (2006) three selected measures are the number of IPOs (NIPO), equity issue in the total issue (EITI) and dividend premium (Div.P). To measure the aggregate trading activities of investors that follow pseudo-signals such as price and volume patterns the paper employs buy-sell imbalance ratio (BSIR) (Kumar and Lee, 2006). The price earnings high-low difference (PEhld) is the proposed new measure. Table 2 presents the description of all the MRISPs. The relationship between the MRISPs, and IS variable can be represented as:

$$IS = TVR + STV + ADR + CMB - PCR + FF - CTA + NIPO + EITI - Div. P + BSIR + PEhld \dots\dots\dots(13)$$

Following Baker and Wurgler (2006) sentiment proxies are orthogonal to six macro-economic fundamental factors such as; industrial production growth rate, term spread, exchange rate, the rate of inflation, percent change in net foreign institutional investors (FII) inflow and excess market returns. In contrast to prior literature, percent change in net FII inflow as an additional fundamental factor has been used, because of the observed sensitivity of the Indian stock market to the behaviour of FII regarding their market participation (Chandra, 2012). The fitted values of the regression capture the rational component of the sentiment proxies and the residuals capture the irrational part of the sentiment. This approach helps to consider the irrational or noise component of MRISPs. The modified proxies are considered as orthogonal sentiment proxies (MRISPs[⊥]). The lead lag relationship between the orthogonal MRISPs and the IS variable is documented using the dual index construction approach of Baker and Wurgler (2006). The principal component analysis helps to filter out idiosyncratic noise in the orthogonal sentiment measures and captures their common component. The first principal component having 42% of the sample variance gives the following measure of our sentiment index.

$$IS_t = 0.328(TVR_{t-1}^{\perp}) + 0.324(STV_{t-1}^{\perp}) + 0.194(ADR_{t-1}^{\perp}) + 0.173(CMB_{t-1}^{\perp}) \\ + 0.060(BSIR_t^{\perp}) - 0.164(PCR_t^{\perp}) + 0.209(NIPO_t^{\perp}) + 0.213(EITI_t^{\perp}) \dots\dots\dots(14) \\ - 0.053(Div.P_t^{\perp}) + 0.025(FF_t^{\perp}) - 0.308(CTA_t^{\perp}) + 0.227(PEhld_t^{\perp})$$

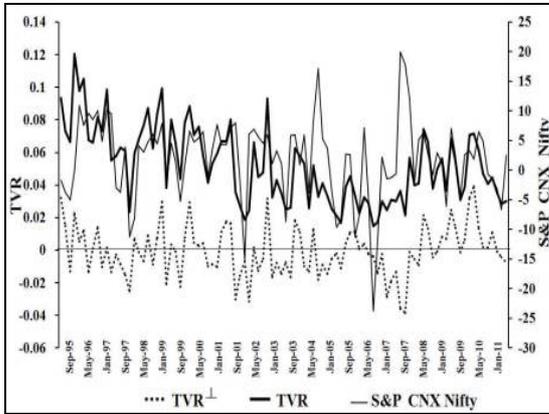
Figure 1 shows the comovement of the raw MRISPs and orthogonal MRISPs ([⊥]) along with the market index (S&P CNX Nifty). Figure 1 displays the essence of our selected MRISPs for clearly depicting the market movement for the whole sample period. Panel (G) of Figure 1 reveals a smooth time path for the CTA measure as compared to other MRISPs, which may be because of the presence of some other source of investment in the total asset figure of mutual funds apart from the cash component.

Table 2 Description of Market Related Implicit Sentiment Proxies

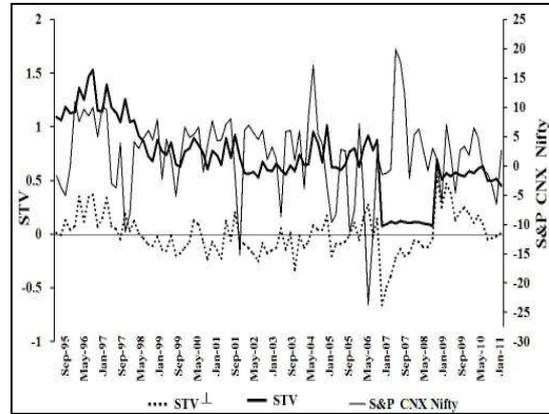
No.	Proxy	Measure	Implication
1	TVR	Market turnover ratio (ratio of the total value of all market transactions to total stock market value) divided by the standard deviation of stock market return.	The high value of TVR is considered to be a measure of overvaluation in the market.
2	STV	The ratio of electronic order book turnover of domestic shares and their market capitalization. It helps to mitigate the TVR measure biases attributable to the concentration trading in fewer stocks and low available free float because of the high promoter holding in Indian stock market.	As an indicator of the breadth and depth of a market, high STV indicates better liquidity or bullish sentiment.
3	ADR	The ratio of the number of advancing and declining stock prices. It helps to measure breadth of market and captures the relative strength of the market regarding aggregate buying and selling.	Rising (declining) values of ADR show the upward (downward) trend in the market.
4	CMB	Change of margin borrowing value on the last trading day of a specific month.	Represents investors' willingness to use borrowed money for stock investment. High value represents a bullish sentiment.
5	PCR	Trading volumes of put options to call options.	Lower (higher) ratio suggests bullish (bearish) sentiment.
6	FF	Fund flows into equity funds = Total mutual fund purchased in a month – (inflows to the money market mutual funds + inflow to the close ended funds)	Indicates flow of funds for equity mutual funds, positively relates to the aggregate market sentiment.
7	CTA	Month end cash balance = Total assets under management – Total equity and debt investment	Considered as a sentiment indicator for the optimism (lower CTA) or pessimism (higher CTA) about the market.
8	NIPO	Number of initial public offerings (IPOs) in a particular month.	Shows the underlying demand for IPOs and sensitive towards market condition. A higher value indicates a bullish sentiment.
9	EITI	The ratio of aggregate equity issuance to total debt and equity issue	Higher value is considered as a bullish market sentiment.
10	Div.P	Difference of the average market-to-book ratios of dividend payer and nonpayer stocks	Proxy for the relative demand for this correlated bundle of characteristics and thus, negatively related to the market sentiment
11	BSIR	The ratio of total volume of buy minus total volume of sell to the total volume of buy plus total volume of sell. It helps to measure the aggregate trading activities of investors follow pseudo-signals such as price and volume patterns.	At an aggregate level when investors are net buyers i.e., BSIR > 0 (sellers i.e., BSIR < 0), indicates a positive (negative) change in the sentiment.
12	PE _{high}	Difference between the average price-to-earnings ratio (PE) of high liquid and low liquid stocks.	High (low) value suggests positive (negative) sentiment in the market.

Figure 1 Comovements of Sentiment Proxies with Market Index S&P CNX Nifty

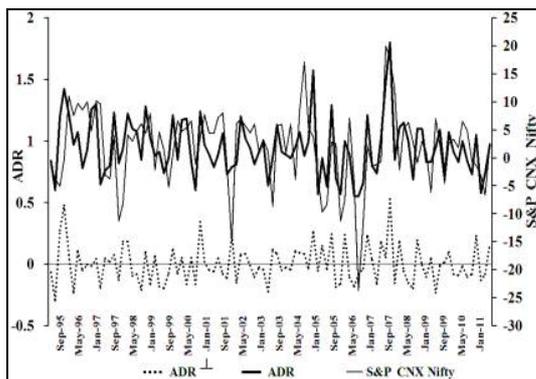
Panel (A) Turnover Volatility Ratio (TVR)



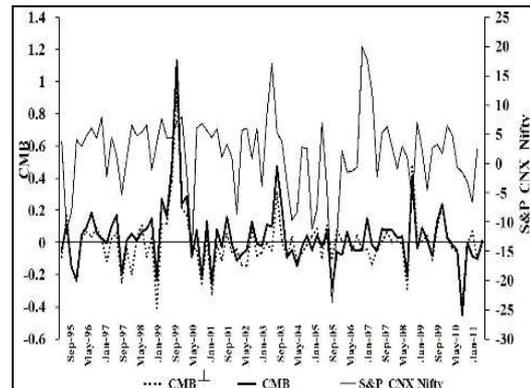
Panel (B) Share Turnover Velocity (STV)



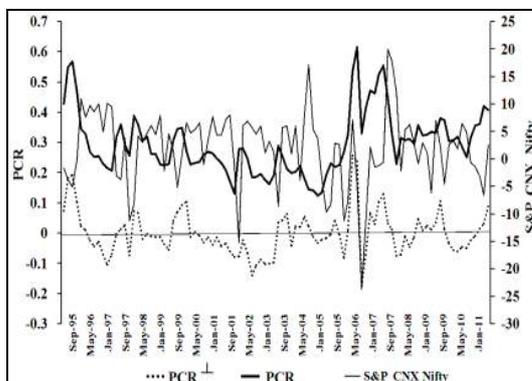
Panel (C) Advance Decline Ratio (ADR)



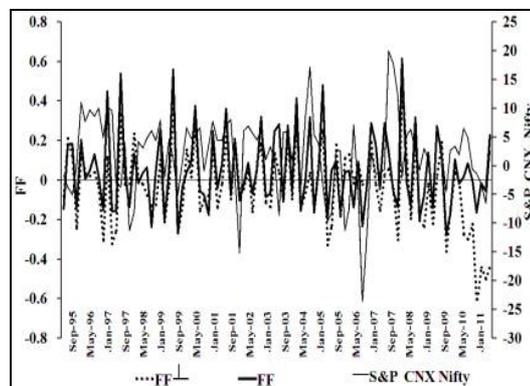
Panel (D) Change in Margin Borrowing (CMB)



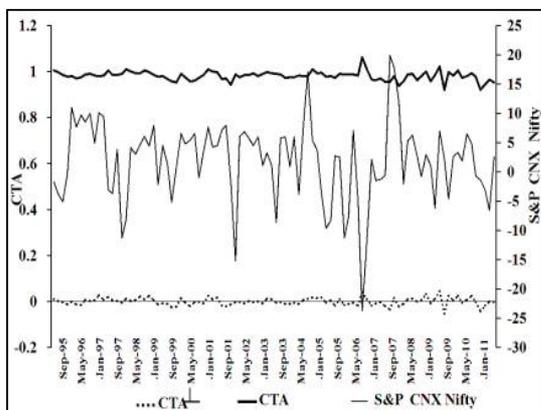
Panel (E) Put-Call Ratio (PCR)



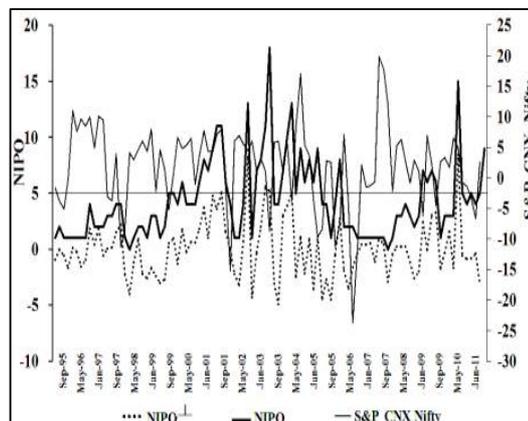
Panel (F) Fund Flow (FF)



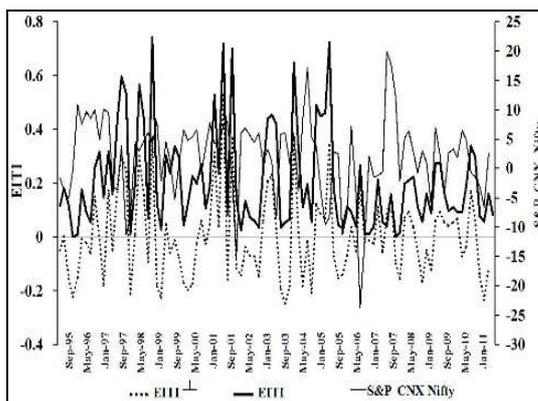
Panel (G) Cash to Total Assets (CTA)



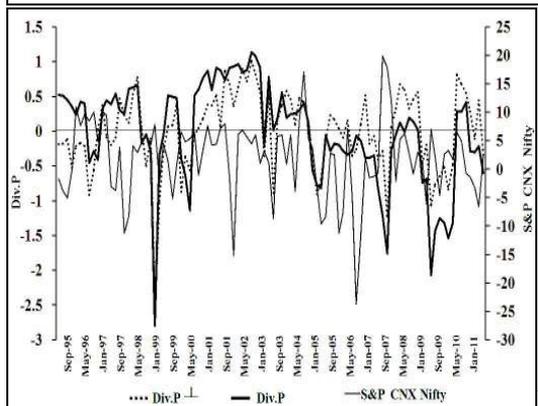
Panel (H) Number of IPOs (NIPO)



Panel (I) Equity Issue in Total Issue (EITI)

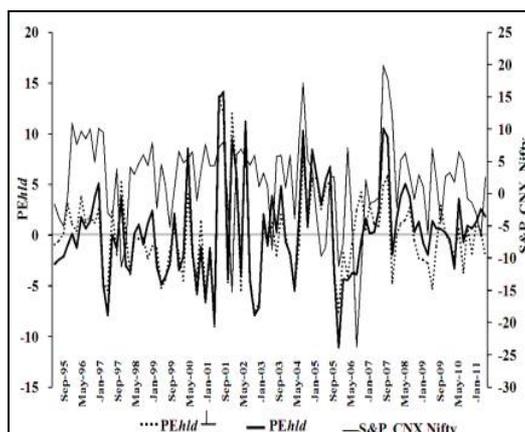
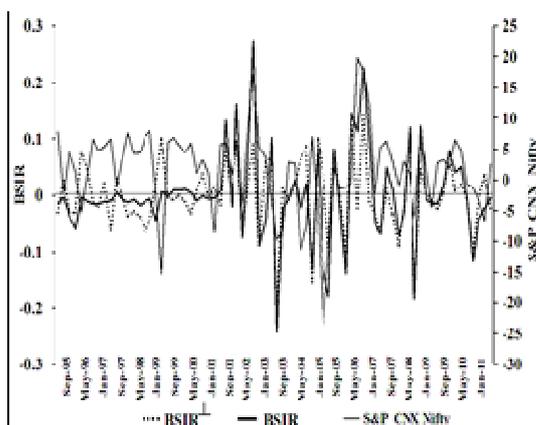


Panel (J) Dividend Premium (Div.P)



Panel (K) Buy-Sell Imbalance Ratio (BSIR)

Panel (L) PE High Low Difference (PEHld)



Notes: Figure 1 shows the comovement of the raw MRISPs and orthogonal MRISPs (\perp) along with the market index (S&P CNX Nifty). The Raw MRISPs and orthogonal MRISPs (\perp) are presented in X-axis while the market index corresponds to Y-axis.

4. Discussion of Results

Table 3 reports the estimation results of the cross-sectional tests (equations 7, 8, 9, 10) of the alternative conditional APMs by using IS as the conditioning information. Panel (A) of Table 3 presents results of the single market factor model scaled with IS information variable. Reported results suggest a statistically significant impact of the scaled and unscaled market excess return on the pricing kernel. This indicates that IS as conditioning information significantly influences the pricing kernel. Regarding the risk premiums reported for the Fama-MacBeth and GMM approach, all variables are found to be statistically significant. Panel (B) of Table 3 shows that, IS scaled risk factors in the TFM significantly influence the pricing kernel while the unscaled SMB and HML factors are found to be statistically insignificant. In terms of the risk premiums associated with conditional TFM risk factors, the conditioning information variable scaled factors can show testable significant pricing for all the risk factors. The associated risk premia in both the Fama-MacBeth and GMM approach are apparently more persuasive in the case of IS conditioned dynamic specifications.

In Panel (C) of Table 3, it can be observed that except for the unscaled market risk factor (MRKT), none of the unscaled risk factors are statistically significant. However, consistent with the findings of conditional CAPM and TFM all the risk factors conditioned on IS significantly influence the pricing kernel. In the case of the conditional specification of CFFM, the associated risk premia for the scaled and unscaled risk factors are not uniform in both the Fama-MacBeth and GMM approach. The significant risk premia is also evident for the scaled risk factors that are found to be significantly influencing the pricing kernel. This result is consistent with Harvey (1995) and Iqbal et al. (2010) where the conditional model is reported to explain time variation in parameters, whereas the associated risk premia are not significant. The results reported in Panel (D) of Table 3 suggest that IS conditioning information retains its implication for the SDF parameters associated with

MRKT, HML, WML and LMHL. The results reported in Panel (D) also corroborate the significance of IS as conditioning information variable in the cross-sectional test of conditional asset pricing model. In terms of the risk premiums reported for the Fama-MacBeth (1973) approach, except for the unscaled WML and LMHL factors, all other risk factors are found to be statistically significant. Under the GMM approach except for the unscaled WML factor and scaled LMHL factor, risk premia associated with other factors are found to be significant. This supports the information content in the IS variable having an impact in making the risk premia time varying.

Table 3 Cross-sectional Tests of Conditional Asset Pricing Models

Panel (A) Capital Asset Pricing Model (CAPM) Scaled by IS Conditioning Information											
	α	β_{MRKT}			β_{MRKT}^{IS}						
SDF Coefficients	0.07* (10.27)	0.01* (8.49)			0.02* (4.02)						
	α	λ_{MRKT}			λ_{MRKT}^{IS}						
Risk Premia (OLS)	-1.60# (-2.03)	-1.74# (-2.10)			-2.60* (-4.93)						
Risk Premia (GMM)	-0.03 (-0.12)	2.64* (3.83)			-5.54* (-7.22)						
Model Specification Tests	Wald test: χ^2 (3) 187.20, J -test: 24.45, HJ -Dist: 0.34, Sup- LM : 5.63 {0.00} {0.86} {0.11}										
Panel (B) Three-factor Model (TFM) Scaled by IS Conditioning Information											
	α	β_{MRKT}	β_{SMB}	β_{HML}	β_{MRKT}^{IS}	β_{SMB}^{IS}	β_{HML}^{IS}				
SDF Coefficients	0.05# (2.52)	0.01* (7.29)	-0.01 (-0.71)	0.01 (1.12)	0.03* (6.58)	-0.01* (-5.98)	0.01* (9.12)				
	α	λ_{MRKT}	λ_{SMB}	λ_{HML}	λ_{MRKT}^{IS}	λ_{SMB}^{IS}	λ_{HML}^{IS}				
Risk Premia (OLS)	-0.32 (-0.49)	-3.46* (-3.91)	1.29* (4.44)	3.39* (3.77)	-5.20* (-3.69)	-7.73 (-1.19)	9.24^ (1.98)				
Risk Premia (GMM)	-0.37 (-0.86)	-0.72 (-0.81)	8.19* (8.19)	8.35^ (1.76)	-2.63* (-3.65)	2.10* (5.50)	-0.57 (-0.21)				
Model Specification Tests	Wald test: χ^2 (7) 189.51, J -test: 45.29, HJ -Dist: 0.38, Sup- LM : 6.87 {0.00} {0.03} {0.06}										
Panel (C) Four-factor Model (CFFM) Scaled by IS Conditioning Information											
	α	β_{MRKT}	β_{SMB}	β_{HML}	β_{WML}	β_{MRKT}^{IS}	β_{SMB}^{IS}	β_{HML}^{IS}	β_{WML}^{IS}		
SDF Coefficients	0.01 (0.09)	0.05^ (1.73)	0.01 (0.72)	-0.01^ (-1.68)	0.01 (0.88)	0.03* (6.33)	-0.02# (-2.70)	0.01* (3.52)	-0.05* (-4.71)		
	α	λ_{MRKT}	λ_{SMB}	λ_{HML}	λ_{WML}	λ_{MRKT}^{IS}	λ_{SMB}^{IS}	λ_{HML}^{IS}	λ_{WML}^{IS}		
Risk Premia (OLS)	-1.03# (-2.41)	-2.47^ (-1.92)	-6.84* (-3.13)	12.50* (3.32)	1.05 (0.84)	-3.38 (-1.61)	-5.03 (1.21)	-4.95# (-1.68)	9.81 (0.98)		
Risk Premia (GMM)	-0.26 (-0.67)	-1.62# (-1.95)	8.54* (5.75)	6.36 (1.47)	0.38# (1.69)	-2.29* (-2.92)	3.33* (5.46)	-0.63 (-0.25)	2.31 (0.33)		
Model Specification Tests	Wald test: χ^2 (9) 72.89, J -test: 19.99, HJ -Dist: 0.33, Sup- LM : 8.11 {0.00} {0.83} {0.22}										
Panel (D) Five-factor Model (FFM) Scaled by IS Conditioning Information											
	α	β_{MRKT}	β_{SMB}	β_{HML}	β_{WML}	β_{LMHL}	β_{MRKT}^{IS}	β_{SMB}^{IS}	β_{HML}^{IS}	β_{WML}^{IS}	β_{LMHL}^{IS}
SDF Coefficients	0.02 (0.10)	0.01* (2.97)	0.01 (0.77)	0.01# (1.90)	-0.06 (-0.20)	0.03* (5.06)	0.01* (3.96)	-0.04* (-3.26)	0.01* (3.59)	0.01 (0.65)	0.02* (4.68)
	α	λ_{MRKT}	λ_{SMB}	λ_{HML}	λ_{WML}	λ_{LMHL}	λ_{MRKT}^{IS}	λ_{SMB}^{IS}	λ_{HML}^{IS}	λ_{WML}^{IS}	λ_{LMHL}^{IS}
Risk Premia (OLS)	-0.60 (-0.86)	-3.80* (-3.90)	1.05* (3.63)	2.41# (2.44)	0.87 (1.17)	0.29 (0.89)	-4.57* (-2.99)	6.30 (0.95)	4.05 (0.82)	-5.56* (-3.57)	1.23* (2.33)
Risk Premia (GMM)	-0.55 (-1.29)	-0.40 (-0.47)	6.80* (4.33)	8.20^ (1.80)	0.29 (1.09)	9.46# (2.15)	-13.35 (-1.16)	19.63* (5.24)	2.51 (0.98)	-0.98 (-0.11)	3.76 (0.74)
Model Specification Tests	Wald test: χ^2 (11) 109.18, J -test: 18.85, HJ -Dist: 0.21, Sup- LM : 4.33 {0.00} {0.81} {0.26}										

Notes: The risk premia are obtained using both the Fama–MacBeth (1973) and GMM Shanken and Zhou (2007) approach. The test assets are 36 SZ-BM-LQ-MM sorted portfolios. Wald test has been used to check whether the coefficients corresponding to the risk factors are cross-sectionally equal to zero. The J -test Hansen (1982) used for over-identifying restriction. The t -statistics are reported in the parenthesis. HJ -Dist is the Hansen and Jagannathan (1997) distance measure for model evaluation and specification. Sup- LM test Andrews (1993) used for structural stability of the parameters of the SDF model. Figures in the curly brackets represent the P-values associated with the model specification test statistics. *, #, ^ indicate significance at 1%, 5% and 10% respectively.

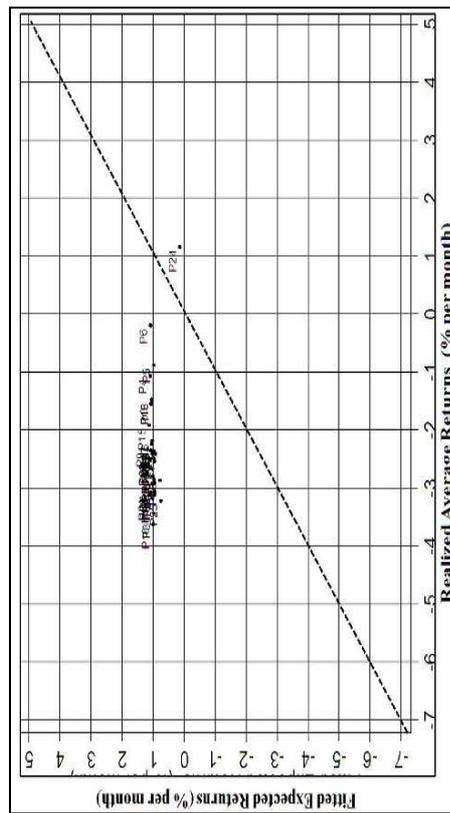
The reported Wald statistics, although able to reject the null hypothesis of zero pricing error in the case of three specified models, the statistics for conditional CFFM are found to be lower as compared to the other conditional specifications. The reported JT-statistics lend support for the conditional model specifications of CAPM, CFFM and FFM. Parameter stability is not a concern for all the specifications as the Andrews (1993) Sup-LM statistic is found to be insignificant. The Hansen and Jagannathan (1997) distance measure of model evaluation and specification suggest that among the alternative conditional specifications, FFM scaled with IS conditioning information performs better with lower pricing errors as compared to other conditional APMs. Overall, results suggest that IS may be a better instrument in the conditional asset pricing model specifications as it directly measures investors' expectations about the stock market in particular and the aggregate economy in general (Ho and Hung, 2009).

Following the graphical representation approach of Schrimpf et al. (2007) and Iqbal et al. (2010) the pricing error plots (realized vs. fitted returns of test asset portfolios) for APMs cross-sectional tests (reported in Table 3) has been presented in Figure 2. For pricing error plots, the proposition is that if the asset pricing model correctly describes the realized average returns, all the portfolios should fall on the line (Iqbal et al., 2010). Different panels in Figure 1 show the graphical representation of realized vs. fitted returns of 36 test asset portfolios (P-1...P-36) in percentage per month for all the four conditional APMs (CAPM, TFM, CFFM and FFM). The pricing errors are generated using SDF parameter estimates of GMM estimation to make the results comparable across models. Panels (A), (B), (C) and (D) of Figure 2 indicate that the predictions of the conditional models are large relative to what is expected if the models are valid. However, in the case of Panel (D) of Figure 2 the FFM scaled with IS generates less pricing errors as compared to the other three conditional model specifications. More selectively, portfolio numbers such as P-3, P-4, P-5, P-6, P-8, P-9, P-10, P-11, P-15, P-18, P-24, P-34 are found to be more predictive as compared to the other portfolios. These portfolios show lower deviation from the ideal line for the best linear combinations between the realized vs. fitted returns. Considering the portfolio numbers allocated to the respective test asset portfolios in Table 1 it can be observed that the aforementioned portfolios significantly represent the small size portfolios.

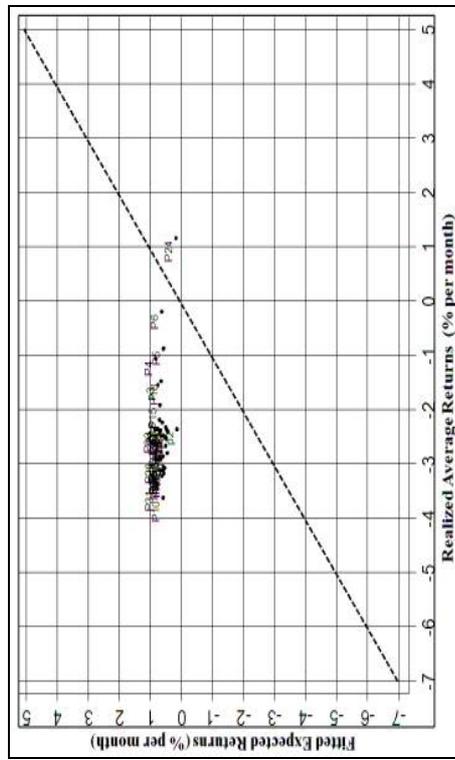
The graphical representation also indicates that in the dynamic specification FFM conditioned upon the IS accounts for the maximum return predictability of small size stocks followed by the large size stocks. The return predictability pattern observed in the graphical representation also shows that considering only the sentiment as a priced source of risk as in Baker and Wurgler (2006) may not reveal the complete relationship between IS and cross-sectional variation in stock return.

Figure 2 Realized vs. Fitted Returns for Conditional Asset Pricing Models

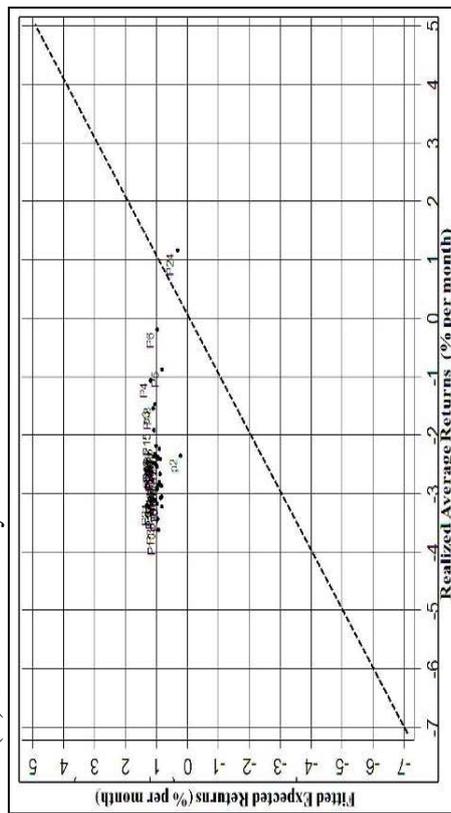
Panel (A) CAPM Scaled by Investor Sentiment



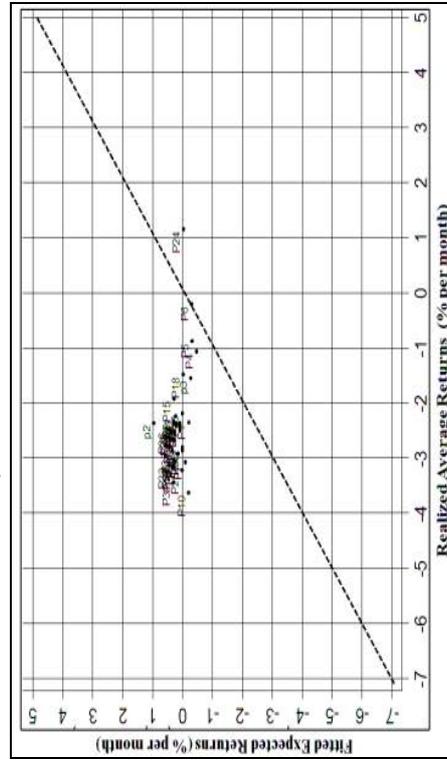
Panel (B) TFM Scaled by Investor Sentiment



Panel (C) CFFM Scaled by Investor Sentiment



Panel (D) FFM Scaled by Investor Sentiment



Notes: Figure 2 shows the pricing error plots for the alternatives conditional asset pricing models reported in Table 3.

As compared to the reported results in Table 3, the graphical representation in Figure 2 delivers a broader insight for the cross-sectional return variation of small size stocks and the role of IS. The graphical representation in Figure 2 shows the sentiment effect heavily influences almost all the small size stock portfolios. This also suggests that irrespective of the other associated risk characteristics like BM, LQ or MM, the small size effect may be a more persuasive reason for the sentiment driven mispricing.

4.1 Robustness Tests

This section attempts to run a robustness test by examining the cross-sectional return predictability of APMs with a sentiment index excluding the new MRISP i.e., *PEhld*. To be convinced about the value addition, due to the use of a new sentiment measure, this section aims to make a comparison of robustness test results with the results presented in Table 3 of Section 4. This will help to validate the findings and significance of the cross-sectional tests. In order to conduct the empirical analysis, a new sentiment index (NSI) has been constructed excluding the *PEhld*. The choice of 36 test asset portfolios, the risk factors and the empirical approach remain the same.

$$\text{NSI} = \text{TVR} + \text{STV} + \text{ADR} + \text{CMB} + \text{BSIR} - \text{PCR} + \text{NIPO} + \text{EITI} - \text{Div. P} + \text{FF} - \text{CTA} \dots\dots\dots(15)$$

Table 4 reports estimation results of the cross-sectional tests (equations 7, 8, 9, 10) of alternative conditional APMs using the new investor sentiment index (NSI). Panel (A), Panel (B), Panel (C) and Panel (D) of Table 4 respectively present results for the conditional asset pricing model scaled with NSI conditioning information variable i.e., CAPM, TFM, CFFM and FFM. As reported in Table 3, the NSI (constructed by excluding *PEhld*) as conditioning information significantly influences the pricing kernel. Consistent with our previous findings, the reported results suggest a statistically significant impact of the scaled and unscaled market excess return on the pricing kernel. This lends support towards the information content in the IS component having an impact in making the risk premia time varying. However, there is no significant difference in the cross-sectional test results excluding the new MRISP measure i.e., *PEhld*. Results using NSI as conditioning information are qualitatively similar to the results reported in Table-3. This clearly indicates the new sentiment MRISP measure (*PEhld*) does not enhance the cross-sectional test performance of conditional asset pricing model with significant uniqueness. Unreported pricing error plots of the alternatives conditional APMs reported in Table 4 do not show any significant difference as compared to the analysis presented in Figure 2. All taken together, support the applicability of IS index as conditioning information for the cross-sectional predictability of APMs.

Table 4 Cross-sectional Tests of Asset Pricing Models with New Sentiment Index

Panel (A) Capital Asset Pricing Model Scaled by New Sentiment Index Measure											
	α	β_{MRKT}	β_{MRKT}^{NSI}								
SDF Coefficients	0.04* (8.49)	0.01* (6.32)	0.01* (5.16)								
Factor Risk Premium	α	λ_{MRKT}	λ_{MRKT}^{NSI}								
Risk Premia (GMM)	-0.02 (-0.18)	1.36* (3.83)	-3.26* (-6.34)								
Model Specification Tests	Wald test: $\chi^2(3)$ 181.10, $JT-test$: 36.45, $HJ-Dist$: 0.31, Sup-LM: 4.26 {0.00} {0.17} {0.13}										
Panel (B) Three-factor Model Scaled by New Sentiment Index Measure											
	α	β_{MRKT}	β_{SMB}	β_{HML}	β_{MRKT}^{NSI}	β_{SMB}^{NSI}	β_{HML}^{NSI}				
SDF Coefficients	0.01^ (1.98)	0.01* (4.36)	-0.01# (-2.13)	0.01# (3.21)	0.01* (4.11)	-0.01* (-5.92)	0.01* (9.01)				
Factor Risk Premium	α	λ_{MRKT}	λ_{SMB}	λ_{HML}	λ_{MRKT}^{NSI}	λ_{SMB}^{NSI}	λ_{HML}^{NSI}				
Risk Premia (GMM)	-0.31 (-0.54)	-0.32 (-0.73)	6.11* (8.01)	7.22# (2.59)	-2.61* (-3.42)	1.41* (4.32)	-0.43 (-0.11)				
Model Specification Tests	Wald test: $\chi^2(7)$ 182.20, $JT-test$: 41.03, $HJ-Dist$: 0.31, Sup-LM: 5.64 {0.00} {0.01} {0.04}										
Panel (C) Four-factor Model Scaled by New Sentiment Index Measure											
	α	β_{MRKT}	β_{SMB}	β_{HML}	β_{WML}	β_{MRKT}^{NSI}	β_{SMB}^{NSI}	β_{HML}^{NSI}	β_{WML}^{NSI}		
SDF Coefficients	0.01 (0.09)	0.05^ (1.73)	0.01 (0.72)	-0.01^ (-1.68)	0.01 (0.88)	0.03* (6.33)	-0.02# (-2.70)	0.01* (3.52)	-0.05* (-4.71)		
Factor Risk Premium	α	λ_{MRKT}	λ_{SMB}	λ_{HML}	λ_{WML}	λ_{MRKT}^{NSI}	λ_{SMB}^{NSI}	λ_{HML}^{NSI}	λ_{WML}^{NSI}		
Risk Premia (GMM)	-0.26 (-0.67)	-1.62# (-1.95)	8.54* (5.75)	6.36 (1.47)	0.38# (1.69)	-2.29* (-2.92)	3.33* (5.46)	-0.63 (-0.25)	2.31 (0.33)		
Model Specification Tests	Wald test: $\chi^2(9)$ 72.89, $JT-test$: 19.99, $HJ-Dist$: 0.33, Sup-LM: 8.11 {0.00} {0.83} {0.22}										
Panel (D) Five-factor Model Scaled by New Sentiment Index Measure											
	α	β_{MRKT}	β_{SMB}	β_{HML}	β_{WML}	β_{LMHL}	β_{MRKT}^{NSI}	β_{SMB}^{NSI}	β_{HML}^{NSI}	β_{WML}^{NSI}	β_{LMHL}^{NSI}
SDF Coefficients	0.02 (0.10)	0.01* (2.97)	0.01 (0.77)	0.01# (1.90)	-0.06 (-0.20)	0.03* (5.06)	0.01* (3.96)	-0.04* (-3.26)	0.01* (3.59)	0.01 (0.65)	0.02* (4.68)
Factor Risk Premium	α	λ_{MRKT}	λ_{SMB}	λ_{HML}	λ_{WML}	λ_{LMHL}	λ_{MRKT}^{NSI}	λ_{SMB}^{NSI}	λ_{HML}^{NSI}	λ_{WML}^{NSI}	λ_{LMHL}^{NSI}
Risk Premia (GMM)	-0.55 (-1.29)	-0.40 (-0.47)	6.80* (4.33)	8.20^ (1.80)	0.29 (1.09)	9.46# (2.15)	-13.35 (-1.16)	19.63* (5.24)	2.51 (0.98)	-0.98 (-0.11)	3.76 (0.74)
Model Specification Tests	Wald test: $\chi^2(11)$ 109.18, $JT-test$: 18.85, $HJ-Dist$: 0.21, Sup-LM: 4.33 {0.00} {0.81} {0.26}										

Notes: Same as Table 3.

4.2 Investor sentiment, Asset Pricing Models and Market Anomalies

This section focuses on the performance of alternative multifactor APMs using IS as a conditioning information variable to capture the impact of the market anomaly effect. Following the empirical approach of Avramov and Chordia (2006) and Ho and Hung (2009) this section attempts to examine whether the systematic risk factors of alternative conditional APMs are sufficient to explain the market anomaly effect. Apart from the sentiment induced stock return

variation, the related literature also confirms the distinct role of investor behavioral bases for the appearance of several market anomalies (Brav and Heaton, 2002). For instance, the BM effect in the context of investor overreaction (Lakonishok et al., 1994), and the MM effect in the context of investors' underreaction or delayed overreaction hypothesis (Hong and Stein, 1999) have long been debated in the asset pricing literature. If the investor behavioural bias or sentiment induced trading behaviour are reasons for market anomaly effects (Brav and Heaton, 2002), then, after adjusting the raw stock return risk by using conditional APMs with IS as conditioning variable, the explanatory power of market anomalies should be insignificant (Ho and Hung, 2009). Thus, the conditional specification of APM that is able to capture the market anomaly effects successfully will result in more insignificant market anomalies in the second step while explaining the risk adjusted returns.

In this regard, the empirical approach follows a twostep process. Employing conditional APMs with IS as one of the conditioning information variables (Ho and Hung, 2009), the first pass time series regression approach of Avramov and Chordia (2006) has been used for deriving risk adjusted returns of each individual security j at time t . Second, a test of the explanatory power of market anomalies has been examined to explain the risk adjusted return. In a more generic form, considering FFM the risk adjustment process can be summarized as:

$$R_{jt} - R_{Ft} = \theta_j + \beta_{MRKT} MRKT_t + \beta_{MRKT}^{IS} MRKT_t IS_{t-1} + \beta_{SMB} SMB_t + \beta_{SMB}^{IS} SMB_t IS_{t-1} + \beta_{HML} HML_t + \beta_{HML}^{IS} HML_t IS_{t-1} + \beta_{WML} WML_t + \beta_{WML}^{IS} WML_t IS_{t-1} + \beta_{LMHL} LMHL_t + \beta_{LMHL}^{IS} LMHL_t IS_{t-1} + \varepsilon_{jt}, \quad (\forall j, t > 0 \text{ and } IS_{t-1} \in I) \quad \dots \dots \dots (16)$$

Where, $R_{jt} - R_{Ft}$ is the excess return of security j over the risk free rate. The risk adjusted return R_{jt}^* for stock j at time t to be used in the second step is equal to $\theta_j + \varepsilon_{jt}$. In the second step for testing the importance of market anomalies for explaining the risk adjusted return can be specified as:

$$R_{jt}^* = \alpha_j + (\mu_{SZ} SZ_{t-1} + \mu_{BM} BM_{t-1} + \mu_{LQ} LQ_{t-1} + \mu_{MM} MM_{t-1}) + \varepsilon_{jt}, \dots \dots \dots (17)$$

Where R_{jt}^* is the risk adjusted return derived from the first step. A panel data model has been used to estimate the equation (17). α_j is the individual effect, which is assumed as constant over time and varies across the individual cross-sectional unit. ε_{jt} is a stochastic error term having mean zero and constant variance. A 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. A 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 test (HM) (1978) has been used to determine the preferred

model (i.e., fixed effect model or random effect model). The explanatory variables SZ, BM, LQ and MM are the market anomaly variables. This section focusses on the same set of market anomalies that have been explored in the portfolio level analysis. The sample consists of National Stock Exchange of India listed 582 continuously traded non-financial companies. With continuously traded stocks our panel is a balanced panel having advantages in exploring panel data models. Goyal (2012) suggests that the popularity of the Fama and MacBeth approach in portfolio based and firm specific studies helps to accommodate unbalanced panels by providing a flexibility to use the returns on only those stocks which exist at time t . Use of the Fama and MacBeth approach thus, helps the risk premium estimation results not to be influenced due to the appearance and delisting of stocks in the exchange (Goyal, 2012). As our individual stock sample focuses on continuously traded stocks, therefore, to explore a different approach as compared to Avramov and Chordia (2006) the empirical analysis focusses on panel data models. With continuously traded stocks the data is a balanced panel having advantages in exploring panel data models.

Table 5 Fixed Effect Estimates for Alternative Conditional Asset Pricing Models

	Capital Asset Pricing Model		Three-factor Model		Four-factor Model		Five-factor Model	
SZ	-3.08* (-7.08)	-3.12* (-7.16)	-3.11* (-7.34)	-3.14* (-7.40)	-3.16* (-7.30)	-3.19* (-7.36)	-3.08* (-7.08)	-3.12* (-7.16)
BM	0.33^ (1.77)	0.33^ (1.81)	0.36# (2.00)	0.38 # (2.05)	0.33^ (1.80)	0.37* (2.44)	0.33^ (1.77)	0.33^ (1.81)
LQ	-2.81* (-6.96)	-3.01* (-7.67)	-2.99* (-7.60)	-2.94* (-7.45)	-2.07* (-5.69)	-2.04* (-5.16)	-2.81* (-6.96)	-2.75* (-6.79)
MM		0.01 (0.93)		0.01 (1.31)		0.01 (0.77)		0.01 (0.93)
LR $\chi^2(581)$	638.3*	641.6*	690.9*	652.8*	632.1*	623.4*	621.2*	638.2*
LM $\chi^2(1)$	6.00*	6.28*	7.01*	7.46*	6.70*	6.96*	6.00*	6.28*
HM [$\chi^2(4)$]	683.5*	184.4*	63.4*	340.4*	72.3*	310.5*	68.5*	184.4*
R^2	0.0629	0.0632	0.0682	0.0688	0.0661	0.0663	0.062	0.0632
F-Test	28.29*	28.45*	30.85*	31.15*	29.82*	29.94*	28.29*	28.45*

Notes: SZ 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 BM 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 . LQ is measured each month as the annual average of monthly turnover ratio i.e., number of shares traded to the number of shares outstanding. MM is the cumulative return over the six months ending six months previously. t -statistics are in parenthesis. *, #, ^ represent significance at 1%, 5%, 10% respectively.

Table 5 reports, estimation results of the equation (17) for alternative conditional APMs, which incorporate IS as conditioning information. All the models specification test statistics like; Likelihood Ratio (LR), Lagrange Multiplier (LM) and Hausman test (HM) reject the use of the random effect model. Reported results suggest that all the alternative conditional APMs with IS as the conditioning information fail to capture SZ, BM, LQ effects. Consistent with Ho and Hung (2009) APMs in their conditional specifications are able to capture only the MM effects. However, in

consistent with Ho and Hung (2009) the results do not support the complete explanation of SZ, BM, LQ effect when conditioning with APMs. Overall the results support the application of IS as conditioning information to capture the MM effect. The role of investor sentiment conditioning information for the complete explanation of momentum effects is in line with the behavioral explanations for momentum trading. In line with the Jegadeesh and Titman (2001) it is possible to conjecture that behavioral models provide at best a partial explanation for the momentum anomaly. The notable evidence suggests that, in the cross-sectional test the explanatory power of the FFM is of little help in capturing the anomaly effects and three out of the four selected anomalies are still persistent. The performance of the FFM conditional model is not found to be very encouraging in capturing the market anomaly effect.

Overall, the results reveal that, IS may be a potential instrument in the conditional asset pricing model specifications as it directly measures investors' expectations about the stock market in particular and the aggregate economy in general. The findings also suggest that the performance of conditional asset pricing models for explaining stock returns behavior and capturing market anomaly effect are not the same. IS as a conditioning information is more useful for the cross-sectional return variation explanation.

5 Summary and Conclusions

This paper explores the possible role of investor sentiment as a conditioning information variable on the cross-sectional tests of alternative asset pricing models. Considering investor sentiment as the conditioning information the cross-sectional tests of alternative asset pricing model reveal that the Five-factor Model that augments the Carhart (1997) four-factor model with a liquidity factor performs better than the other conditional models. In conditional specifications, all the risk factors scaled with investor sentiment significantly influence the pricing kernel. The results also reveal that in the case of all conditional specifications the associated risk premia for the scaled risk factors are found to be significant. This lends support for the information content in the investor sentiment component having an impact in making the risk premia time varying. Furthermore, the graphical representation for comparing the realized vis-à-vis the fitted values of returns, five-factor model scaled with the investor sentiment variable accounts for the maximum return predictability of small size stocks. Overall the small size effect appears to be a more persuasive explanation for the sentiment driven mispricing. The results are found to be consistent under robustness tests. Focusing on the applicability of investor sentiment scaled conditional asset pricing models to capture market anomaly effects, the results reveal that application of investor sentiment conditioning information only helps to capture the momentum effect.

Investor sentiment may be a potential instrument in conditional asset pricing model

specifications as it directly measures investors' expectations about the stock market in particular and the aggregate economy in general. The potential benefit of the conditional five-factor model can be leveraged for the cost of capital determination, and mutual fund manager's portfolio performance evaluation when the portfolio is heavily weighted with sentiment-sensitive hard to value and difficult to arbitrage stocks. During high volatility and boom periods in the stock markets the investor sentiment scaled conditional asset pricing models may be helpful for determining the intrinsic value of investor sentiment-sensitive stocks.

Acknowledgements

Author wish to thank the conference participants at the India Finance Conference-2013 and the Australian Academy of Business and Social Sciences Conference 2014 for their valuable comments. A special and sincere gratitude to Dr. Jitendra Mahakud for his constructive advice, review comments on preliminary drafts and encouragement throughout the doctoral research work. All remaining errors are mine.

References:

- Andrews, D. (1993), "Tests for parameter instability and structural change with unknown change point", *Econometrica*, Vol.61, No.4, pp. 821-856.
- Avramov, D. and Chordia, T. (2006), "Asset pricing models and financial market anomalies", *Review of Financial Studies*, Vol. 19, No.3, pp. 1001-1040.
- Baker, M., and Wurgler, J. (2006), "Investor sentiment and the cross-section of stock returns", *Journal of Finance*, Vol.61, No.4, pp.1645-1680.
- Baker, M., and Stein, J. C. (2004), "Market liquidity as a sentiment indicator", *Journal of Financial Markets*, Vol. 7, No.3, pp. 271-299.
- Baker, M., Wurgler, J., and Yuan, Y. (2011), "Global, local, and contagious investor sentiment", *Journal of Financial Economics*, Vol.104, No.2, pp.272-287.
- Barberis, N., Shleifer, A., and Vishny, R. (1998), "A model of investor sentiment", *Journal of Financial Economics*, Vol. 49, No.3, pp. 307-343.
- Barberis, N.R., and Thaler, R.H. (2003), "A survey of behavioral finance", Chapter- 18, Handbook of the Economics of Finance, Elsevier, North Holland.
- Bekart, G., Harvey, C.R., Lundblad, C., and Siegel, S. (2007), "Global growth opportunities and market Integration", *The Journal of Finance*, Vol.62, No.3, pp.1081-1137.
- Berger, D., and Turtle, H. J. (2012), "Cross-sectional performance and investor sentiment in a multiple risk factor model", *Journal of Banking and Finance*, Vol.36, No.4, pp.1107-1121.
- Brown, G.W., and Cliff, M.T. (2004), "Investor sentiment and the near-term stock market", *Journal of Empirical Finance*, Vol.11, No.1, pp.1-27.
- Brav, A. and Heaton, J.B. (2002), "Competing theories of financial anomalies", *The Review of Financial Studies*, Vol.15, No.2, pp.575-606.
- Carhart, M. M. (1997), "On persistence in mutual fund performance". *Journal of Finance*, Vol.52, No.1, pp.57-82.
- Chandra, A. (2012), "Cause and effect between FII trading behaviour and stock market returns: the Indian experience", *Journal of Indian Business Research*, Vol.4, no.4, pp. 286-300.
- Chi, L., Zhuang, X., and Song, D. (2012), "Investor sentiment in the Chinese stock market: an empirical analysis", *Applied Economics Letters*, Vol.19, No.4, pp.345-348.
- Chuang, W.J., Ouyang, L.Y., and Lo, W.C. (2010), "The impact of investor sentiment on excess returns: a Taiwan stock market case", *International Journal of Information and Management Sciences*, Vol.21, No.1, pp.13-28.
- Cochrane, J.H. (1996), "A cross-sectional test of an investment based asset pricing model", *Journal of Political Economy*, Vol.104, No.3, pp.572-621.
- Cochrane, J.H. (2001), "Asset pricing", Princeton University Press, Princeton, New Jersey

- Daniel, K., Hirshleifer, D., and Teoh, H. (2002), "Investor psychology in capital markets: evidence and policy implications", *Journal of Monetary Economics*, Vol.49, No.1, pp.139-209.
- Das, S. (2015), "Empirical evidence of conditional asset pricing in the Indian stock market", *Economic Systems*, Vol.39, No.2, pp.225-239.
- Dasgupta, R. and Chattopadhyay, S. (2014), "Stock market-driven factors of investors' sentiment a review of the stylized facts", *European Journal of Business and Management*, Vol.6, No.17, pp.208-217.
- Drobetz, W., Sturmer, S., and Zimmermann, H. (2002), "Conditional asset pricing in emerging stock markets", *The Swiss Journal of Economics and Statistics*, Vol.138, No.4, pp.507-526.
- Fama, E.F., and MacBeth, J. (1973), "Risk return and equilibrium: empirical tests". *Journal of Political Economy*, Vol.81, No.3, pp.607-636.
- Fama, E.F., and French, K.R. (1993), "Common risk factors in the returns on stocks and bonds", *Journal of Financial Economics*, Vol.33, No.1, pp.3-56.
- Finter, P., Niessen-Ruenzi, A., and Ruenzi, S. (2011), "The impact of investor sentiment on the German stock market", CFR-Working Paper No.10-03, Centre for Financial Research (CFR), University of Cologne, Germany.
- Fisher, K.L., and Statman, M. (2000), "Investor sentiment and stock returns", *Financial Analysts Journal*, Vol.56, No.2, pp.16-23.
- Goyal, A. (2012), "Empirical cross-sectional asset pricing: a survey", *Financial market and Portfolio Management*, Vol.26, No.1, pp.3-38.
- Hansen, L.P. (1982), "Large sample properties of the generalized method of moments", *Econometrica*, Vol.50, No.4, pp.1029-1054.
- Hansen, L.P., and Jagannathan, R. (1997), "Assessing specification errors in stochastic discount factor models", *Journal of Multinational Financial Management*, Vol.52, No.2, 557-590.
- Harvey, C.R., and Kirby, C.M. (1995), "Analytic tests of factor pricing models", Working Paper, Duke University.
- Ho, C., and Hung, C.H. (2009), "Investor sentiment as conditioning information in asset pricing", *Journal of Banking and Finance*, Vol.33, No.5, pp.892-903.
- Ho, C.W. (2012), "The role of investor sentiment in asset pricing", Doctoral Thesis, Durham University.
- Hong, H., and Stein, J.C. (1999), "A unified theory of underreaction, momentum trading, and overreaction in asset markets", *The Journal of Finance*, Vol.54, No.6, pp. 2143-2184.
- Iqbal, J., Brooks, R., and Galagedera, U.A.D. (2010), "Testing conditional asset pricing models: an emerging market perspective", *Journal of International Money and Finance*, Vol.29, No.5, pp.897-918.
- Jagannathan, R., and Wang, Z. (1996), "The conditional CAPM and the cross-section of expected returns", *Journal of Finance*, Vol.51, No.1, pp.3-53.
- Jagannathan, R., and Wang, Z. (2002), "Empirical evaluation of asset-pricing models: a comparison of the SDF and beta methods", *The Journal of Finance*, Vol.57, No.5, pp.2337-2367.
- Jegadeesh, N., and Titman, S. (1993), "Returns to buying winners and selling losers: implications for stock market efficiency", *Journal of Finance*, Vol.48, No.1, pp.65-91.
- Jegadeesh, N., and Titman, S. (2001), "Profitability of momentum strategies: an evaluation of alternative explanations", *The Journal of Finance*, Vol.56, No.2, pp.699-720.
- Keene, A.M., and Peterson, R.D. (2007), "The importance of liquidity as a factor in asset pricing", *Journal of Financial Research*, Vol.30, No.1, pp.91-109.
- Kim, Soon-Ho, Kim, D., and Shin, Hyun-Soo (2012), "Evaluating asset pricing models in the Korean stock market", *Pacific-Basin Finance Journal*, Vol.20, No.2, pp.198-227.
- Korajczyk, R., and Sadka, R. (2008), "Pricing the commonality across alternative measures of liquidity", *Journal of Financial Economics*, Vol.87, No.1, pp.45-72.
- Kumar, A., and Lee, C.M.C. (2006), "Retail investor sentiment and return comovements", *The Journal of Finance*, Vol.51, No.2, pp.2451-2486.
- Lam, K.S.K., and Tam, K.H.L. (2011), "Liquidity and asset pricing: evidence from the Hong Kong stock market", *Journal of Banking and Finance*, Vol.35, No.9, pp.2217-2230.
- Lakonishok, J., Shleifer, A. and Vishny, W.R. (1994), "Contrarian investment, extrapolation, and risk", *Journal of Finance*, Vol.49, No.5, pp.1541-1578.

- Laopodis N. T. (2011), "Equity prices and macroeconomic fundamentals: International evidence", *Journal of International Financial Markets, Institutions and Money*, Vol. 21, No.1, pp.247–276.
- Lischewski, J., and Voronkova, S. (2012), "Size, value and liquidity.do they really matter on an emerging stock market?" *Emerging Markets Review*, Vol.13, No.1, pp.8-25.
- Lintner, J. (1965), "The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets", *Review of Economics and Statistics*, Vol.47, No.1, pp.13-37.
- Schrimpf, A., Schröder, M., and Stehle, R. (2007), "Cross-sectional tests of conditional asset pricing models: evidence from the German stock market", *European Financial Management*, Vol.13, No.5, pp.880-907.
- Shanken, J., and Zhou, Z. (2007), "Estimating and testing beta pricing models: alternative methods and their performance in simulations", *Journal of Financial Economics*, Vol.84, No.1, pp. 40-86.
- Sharpe, W.F. (1964), "Capital asset prices: a theory of market equilibrium under conditions of risk", *Journal of Finance*, Vol.19, No.3, pp.425-442.
- Shefrin, H. (2005), "A behavioural approach to asset pricing", Elsevier Academic Press, New York.
- Shleifer, A., and Vishny, R. (1997), "The limits of arbitrage", *Journal of Finance*, Vol.52, No.1, pp.35-55.
- Stambaugh, R.F., Yu, J., and Yuan, Y. (2012), "The short of it: Investor sentiment and anomalies", *Journal of Financial Economics*, Vol.104, No.2, pp.288-302.
- Xu, Y. (2010), "Behavioral asset pricing in Chinese stock markets", Doctoral Thesis, School of Business and Economics, Loughborough University.

ⁱ Maalde Pankaj (2013), "Is current rally in Indian equity markets justified?", www.moneycontrol.com.