IMPACT OF INVESTOR SENTIMENT ON CROSS SECTIONAL TESTS OF
ALTERNATIVE ASSET PRICING MODELS: EVIDENCES FROM INDIAN
EQUITY MARKET

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ABSTRACT

This paper tests the cross sectional return predictability of alternative asset pricing models in Indian stock market by considering investor sentiment as conditioning information variable. The sample period spans over January 2003 till March 2011. For the cross sectional tests of alternative asset pricing models we have used both the Fama and Macbeth and Generalized Method of Moments estimation techniques. Cross sectional test results suggest that investor sentiment as a conditioning information variable contains significant information for making the discount factors time varying. In the conditional specifications all the risk factors scaled with investor sentiment significantly influence the pricing kernel. Model comparison test statistics suggests that for Indian stock market considering investor sentiment as the conditioning information the cross sectional tests of alternative asset pricing model reveal that the Five Factor Model that augments Carhart four factor model with a liquidity factor performs better than the other conditional models.

JEL code: C51, G12, E21

Keywords: Asset pricing model, investor sentiment, discount factor, stock returns, generalised method of moments.

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INTRODUCTION

The traditional asset pricing models show that the expected return on a security is a linear function of betas with respect to the innovations in pervasive macroeconomic and market wide risk factors (Sharpe, 1964; Lintner, 1965; Merton, 1973; Ross, 1976). In recent years following the pricing evidence of firm specific characteristics as the determinant of cross sectional and time series behavior of stock return (see for e.g., Schwert, 2003) and motivated with the rational risk based argument of such firm characteristics (see for e.g., Baker and Nofsinger, 2002; Barberis and Thaler, 2003; Brav and Heaton, 2002 for a detail discussion), a current body of literature proposes several multifactor asset pricing models such as Fama and French three factor model (Fama and French, 1993), Carhart four-factor model (Carhart, 1997) and the five factor model that augments Carhart four-factor model with liquidity factor (Pastor and Stambaugh, 2003) for the explanation of stock return behavior.

At a fundamental level, although the multifactor models are well responded in the asset pricing literature for their empirical consistency for describing cross section of stock return behavior in both developed and emerging stock markets (see for e.g., Fama and French, 2012; Her et al., 2004; Lam and Tang, 2011; Sehgal and Jain, 2011; Shum and Tang, 2005) the key risk factors of these models fail to explain time and again the spontaneous optimism or pessimism in the market behaviour due to the uninformed demand and supply shocks. The key assumptions of several asset pricing models including the recent multifactor models such as efficient financial market (Fama, 1970) and rational investor behaviour (Friedman, 1979) fail to explain time and again the irrational exuberance (Shiller, 2005) of market with several boom and bust cycles, which in turn limits the investor’s ability to quantify risk premium and to diversify portfolio risk in a state of persistent noise trading (Black, 1986), and limit to arbitrage (Shleifer and Vishny, 1997). Given the empirical failure of traditional financial paradigm to justify the quantification of risk return behaviour during excessive optimism or pessimism in market, over the past decades apart from the fundamental risk factors, possible impact of investor sentiment risk on stock returns behavior has been a subject of considerable debate in finance literature.

Motivated from the literature of experimental psychology, the behavioural asset pricing theory assumes that investors are not completely rational but normal and subject to cognitive biases. Such inherent cognitive biases of investors’ (Baker and Nofsinger, 2002; Ritter, 2003) with some combinations of limited arbitrage opportunity and short-sell constraint (Shleifer and Vishny, 1997) succumb their ability to differentiate between
instinct and rationality, noise and information (Black, 1986), strength and weight of information signals (Hirshleifer, 2001). In this regard, behavioural finance theories contend that, the systematic cognitive bias or irrational sentiment leads to incorrect heterogeneous probability beliefs about the discounted value of expected cash flow of an asset, and which in turn can have a cumulative effect on asset prices in the aggregate market level (Barberis and Thaler, 2003). Behavioural asset pricing theory posit that, within a dynamic interplay between irrational investors or noise traders and rational arbitrageurs for the determination of security prices, rational arbitrageurs may limit their positions in the market to avoid their loss because of the persistent noise trader risk (Black, 1986; De Long et al., 1990), high arbitrageur cost and short sell constraints (Shleifer and Summers, 1990). In common, the existing literature supports a positive relationship between investors sentiment and contemporaneous stock returns but negative relationship for expected stock returns (Baker and Wurgler, 2007; Baker et al., 2011; Brown and Cliff, 2004; Changsheng and Yongfeng, 2012; Finter et al., 2011; Schmeling, 2009). Specifically, for stocks that are hardest to arbitrage and whose valuations are more subjective are found to be most vulnerable to sentiment risk (Baker and Wurgler, 2006).

Consistent with the theoretical conjecture of time varying risk and economic risk premia the related literature across different markets suggests that conditional multifactor models perform better as compared to the unconditional models in both developed and emerging stock markets (see for e.g., Drobtetz et al., 2002; Iqbal et al., 2010; Jagannathan and Wang, 1996; Schrimpf et al., 2007). In recent years deriving motivation from the conditional asset pricing literature Ho and Hung (2009), Xu (2010) and Ho (2012) suggest the use investor sentiment as conditioning information for the test of asset pricing models. The fundamental argument in this regard suggests that since investor sentiment variable reflects investors’ expectations about the current state and future prospects of financial markets or business-cycle conditions it can be considered as the suitable candidate for conditioning information variable for the test of asset pricing models. The fundamental argument in this regard suggests that since investor sentiment variable reflects investors’ expectations about the current state and future prospects of financial markets or business-cycle conditions it can be considered as the suitable candidate for conditioning information variable for the test of asset pricing models. Following the approach of Avramov and Chordia (2006) for deriving risk adjusted return, Ho and Hung (2009) find that incorporating investor sentiment as conditioning information in asset-pricing models helps to capture the impacts of the size, value, liquidity and momentum effects on risk-adjusted returns of individual stocks. More specifically, Xu (2010) argue that if investor sentiment is a determinant of the pricing factors themselves, sentiment also drives asset returns indirectly by affecting the cognitive pricing factors that are the fundamental measures of risk in classical finance. Incorporating investor sentiment as a conditional information for accessing the stock pricing implication in Chinese stock market, Xu (2010) find that sentiment conditionally affect the loadings of risk factors in the conventional Fama and French (1993) three factor model.

The present paper seeks to answer do investor sentiment qualifies to be considered as a conditioning information variable in the dynamic specification of alternative asset pricing models? While investigating the aforementioned research question we examine the stock return and investor sentiment data from an emerging stock market like India. Our motivation to select an emerging stock market for the empirical investigation is motivated from the unique nature of Indian stock market in terms of the aggregate level of investor participation. The major argument towards the pricing of sentiment risk for explaining stock return behavior is followed from the aggregate level of investor participation in the market. In the context of developed markets like U.S. available empirical evidences formally validate the aggregate behavioral biases of investors in the form of market wide sentiment risk (Baker and Wurgler, 2006, 2007), implicitly derived from the assumption of high level of retail investors' participation (Kumar and Lee, 2006). It has been argued in the literature that cognitive biases and valuation errors are more commonly made by less sophisticated retail investors as compared to the informed institutional investors (Kumar and Lee, 2006). However, in an emerging market like India with the high level of institutional and promoter ownership (Indian stock market a review, National Stock Exchange of India, 2011) it is also perceptible to validate the pervasiveness of investor sentiment as a conditioning information variable. While investigating the role of investor sentiment as conditioning information variable we extend the existing literature in two ways. First, this study extends the available literature in the context of both developed and emerging stock markets by exploring the cross sectional tests of conditional asset pricing models using investor sentiment as the conditioning information variable. None of the existing literature has explored the role of investor sentiment as the conditional information for making the risk factors time varying. Second, in the context of Indian stock market the present study also makes first ever imperial examination of the cross sectional return variation associated with the sentiment risk and construct the first ever investor sentiment index for India using implicit sentiment proxies. Although construction of the sentiment index follows the approach recommended by the related literature, it uses some of the implicit proxies which have never been used in prior literature. In the context of Indian stock market the present study retains its importance not only because of the first ever study of its kind, but because of the stock market’s unique nature in terms of the investor participation and the decade long institutional reform process for enhancing the price informativeness.

The reminder of this paper is organized as follows. Sections 2 and 3 present the model specifications and methodology. Section 4 discusses the data and the construction of investor sentiment index. Section 5 presents the empirical findings. Section 6 offers summary and conclusions.
2. MODEL SPECIFICATIONS

In this section we specify the estimation framework for cross sectional tests of alternative asset pricing models by incorporating investor sentiment as conditioning information. Assuming zero arbitrage condition, the positive stochastic discount factor (SDF) or pricing kernel \( M_{t+1} \) that prices all payoffs for all test assets \( i (i = 1 \ldots N) \) in the economy, the Euler equation of necessary condition can be expressed as:

\[
E_t(M_{t+1}R_{it+1}) = E(M_{t+1}R_{i+1} | I_t) = 1, \quad \cdots (1)
\]

Where, \( R_{it+1} \) denotes 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 \( (r_{it+1}) \) on a risky asset from time \( t \) to \( t+1 \) and following the law of iterated expectations equation specification (1) can be represented as:

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

Consistent with the general linear factor model we assume a model in which the discount factor is linear in factors and it is specified as:

\[
\tilde{M}_{t+1} = \alpha_t + \beta_t f_{t+1} \quad \cdots (3)
\]

Where, \( \tilde{M}_{t+1} \) is an approximation of the true SDF \( (M_{t+1}) \) such that \( \forall M_{t+1} \in M_{t+1}, f_{t+1} \) is an \( L \)-dimensional vector of factors. Equation (3) indicates a conditional linear factor model since the parameters \( \alpha_t \) and \( \beta_t \) 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 (Lettau and Ludvigson, 2001). However, following the approach of Jagannathan and Wang (1996) by taking conditional expectation of equation (3) we may encounter the problem of equating the conditional mean variance efficiency with the unconditional mean variance efficiency i.e., \( [E(M_{t+1}, R_{it+1} | I_t) = 1] \neq [E(M_{t+1}, R_{it+1}) = 1] \). To overcome this problem we follow the scaled factor model approach of Cochrane (1996, 2001) to set the parameters of the SDF \( \alpha_t \) and \( \beta_t \) to depend linearly on the time \( t \) information set \( Z_t \) (\( \forall Z_t \in I_t \)) as:

\[
\alpha_t = \alpha_0 + \beta_0 Z_t, \quad \beta_t = \beta_0 Z_t \quad \cdots (4)
\]

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

\[
\tilde{M}_{t+1} = (\alpha_0 + \beta_0 Z_t) + (\beta_2 + \beta_3 Z_t) f_{t+1} = \alpha_0 + \beta_0 Z_t + \beta_2 f_{t+1} + \beta_3 Z_t f_{t+1} + \beta_3 (f_{t+1} Z_t) \quad \cdots (5)
\]

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.

Extending the equation (5) for the different linear factor models that we are intended to test can be specified as follows:

Single market factor based CAPM,

\[
\tilde{M}_{t+1} = \alpha_0 + \alpha_1 Z_t + \beta_{MRKT}^MRKT_{t+1} + \beta_{HML}^HML_{t+1} (Z_{HML_{t+1}}) \quad \cdots (6)
\]

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

\[
\tilde{M}_{t+1} = \alpha_0 + \alpha_1 Z_t + \beta_{MRKT}^MRKT_{t+1} + \beta_{SMB}^SMB_{t+1} + \beta_{HML}^HML_{t+1} (Z_{HML_{t+1}})
\]

\[
+ \beta_{MRKT}^MRKT_{t+1} (Z_{MRKT_{t+1}}) + \beta_{SMB}^SMB_{t+1} (Z_{SMB_{t+1}}) + \beta_{HML}^HML_{t+1} (Z_{HML_{t+1}}) \quad \cdots (7)
\]
Carhart (1997) four factor model (CFFM),
\[
\tilde{M}_{t+1} = \alpha_0 + \alpha_1 Z_t + \beta_{MRKT}^{1} MRKT_{t+1} + \beta_{SMB}^{1} SMB_{t+1} + \beta_{HML}^{1} HML_{t+1} + \beta_{WML}^{1} WML_{t+1} + \beta_{LMHL}^{1} LMHL_{t+1} Z_{MRKT_{t+1}} + \beta_{LMHL}^{2} Z_{SMB_{t+1}} + \beta_{LMHL}^{3} Z_{HML_{t+1}} + \beta_{LMHL}^{4} Z_{WML_{t+1}} + \beta_{LMHL}^{5} Z_{LMHL_{t+1}}
\]  

(8)

Five Factor Model (FFM),
\[
\tilde{M}_{t+1} = \alpha_0 + \alpha_1 Z_t + \beta_{MRKT}^{1} MRKT_{t+1} + \beta_{SMB}^{1} SMB_{t+1} + \beta_{HML}^{1} HML_{t+1} + \beta_{WML}^{1} WML_{t+1} + \beta_{LMHL}^{1} LMHL_{t+1} Z_{MRKT_{t+1}} + \beta_{LMHL}^{2} Z_{SMB_{t+1}} + \beta_{LMHL}^{3} Z_{HML_{t+1}} + \beta_{LMHL}^{4} Z_{WML_{t+1}} + \beta_{LMHL}^{5} Z_{LMHL_{t+1}}
\]  

(9)

Where, \( \beta_{MRKT}^{1} \) : \( \beta_{SMB}^{1} \) : \( \beta_{HML}^{1} \) : \( \beta_{WML}^{1} \) : \( \beta_{LMHL}^{1} \) represents the factor loading on systematic risk factors namely MRKT, SMB, HML, WML and LMHL. \( \beta_{MRKT}^{1} \) : \( \beta_{SMB}^{1} \) : \( \beta_{HML}^{1} \) : \( \beta_{WML}^{1} \) : \( \beta_{LMHL}^{1} \) represents the factor loading on systematic risk factors scaled with IS(z) conditioning information variable.

It is also perceptible to analyse if a particular factor that considered as a determinant of the pricing kernel carries a significant risk premium, referred as \( \lambda_{i} \). In other words \( \lambda_{i} \) indicates the factor risk price. The conditional expected return beta representation can be mentioned as:
\[
E_t(R_{i,t+1}) = \lambda_i + \lambda^* \beta_i
\]

(10)

Where, \( \beta_i = \text{Cov} (1_{t+1}, f_{t+1} - \beta' f_1) \) are the conditional betas of test asset i, the elements of \( \lambda^* \beta_i \) 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 the risk premium for the pricing kernel of single market factor based CAPM, can be specified as:
\[
E_t(R_{i,t+1}) = \lambda_0 + \lambda^{MRKT} \beta_{MRKT_{t+1}} + \lambda^{SMB} \beta_{SMB_{t+1}} + \lambda^{HML} \beta_{HML_{t+1}} + \lambda^{WML} \beta_{WML_{t+1}} + \lambda^{LMHL} \beta_{LMHL_{t+1}}
\]

(11)

Similar to the specification (11) we estimate the equation specification (10) for the other three alternative conditional asset pricing models specified in equations (7), (8) and (9) respectively.

3. METHODOLOGY

Equations (6), (7), (8) and (9) have been estimated by using the two-step procedure of Fama and MacBeth (1973) and by the GMM approach of Ogaki (1992) and Shanken and Zhou (2007). The link between the discount factor approach and the beta representation approach and their relative merits have been discussed by many authors extensively (for e.g., Cochrane, 2001; Kan and Zhou, 1999; Wang, 2005). However, Jagannathan and Wang (2002) conclude that the specification test based on the SDF method is as powerful as the one based on the beta method. In this regard we consider both the approaches for the cross sectional tests of alternative asset pricing models. For model specification tests, while estimating SDF parameters in equation (6), (7), (8) and (9) we use JT-statistics (Hansen, 1982) for the over identification of restrictions, and Wald test to check whether the coefficients corresponding to the specific factors are cross sectionally equal to zero. Hansen and Jagannathan (1997) distance (HJ-Dist) measure has been used to compare and evaluate alternative asset pricing models. Sup-LM test formulated by Andrews (1993) has been used to test structural stability of the SDF parameters. Consistent with the related literature, the test assets \( f_i \) that have been used for the cross sectional test of alternative asset pricing models are the value weighted portfolio returns.

4. DATA AND VARIABLES

The basic data consists of monthly returns and other firm specific characteristics of non-financial companies listed in National Stock Exchange (NSE) of India for the period February 1995 to March 2011. The S&P CNX Nifty has been taken as the market proxy. The 91-days Treasury bill rate is considered as the proxy
for risk free rate. The required data on stocks return and other firm specific information has been collected from Centre for Monitoring Indian Economy (CMIE) PROWESS database, risk free rate data have been collected from Reserve Bank of India (RBI) website. Data for the sentiment proxies have been collected from the NSE, Securities and Exchange Board of India (SEBI) and Association of Mutual Funds in India (AMFI) websites. We begin portfolio formation on September 1 every year since around 80% of the listed firms in the NSE have their fiscal year end in March. Therefore, the accounting data for the year ending March of year \( y \) have been compared with stock return from September of year \( y \) to August of year \( y+1 \) i.e., giving a period of five months lag for the disclosure of available accounting information to market participants. The minimum five months time lag between the financial year end and the formation of test assets and risk factors has been maintained to avoid the look-ahead bias. We control for various stock selection criteria as discussed in Fama and French (1992) and exclude the firms with negative book-to-market equity value while constructing the test asset portfolios.

**Construction of Test Asset Portfolios**

Our approach towards the formation of test asset portfolios is similar to that of 25 size and book-to-market equity portfolios construction approach of Fama and French (1993). However, unlike commonly used 25 SZ-BM portfolios as test assets we use value weighted returns of 36 portfolios created, encompassing the four risk characteristics such as firm size (SZ), book-to-market equity (BM), momentum (MM) and liquidity (LQ). Motivation to construct 36 portfolios encompassing all the four major firm characteristics is derived from three arguments. First, Lewellen et al. (2010) raised their concern towards the validity of Fama and French (1993) three factor model (TFM) on samples expanded beyond the SZ-BM portfolios. Lewellen et al. (2010) suggest that inference based on 25 SZ-BM portfolios for the validation of a specific asset pricing model might be misleading because such portfolios may exhibit a strong factor structure with very few idiosyncratic components. Therefore, it is important to test the validity of TFM on samples or test assets expanded beyond the SZ-BM portfolios. Second, the choice of SZ, BM, MM and LQ characteristics as the most selective components for the construction of test assets is motivated from the findings of available literature that support the pervasiveness of such characteristics as important determinants of cross section of stock return variation in both developed and emerging stock markets (Fama and French, 2012; Groot, and Verschoor, 2002; Lam and Tam, 2011; Lischewski and Voronkova, 2012; Rouwenhorst, 1999). Third, our approach is also consistent with the philosophy of practical investment scenario. In a real world investment scenario an investor not only concerns with any single risk characteristic rather all the risk characteristics of a stock taken together. Therefore, it is also apparent to investigate the cross sectional tests of alternative asset pricing models on portfolios that encompasses all the major fundamental characteristics and not concentrated on a single firm characteristic.

For the construction of test asset portfolios, SZ is measured as the natural logarithm of market capitalization (stock prices times outstanding shares) at the end of August of year \( y \) (Fama and French, 1992). BM in year \( y \) is the ratio between book equity for the fiscal year ending in calendar year \( y \) by the market value of equity at the end of August in calendar year \( y \) (Fama and French, 1992). MM is the cumulative return of a stock in month \( t-12 \) through month \( t-1 \) preceding August of year \( y \). Following Jegadeesh and Titman (2001) we skip one month between portfolio formation and holding period to avoid the effects of bid-ask spread, price pressure, and any lagged reaction. LQ is measured as the annual average of monthly turnover ratio i.e., value shares traded to the value of shares outstanding at the end of August of calendar year \( y \) (Amihud, 2002). We use the above mentioned measures of four firm characteristics to construct 36 SZ-LQ-BM-MM (3x2x2x3) portfolios (P-1….P-36) as test assets by using three SZ groups, two LQ groups, two BM groups and three MM groups. For the three SZ groups, we follow the market capitalization break points of National Stock Exchange of India.

**Construction of Systematic Risk Factors**

Following previous studies by Fama and French (1993), Carhart (1997), L’her et al. (2004), Knee and Peterson (2007), Lam and Tam (2011) we have constructed five market wide risk factors namely: MRKT i.e., market return in excess of risk free rate, SMB is the simple average of the returns on the three small-stock portfolios (small-low, small-medium, small-high) minus the returns on the three big-stock portfolios (big-low, big-medium, big-high). HML is the simple average of the returns on the two high-BM portfolios minus the returns on the two low-BM portfolios. WML is the simple average of the returns on the winner-stock portfolios (small winner, big winner) minus the returns on the loser-stock (small-looser, big-loser) portfolios. LMHL is the simple average of the return on the two low liquid portfolios (big-low liquid, small-low liquid) minus the return on two high liquid portfolios (small-high liquid, big-high liquid).

**Construction of Investor Sentiment Index**

Prior literature suggests that there are three different approaches to measure the unobservable sentiment variable. First one is based on the survey method of individual investors’ response for the anticipated movement of stock
market and the aggregate economy (Fisher and Statman, 2000; Schmeling, 2009). The second approach is the market related implicit sentiment proxies (MRISPs) derived from the selected market statistics (Baker and Wurgler, 2006, 2007; Baker et al., 2011; Brown and Cliff, 2004). The third approach is a combination of both the explicit and implicit sentiment proxies in the form of a composite sentiment measure (Ho and Hung, 2009; Ho, 2012). Although there is no uncontroverted and universal proxy for measuring investor sentiment, our approach for the construction of aggregate investor sentiment index (AISI) closely follows the top down approach of Baker and Wurgler (2006, 2007). As there is no theoretical argument as to how many exact number of MRISPs that can be considered for constructing a sentiment index we use the common variation in 12 MRISPs that have been identified in related literature. The selected 12 MRISPs are: turnover volatility ratio (TVR), share turnover velocity (STV), advance decline ratio (ADR), change in margin borrowing (CMB), buy-sell imbalance ratio (BSIR), put-call ratio (PCR), number of IPOs (NIPO), equity issue in total issue (EITI), dividend premium (Div. P), fund flow (FF) and cash to total assets (CTA) in the mutual fund market, and price-to-earnings high-low difference (PEhld). However, when an investor is bullish or bearish, this could be a rational expectation of future period’s expected cash flow or irrational optimism or a combination of both (Baker and Wurgler, 2006, 2007; Brown and Cliff, 2004, 2005; Verma and Soydemir, 2009; Shleifer and Summers, 1990).

Therefore, it is likely that each of the MRISPs may include a non fundamental (i.e., irrational) and a fundamental (i.e., rational) component. Since our objective is to deal with the irrational component of the sentiment, we have tried to circumvent this problem by regressing each of the 12 MRISPs on six fundamental factors such as; industrial production growth rate, term spread, exchange rate, rate of inflation, percent change in net foreign institutional investors (FII) inflow and market excess returns. In contrast to prior literature, we use percent change in net FII inflow as an additional fundamental factor, because of the observed sensitivity of Indian stock market to the behaviour of FII in terms of their market participation (Chandra, 2012).

Retaining the theoretical sign or the direction of the relationship between the MRISPs and aggregate investor sentiment index (AISI) for the month $t$ can be represented as:

$$
AISI_t = TVR_t + STV_t + ADR_t + CMB_t + BSIR_t + PCR_t + NIPO_t + EITI_t - Div. P_t + FF_t - CTA_t + PEhld_t \ldots \ldots (12)
$$

Following Verma and Soydemir (2009) we estimate equation (14) to measure the irrational sentiment component from our respective sentiment measures (MRISPs) by isolating the $k$ fundamental factors ($FUNDA_k$):

$$
MRISP_t = \alpha_k + \gamma_k \sum_{s=1}^{k} FUNDA_{kt} + \varepsilon_t \ldots \ldots \ldots (13)
$$

Where, $\alpha_0$ indicates the constant, $\gamma_k$ is the parameter to be estimated with respect to fundamental factors, $\varepsilon_t$ is the random error term. $FUNDA_{kt}$ is the above mentioned six fundamental factors. The fitted values of equation (13) capture the rational component of market wide sentiment proxies (i.e. MRISP$_{kt}$). On the other hand the residuals of equation (14) capture the irrational component of the sentiment. This approach helps to consider the irrational or noise component of MRISPs. The modified proxies are considered as orthogonal sentiment proxies (MRISP$_{k^\perp}$). Consistent with the related literature (Baker and Wurgler, 2006, 2007; Brown and Cliff, 2004) our approach for using the residuals of the first step regression in the subsequent analysis is also in line with the argument of Pagan (1984). After making the MRISPs orthogonal to fundamental factors we use principal components analysis for measuring the common variation and to isolate the common components from the respective MRISP$_{k^\perp}$.

The principal component analysis filters 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:

$$
AISI_t = 0.328(TVR_{t-1}^\perp) + 0.324(STV_{t-1}^\perp) + 0.194(ADR_{t-1}^\perp) + 0.173(CMB_{t-1}^\perp) + 0.060(BSIR_{t-1}^\perp) - 0.164(PCR_{t-1}^\perp) + 0.209(NIPO_{t-1}^\perp) + 0.213(EITI_{t-1}^\perp) + 0.053(Div. P_{t-1}^\perp) + 0.025(FF_{t-1}^\perp) - 0.308(CTA_{t-1}^\perp) + 0.227(PEhld_{t-1}^\perp) \ldots \ldots \ldots \ldots \ldots (14)
$$

**FIGURE 1. COMOVEMENT OF SENTIMENT INDEX WITH MARKET INDEX**
Notes: AISI indicates aggregate investor sentiment index constructed using the market related implicit sentiment proxies. S&P CNX Nifty index returns has been taken as market proxy. Sample period spans over September 1995 till March 2011.

Table 1 Correlation Matrix of Sentiment Index with Systematic Risk Factors

<table>
<thead>
<tr>
<th></th>
<th>MRKT</th>
<th>SMB</th>
<th>HML</th>
<th>WML</th>
<th>LMHL</th>
<th>AISI</th>
</tr>
</thead>
<tbody>
<tr>
<td>MRKT</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SMB</td>
<td>0.15</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HML</td>
<td>-0.08</td>
<td>-0.06</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WML</td>
<td>-0.26#</td>
<td>0.04</td>
<td>0.01</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LMHL</td>
<td>-0.24#</td>
<td>0.01</td>
<td>0.21#</td>
<td>0.05</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>AISI</td>
<td>0.02</td>
<td>0.05</td>
<td>-0.13</td>
<td>-0.06</td>
<td>0.02</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Notes: # represents statistical significance at 5% level.

Figure 1 shows the comovement of the investor sentiment index (AISI) with the market index (S&P CNX Nifty). Table 1 reports the correlation matrix of the sentiment index with other market wide risk factors. Reported figures in Table 1 show that AISI is positively correlated with the MRKT and LMHL factors. The positive relationship between the LMHL and AISI corroborates to positive impact of aggregate market liquidity on aggregate market sentiment as hypothesized by Baker and Stein (2004). The positive relationship of AISI with the MRKT may be because of the fact that market index movement considered as a lead indicator for the aggregate macroeconomic condition. Consistent with the findings of Verma and Soydemir (2009) we observe a contemporaneous negative correlation observed between AISI and WML factor and a positive correlation observed with the SMB. Overall Table 1 gives an indication that our constructed proxy for investor sentiment (AISI) is insignificantly related to other market wide risk factors.

5. DISCUSSION OF RESULTS

Table 2 reports the estimation results for the cross sectional tests (equations 6, 7, 8, and 9) of alternative conditional asset pricing models by using investor sentiment as the conditioning information. Panel (A) of Table 2 presents result for the single market factor model scaled with investor sentiment information variable. Reported results suggest statistically significant impact of the scaled and unscaled market excess return on the pricing kernel. This indicates that investor sentiment as conditioning information significantly influences the pricing kernel. In terms of the risk premiums reported for the Fama-MacBeth and GMM approach, all variables are found to be statistically significant. Panel (B) of Table 2 shows that, sentiment scaled risk factors in the TFM significantly influences 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 are able to 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 case of investor sentiment conditioned dynamic specifications.

TABLE 2 CROSS SECTIONAL TESTS OF CONDITIONAL ASSET PRICING MODELS

Panel (A) CAPM Scaled by Investor Sentiment (IS)

<table>
<thead>
<tr>
<th></th>
<th>SDF</th>
<th>MRKT</th>
<th>SMB</th>
<th>HML</th>
<th>WML</th>
<th>LMHL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\alpha)</td>
<td>0.07* (10.27)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\beta_{MRKT})</td>
<td>0.01* (8.49)</td>
<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>(\gamma_{MRKT})</td>
<td>0.02* (4.02)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Factor Risk Premium</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\alpha)</td>
<td>-1.60# (-2.03)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\lambda_{MRKT})</td>
<td>-1.74# (-2.10)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\gamma_{MRKT})</td>
<td>-2.60# (-4.93)</td>
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<td></td>
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<tr>
<td>Risk Premia (OLS)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\alpha)</td>
<td>-0.03 (-0.12)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>(\lambda_{MRKT})</td>
<td>2.64* (3.83)</td>
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<td></td>
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<td></td>
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</tr>
<tr>
<td>(\gamma_{MRKT})</td>
<td>-5.54* (-7.22)</td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td>Risk Premia (GMM) Model Specification</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Wald test: (X^2) (3) 187.20,</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>(Jr -test)</td>
<td>24.45 ,</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(HJ)-Dist: 0.34,</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Sup-LM: 5.63</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Notes: SDF indicates market related implicit sentiment proxies. Sample period spans over September 1995 till March 2011. All variables are found to be statistically significant.
Panel (B) TFM  Scaled by Investor Sentiment (IS)

<table>
<thead>
<tr>
<th>Specification</th>
<th>Wald test: $\chi^2$ (7)</th>
<th>$J^r$-test: 45.29</th>
<th>$HJ$-Dist: 0.38</th>
<th>Sup-LM: 6.87</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel (D) FFM Scaled by Investor Sentiment (IS)</td>
<td></td>
<td></td>
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<td></td>
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</tbody>
</table>

Panel (C) CFFM Scaled by Investor Sentiment (IS)

|---------------|--------------------------|-------------------|----------------|--------------|

Panel (D) FFM Scaled by Investor Sentiment (IS)

|---------------|--------------------------|-------------------|----------------|--------------|

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

Panel (C) of Table 2 shows that except the for the unscaled market risk factor (MRKT) none of the other unscaled risk factors are found to be statistically significant. However, consistent with the findings of the conditional CAPM and TFM all the risk factors conditioned on investor sentiment significantly influences the pricing kernel. In 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 insignificant 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. Reported results in Panel (D) of Table 2 suggest that investor sentiment conditioning information retains its implication for the SDF...
parameters associated with MRKT, HML, WML and LMHL. This again corroborates the significance of investor sentiment 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 approach, except 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 leads the support for the information content in the investor irrational sentiment component to have an impact for making the risk premia time varying.

The reported Wald statistics although able to reject the null hypothesis of zero pricing error in case of the entire three specified models, the statistics for the conditional CFFM 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 as the Andrews (1993) Sup-LM statistic found to be insignificant. The Hansen and Jagannathan (1997) distance measure of model evaluation and specification suggest that among the alternative conditional specifications, Five Factor Model scaled with investor sentiment conditioning information performs better with lower pricing errors as compared to other conditional asset pricing models. Over all our results suggest that, investor sentiment may be a better instrument in the dynamic asset pricing model specifications as it directly measures investors’ expectations about the stock market in particular and aggregate economy in general (Ho and Hung, 2009).

FIGURE 2. REALIZED VS. FITTED RETURNS FOR CONDITIONAL ASSET PRICING MODELS

The graphical representation through the pricing error plots for the alternatives conditional asset pricing models indicates that in the dynamic specification FFM conditioned upon the investor sentiment 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 sentiment as a priced source of risk may not reveal the complete relationship between investor sentiment and cross sectional variation in stock return. As compared to the reported results in Table 2, graphical representation of pricing error plots delivers a broader picture for the cross sectional return variation of small size stocks and the role of investor sentiment, which was subtle in the previous analysis by considering sentiment as a priced source of risk. The graphical representation suggest that almost all the small size stock portfolios are heavily influenced with the sentiment effect. This also suggest 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.

6. SUMMARY AND CONCLUSIONS
This paper explores several alternative explanations for the role of investor sentiment on the behaviour of stock returns. We investigate the possible role of investor sentiment on the cross sectional tests of conditional 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 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 irrational sentiment component to have an impact for 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 conditioned upon the investor sentiment accounts for the maximum return predictability of small size stocks. Overall the small size effect appears to be a more persuasive reason for the sentiment driven mispricing. Investor sentiment may be a potential instrument in the dynamic asset pricing model specifications as it directly measures investors’ expectations about the stock market in particular and aggregate economy in general. Our findings also suggest that considering sentiment only as a priced source of risk may not reveal the various roles that investor sentiment may play in pricing risky assets like equity.

REFERENCES

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