Investor Sentiment: Does it augment the performance of asset pricing models?

Deven Bathia
Queen Mary University of London*

Don Bredin
University College Dublin†

Abstract

This paper examines whether incorporating various investor sentiment measures in conditional asset pricing models can help to capture the impacts of the size, value, liquidity and momentum effects on risk-adjusted returns of the U.S. individual stocks. Using monthly data for the period January 1980 to December 2014, we determine the significance of equity fund flow, IPO first day returns, IPO volume, closed-end fund discount, equity put-call ratio, dividend premium, change in margin debt and sentiment index, by including them as conditioning information in asset pricing models. Our results show that sentiment augmented asset pricing models significantly capture the impacts of the size, value, liquidity and momentum effects on risk-adjusted returns. In particular, we observe that conditioning beta on equity fund flow, IPO first day return and put-call ratio capture the predictive power of equity characteristics for all the asset pricing models.

Keywords: Investor sentiment, Asset pricing, Anomalies
JEL Classification: G02, G12, G14

*E-mail: d.bathia@qmul.ac.uk
†E-mail: don.bredin@ucd.ie **Corresponding author:** Deven Bathia, School of Business and Management, Queen Mary University of London, London E1 4NS, U.K.

1 Introduction

The static capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) assumes that a stock beta remains constant over time. However, it may be difficult to rely on this implausible assumption, as stock's beta continuously changes over a period of time due to the dynamic nature of the economy, as well as the nature of information available to investors. Furthermore, the CAPM argues that securities' systematic risk alone can explain its expected returns. However, the CAPM assumption was later invalidated by Fama and French (1992) who find a 'flat' relationship between market beta and average returns. Previous studies have shown that firm specific factors also play a significant role in explaining expected stock returns. Some of these factors that are considered to explain average stock returns are firm size (Banz (1981), Chan et al. (1985), Chan and Chen (1988)), earnings yield (Basu (1977), Ball (1978)), book-to-market ratio (Rosenberg et al. (1985), Chan et al. (1991), Fama and French (1992)), dividend yield (Litzenberger and Ramaswamy (1979)), and leverage (Bhandari (1988)). Several studies have shown that time-varying beta versions of multi-factor models can significantly capture the impact of firm pricing anomalies. Ferson et al. (1987) test asset pricing model where they allow expected risk premium and market betas to vary over time. They note that conditional models outperform unconditional models in capturing dynamics of factor loadings. Avramov and Chordia (2006) show that the time-varying beta version of the Fama-French model captures the predictive ability of size and book-to-market ratio.[1]

Previous studies have attributed security mispricing to irrational behaviour of investors. For instance, the presence of investors' under-reaction and overreaction are cited as main reasons for securities mispricing (De Bondt and Thaler (1985, 1987), and Barberis et al (1998)). Furthermore, Black (1986) and De Long et al. (1990) note that investors trade on 'noise' rather than fundamentals, resulting in securities mispricing. Using different firm-level proxies for noise trading, Antoniou et al. (2016) find that when sentiment is high, noise traders are relatively more bullish and active for high beta stocks. The presence of uninformed demand shocks and limits to arbitrage were highlighted as potential explanations for securities mispricing (e.g. Brown and Cliff (2005) and Baker and Wurgler (2007)). Furthermore, Baker and Wurgler (2006) find that stocks that have subjective valuations and are difficult to arbitrage mostly tend to be small, young, highly volatile, unprofitable,

[1]Also see Hansen and Richard (1987), Guo (2006) and Li (2007), who show that conditional models are better than unconditional models in explaining asset pricing anomalies.

non-dividend paying, extreme growth and distressed stocks, and these stocks are main victims of investor sentiment. By constructing sentiment indices for six major stock markets and global markets as a whole, Baker et al (2012) find that both global and local sentiment are contrarian predictors of the time-series of cross-sectional returns within markets.[2] All of the above studies have, therefore, addressed the significance of investor sentiment in affecting security prices.

In this paper, we incorporate a comprehensive range of sentiment measures, as conditioning information, in different asset pricing models and determine whether it enhances the performance of these models. In other words, we assess the significance of various sentiment measures to determine whether it effectively captures the impact of the size, value, liquidity and momentum effects on risk-adjusted returns of individual stocks. The asset pricing models that we include in our study is the capital asset pricing model (CAPM), the Fama-French (1993) three-factor model (FF), FF model augmented with Pastor and Stambaugh (2003) liquidity factor (FFL), FF model augmented with momentum factor as explained by winners-minus-losers portfolio (FFM) and FF model augmented with liquidity factor and momentum factor (FFLM). In determining the significance of investor sentiment in asset pricing models, we adopt the two-pass regression framework of Avramov and Chrodia (2006). In the first pass, we run time-series regression of excess returns of individual stocks on the risk factors of asset pricing models. In doing so, we allow factor loadings to vary with conditioning variables. Besides different sentiment proxies, the other conditioning variables that we include in specifying time-varying betas are firm-level variables, represented by market capitalization and book-to-market ratio (B/M) (e.g. Lewellen (1999), Gomes et al. (2003)), and macro-economic variables, represented by default spread (e.g. Ferson and Harvey (1999), Lettau and Ludvigson (2001)). In the second pass regression, we run cross-sectional regression of risk-adjusted returns from the first pass regression, on the factors representing asset pricing anomalies. The risk-adjusted returns from the first pass regression is the sum of intercept and residuals. The variables representing asset pricing anomalies are firm size, measured by market capitalization; firm value, measured by book-to-market ratio; liquidity, measured by turnover; and momentum, measured by cumulative prior returns.

Ho and Hung (2009) determine the significance of survey based sentiment measure in

[2]Also see Stambaugh et al. (2012) who explore the role of investor sentiment in a broad set of anomalies in cross-section of stock returns. They observe that sentiment's predictive power is concentrated during the period of high sentiment.

conditional asset pricing models.[3] As a proxy for survey sentiment measure, they include consumer confidence index of the University of Michigan surveys of consumers, individual investor sentiment index of the American Association of individual investors (AAII) and institutional investor sentiment index of the Intelligence Investors (II). The predictive ability of survey based sentiment measure on future stock returns have been explored by many studies. These studies have shown positive (negative) association between consumer confidence index, measured by the UMCC index and concurrent (future) stock returns (e.g. Lemmon and Portniaguina (2006), Schmeling (2009), etc). However, a number of studies have cast doubt on the predictive ability of survey based sentiment proxies. For instance, Fisher and Statman (2000) find that II sentiment index does not have any significant effect on future Standard and Poor equity returns.
footnoteSimilar findings were also observed by Solt and Statman (1988) and Clarke and Statman (1998). Furthermore, Ho and Hung (2009) do not consider removing business cycle variation from each of the three survey based sentiment proxies, suggesting that their composite sentiment index may not represent cleanest measure of investor sentiment.[4] Given the mixed findings of survey based sentiment measure in previous studies and the concern over Ho and Hung's (2009) sentiment index, we determine the significance of various indirect sentiment measures in asset pricing models.[5]

Specifically, we assess the significance of various indirect sentiment measures in capturing the impacts of size, value, liquidity and momentum effects on risk-adjusted returns of US individual stocks. The indirect sentiment measures included in our study are equity fund flow, IPO first day returns, IPO volume, closed-end fund discount, equity put-call ratio, dividend premium and percentage change in margin debt. These sentiment proxies are referred to as *indirect sentiment measure* as they are not directly observable, but instead are derived from market-based measure that reflects investors' behaviour (investors' optimism or pessimism). These measures reflect investor's behaviour in real time; unlike consumer surveys, refereed to as *direct sentiment measure*, which are based on consumers' expectations. We also determine whether a composite sentiment index, constructed using principal component analysis (PCA), plays any significant role in capturing any of the

[3]The survey sentiment measures are referred to as *direct measure* of investor sentiment as they are readily observable and are directly derived from the responses to consumer survey questionnaire.

[4]In their composite sentiment index construction, Baker and Wurgler (2006) remove business cycle variation from each of the six raw sentiment proxies using first principal component analysis.

[5]Also see Poti and Shefrin (2014) who show that sentiment augmented consumption CAPM helps to reconcile investors' optimizing behaviour with the cross-section of average stock returns.

market anomalies.

Our paper contributes to the existing literature in the following areas. First, we expand the set of sentiment proxies, to be included as conditioning information, in an asset pricing setting. To our knowledge, this is the first study that incorporates a range of indirect sentiment measures, as conditioning variables, in different asset pricing models to determine its significance in capturing firm pricing attributes. As a measure of investor sentiment, we include various market based sentiment measures that reflects investors' optimism or pessimism. These include, equity find flow (EFF), IPO first day returns (IPOR), IPO volume (IPOV), closed-end fund discount (CEFD), put-call ratio (PCR), dividend premium (DP), change in margin debt (MD), and sentiment index, constructed from the above seven proxies using first PCA. Previous studies have assessed the significance of various indirect sentiment measures and its relationship with stock returns, and have found that positive sentiment generally results into concurrent positive returns and subsequent negative returns (e.g. Baker and Wurgler (2006), Bathia and Bredin (2013), etc). We determine the significance of these indirect sentiment measures in asset pricing framework to see whether it improves the performance of the asset pricing models. Second, we attempt to determine the significance of various sentiment measures by including them as conditioning information in different asset pricing models. Specifically, we attempt to determine the significance of various sentiment measures in enhancing the performance of the conditional versions of the CAPM, FF, FFL, FFM, and FFLM model. In particular, we seek to determine the extent the role of each sentiment measure is relevant when it enters into beta conditioning process with risk factors of different asset pricing models. Third, our findings will highlight the significance of different sentiment measures and the role in capturing asset-pricing anomalies. A number of sentiment proxies (e.g. closed-end funds, equity fund flow, etc) have been considered controversial in behavioural finance literature (see Lee et al. (1991), Warther (1995), Bathia and Bredin (2013), etc). Our findings will shed light on their significance as sentiment measures further implying whether its inclusion in asset pricing models can capture asset-pricing anomalies. Finally, we consider a range of sentiment proxies as well as sentiment index in our study, our findings will facilitate the comparison and performance of different measures in improving the performance of asset pricing models.

Our findings show that the sentiment augmented asset pricing models captures the impact of the size, value, liquidity and momentum effects on cross-section of risk-adjusted returns. Although previous studies have shown that the conditional models often fail to capture the impact of liquidity and momentum effects (e.g. Avaramov and Chordia (2006)), our results show that the sentiment augmented asset pricing models successfully captures the impact of both liquidity and momentum effects on the risk-adjusted returns. Our findings of sentiment augmented conditional CAPM show that the size effect is captured for all sentiment proxies (except for PCR). Similarly all sentiment proxies except EFF captures the impact of value effect on risk-adjusted returns. However, only CEFD, PCR and dividend premium explains both liquidity and momentum effect on risk-adjusted returns. Furthermore, when each of the EFF, IPOR and PCR along with firm-specific characteristics and default spread are included in specifying time-varying betas, sentiment augmented conditional FF model captures all anomalies. Furthermore, when only the sentiment variable enters into beta scaling process in conditional FFL model, size effect is effectively captured by all sentiment proxies.

The inclusion of PCR and the sentiment index as conditioning information effectively explains asset pricing anomalies. When we incorporate investor sentiment in the Fama-French (1993) three factor model, we find that liquidity and momentum effect is captured for all sentiment variables. Furthermore, equity fund flow, investor survey and sentiment index display their prominence in explaining predictive power of firm pricing attributes. Similarly, when FF model is augmented with Pastor and Stambaugh (2003) liquidity factor, we find that the impact of the momentum effect on the risk-adjusted returns is captured for all sentiment proxies. The inclusion of PCR in specifying time-varying betas of Fama-French three factor model augmented with momentum factor (FFM) successfully explains momentum effect for all beta specifications. The results of the conditional FFLM model are qualitatively similar relative to the earlier models. In all, we note that sentiment augmented conditional models successfully captures the impact of the size, value, liquidity and momentum effects on risk-adjusted returns. The rest of the paper is structured as follows. In section 2 we discuss the relevant literature followed by the discussion of methodology in section 3. We provide the description of data in section 4. Section 5 discusses the empirical results followed by conclusion in section 6.

2 Literature Review

2.1 Asset Pricing

The CAPM argues that securities' systematic risk alone can explain its expected returns. The static CAPM assumption was, however, invalidated by Fama and French (1992), who found a 'flat' relationship between market beta and average returns. Besides, the systematic risk factor, previous studies have also shown that firm-specific variables play a significant role in explaining average stock returns. Some of these factors include firm size, book-to-market ratio, earnings yield, dividend yield, leverage, etc to name a few.[6] Fama and French (1993) in its three-factor model, show that the firm size (market capitalization) and firm value (book-to-market ratio) play a significant role in capturing cross-sectional variation in average stock returns.[7] Furthermore, Fama and French (1996) highlight the significance of multi-factor models in explaining the returns of portfolios formed on earnings/price, cash flow/price and sales growth. However, the CAPM and Fama and French (1993) three-factor model failed to explain asset-pricing anomalies associated with the momentum effect as shown by Jegadeesh and Titman (1993, 2001) and Grundy and Martin (2001). Furthermore, previous studies have also explored the significance of difference measures, as risk factors, in explaining anomalies (e.g. liquidity factor (Pastor and Stambaugh (2003)), downside risk factor (Post and Vliet (2006)), etc).

The failure of static CAPM in accounting for risk dynamics across individual stocks, led academics to consider conditional asset pricing models in explaining firm pricing anomalies. In these models, factor loadings are allowed to vary over time. In specifying time-varying betas, previous studies have considered firm specific variables, for example book-to-market ratio, dividend yield, market capitalization, etc (Lewellen (1999)), and variables related to business cycle conditions, for example, default spread, consumption-wealth ratio, etc (Lettau and Ludvigson (2001)). Jagannathan and Wang (1996) study the ability of the conditional CAPM in explaining the cross-sectional variation in average returns of stock portfolios and found that the conditional models perform substantially better than the static model. Furthermore, Avramov and Chordia (2006) examine the empirical performance of conditional CAPM where they allow factor loadings to vary with the conditioning information. They apply conditional framework to single securities rather than to the large numbers of stock portfolios. They observe that the time-varying betas efficiently captures size and value effects.[8] We, therefore, consider conditional asset pricing models in our study, where we scale factor loadings with firm specific variables (size and book-to

[6]See Basu (1977), Banz (1981), Rosenberg (1985), Bhandari (1988), Litzenberg and Ramaswamy (1979) for detailed discussion and significance of these variables in explaining the average stock returns.

[7]The significance of three-factor model in explaining industry returns was shown by Fama and French (1997).

[8]Also see He et al. (1996), Ferson and Harvey (1999), Gomes et al. (2003), Wang (2003), who show that conditional models outperform unconditional models in explaining stock returns.

market ratio) and macro-economic variable (default spread), besides investor sentiment. The different conditional specifications considered in our analysis are discussed later in methodology section.

2.2 Investor Sentiment

Previous studies have identified several measures which reflect sentiment of investors. Some of these proxies are widely accepted as sentiment measures by industry experts (e.g. equity fund flow, percentage change in margin debt, etc), which for some, there still exists controversy (e.g. closed-end fund discount, etc). In our conditional asset pricing framework, we study the significance of sentiment proxies in capturing the impacts of the size, value, liquidity and momentum effects of risk-adjusted returns.

We include equity fund flow as a measure of investor sentiment. Previous studies have found mixed evidence for this sentiment measure. These studies point to the positive association between concurrent fund flow and stock returns as either a price pressure effect or an information effect (e.g. Warther (1995), Edelen and Warner (2001)). However, few studies have found evidence of price pressure effects, in that increases in fund flow results in increases in concurrent stock returns, and price reversals in subsequent months (e.g. Bathia and Bredin (2013)).[9] Furthermore, Brown et al. (2003) show that daily mutual fund flow can be considered as an instrument of investor sentiment. Frazzini and Lamont (2006) use mutual funds flows as a measure of investor sentiment, and find that high sentiment predicts lower future returns, and growth stocks tend to be main victims of high sentiment.

As a proxy for small investor sentiment, we include closed-end fund discount (CEFD). This measure continues to remain popular, although controversial amongst academics. There remains very little consensus on whether the discount on closed-end funds, the percentage difference between funds NAV and funds share price, can be considered as measures of investor sentiment. As fixed number of shares are issued in the closed-end fund, the fund NAV should be equal to fund share price. However, Weiss (1989) have shown that the closed-end funds start trading at an average of 10 percent discount within 120 days of trading. Furthermore, Lee et al. (1991) show that when CEFD is high (low), investors are pessimistic (optimistic) about the future returns. However, these findings were subsequently challenged by several authors (for example Chen et al. (1993), Elton et

[9] Bathia and Bredin (2013) note that the causality running from the equity fund flow to returns for value stocks and overall market is due the price pressure effect.

al. (1998), etc). We determine the significance of the CEFD by including it as a conditional variable in specifying time-varying beta.

Previous studies have also shown that the information contained in non-price derivative measure can be helpful in determining prevailing sentiment levels in the stock markets. Some of these measures include open interest, volatility index (VIX) and equity put-call ratio (PCR). Studies by Easely et al. (1998) and Pan and Poteshman (2006) show that information contained in options volume are useful in determining future stock prices. Ahoniemi (2008) find that ARIMA (1, 1, 1) model augmented with GARCH errors helps in forecasting directional change in the VIX by up to 58.5%.

Numerous trading indicators are often considered to reflect sentiment levels of investors. Some of these measures include trading volume, percentage change in short interest, percentage change in margin debt, etc. These measures have been included in previous studies to determine its effect on stock returns (Brown and Cliff (2004)). In our study, we include the percentage change in margin debt. The increase in margin debt is often considered as a bullish indicator since investors' rely heavily on margin debt when they perceive excessive optimism about the future economy. Baker and Wurgler (2006, 2007) consider 'dividend premium' as a measure of sentiment, as they note that it helps to assess the relative demand of an investors for dividend paying stocks.[10] Similarly, IPO first day average returns are associated with investors' enthusiasm, as previous studies have shown that IPO are mostly underpriced.[11] Similarly, IPO volume is often considered to be a measure of sentiment, due to the presence of phenomenon which is often termed as "hot-issue" markets. Previous studies have shown that IPO activity usually happens during boom times or when investor sentiment is high.[12]

In our sentiment-augmented conditional asset pricing study, we include all of the above measures in isolation and also construct composite sentiment index using first principal component analysis (PCA). The data source of different sentiment measures as well as description of sentiment index construction is discussed later in data section.

[10]Baker and Wurgler (2004) define 'dividend premium' as the difference between the average market-to-book ratio of dividend payers and non-payers. They show that dividend non-payers tend to pay dividends when demand from investors is high and tend to avoid paying dividend when demand is low.

[11]See Ritter (2003) and Ljungqvist (2006) for detailed explanation of IPO underpricing.

[12]Also see Ritter (1991) and Ibbotson and Ritter (1995) for detailed discussion of the IPO and relevant literature.

3 Methodology

In assessing the significance of different sentiment measures, as conditioning variables, in explaining asset pricing anomalies, we extend the two-pass regression framework of Avramov and Chordia (2006). In the first pass regression, we regress excess stock returns on the asset pricing factors where we allow factor loadings to vary conditionally over time. In the second pass regression, we run cross-sectional regressions of the risk-adjusted returns, which is the sum of the pricing error and the residual from the first pass regression, on the firm characteristics of size, book-to-market ratio, and other variables that represent liquidity (turnover) and momentum effects (cumulative prior returns). The conditional framework for testing sentiment-augmented asset pricing models is explained below.

Under the conditional framework of K-factor model, returns for security i is given by,

$$[R_{it} \mid I_{t-1}] = R_{ft} + \Sigma_{k=1}^{K}\gamma_{kt-1}\beta_{ikt-1} \tag{1}$$

where, R_{it} is return on stock i at time t, I_{t-1} is the common information available to an investors at *t-1*, R_{ft} is the risk-free rate, γ_{kt-1} is the risk premium for factor K at *t-1*, and β_{ikt-1} is the conditional beta of asset i corresponding to factor K at *t-1*. We run on the risk premium of the K[th] factor in the first pass regression, where the excess return on security i is regressed on risk premium of Kth factor and conditional beta.

$$[R_{it} \mid I_{t-1}] - R_{ft} = \alpha_i + \Sigma_{k=1}^{K}\gamma_{kt-1}\beta_{ikt-1} + \epsilon_{it} \tag{2}$$

where, $[R_{it} \mid I_{t-1}] - R_{ft}$ is excess return of stock i, α_i is the intercept of asset i, γ_{kt-1} is risk premium for factor K at *t-1*, β_{ikt-1} is scaled beta for factor K at *t-1* and ϵ_{it} is the residual error of asset i at time t. We then run the second pass regression, where we regress estimated risk-adjusted returns from the first pass regression on the firm characteristics of size and book-to-market ratio as well as variables representing liquidity and momentum effects. The general form of second-pass regression framework is given by:,

$$R_{it}^{*} \equiv R_{it} - [R_{ft} + \beta(\theta; s_{t-1}, f_{t-1}, m_{it-1})' X_t] \tag{3}$$

$$R_{it}^{*} = \alpha_{0t} + \beta_t^{*} Y_{it-1} + e_{it} \tag{4}$$

where, R_{it}^{*} is the estimated risk-adjusted return of stock i at time t and is the sum of pricing errors (intercept) and residual, both obtained from the first-pass regression as per different specification explained later in this section. θ represent the parameters that captures the dependence of β on investor sentiment, s_{t-1}, firm specific characteristics (size and book-to-market ratio), f_{it-1}, and macro-economic variable (default spread), m_{t-1}. X_t represents vector of risk factors specified in the asset pricing model. Y_{it-1} includes all the factors that represents size, value, liquidity and momentum effects. Since the null hypothesis of exact pricing should successfully capture asset pricing anomalies in the first pass time-series regression, we expect to find the factor loadings, represented by β_t^* in equation 4, to be statistically no different from zero. In specifying firm characteristics variables, we use lagged value at one period (*t-1*) so as to account for bid-ask effects and thin trading, due to possible biases of the risk-adjusted returns.

We model the beta (β) in the first-pass regression into four different specifications discussed below. The conditional beta equation is given by,

$$\beta_{i,t-1} = f(z_{t-1}) \tag{5}$$

$$\beta_{i,t-1} = \beta_{i,0} + \beta_{i,1}(z_{t-1}) \tag{6}$$

where, $\beta_{i,t-1}$ is the conditional beta to be modelled, and $f(z_{t-1})$ is the function of all 'z' exogenous variables at t-1. In our conditional asset pricing framework, we condition beta as a function of sentiment measure (s_{t-1}), macro-economic variable (default spread, (m_{t-1})) and firm characteristics (($size_{t-1}$) and (B/M_{t-1})). As noted before, the justification for specifying macro-economic variable and firm specific variables is derived from the pervious studies (e.g. Lewellen (1999), Lettau and Ludvigson (2001)). The conditional beta can then be expressed in the following form,

$$\begin{aligned} \beta_{i,t-1} = \ & \beta_{i,0} + \beta_{i,1}(s_{t-1}) + \beta_{i,2}(m_{t-1}) + \beta_{i,3}(m_{t-1})(s_{t-1}) \\ & +(\beta_{i,4} + \beta_{i,5}(s_{t-1}) + \beta_{i,6}(m_{t-1}))size_{i,t-1} \\ & +(\beta_{i,7} + \beta_{i,8}(s_{t-1}) + \beta_{i,9}(m_{t-1}))B/M_{i,t-1} \end{aligned} \tag{7}$$

The following four specifications are implemented for modeling beta with conditioning variables:

Specification A: function of (size + B/M) and s [i.e. $\beta_{i,2} = \beta_{i,3} = \beta_{i,6} = \beta_{i,9} = 0$]
Specification B: function of m and s [i.e. $\beta_{i,4} = \beta_{i,5} = \beta_{i,6} = \beta_{i,7} = \beta_{i,8} = \beta_{i,9} = 0$]
Specification C: function of s [i.e. $\beta_{i,2} = \beta_{i,3} = \beta_{i,4} = \beta_{i,5} = \beta_{i,6} = \beta_{i,7} = \beta_{i,8} = \beta_{i,9} = 0$]
Specification D: function of all variables; s, m, size and B/M [i.e. all $\beta \neq 0$]

We also test for unconditional case for each model, where we do not incorporate sentiment measures, firm characteristics (size and B/M) and macro-economic variable. We illustrate first pass regression using conditional beta for a single factor CAPM. For instance, the first-pass regression of Specification D of the CAPM will be given by,

$$\begin{aligned} R_{it} - R_{ft} = \alpha_i + \gamma_t[\beta_{i,0} + \beta_{i,1}(s_{t-1}) + \beta_{i,2}(m_{t-1}) + \beta_{i,3}(s_{t-1})(m_{t-1}) \\ +(\beta_{i,4} + \beta_{i,5}(s_{t-1}) + \beta_{i,6}(m_{t-1}))size_{i,t-1} \\ +(\beta_{i,7} + \beta_{i,8}(s_{t-1}) + \beta_{i,9}(m_{t-1}))B/M_{i,t-1}] + \epsilon_{i,t} \end{aligned} \tag{8}$$

$$\begin{aligned} R^*_{it} = \alpha_i + \beta_{i,0}\gamma_t + \beta_{i,1}(s_{t-1})\gamma_t + \beta_{i,2}(m_{t-1})\gamma_t + \beta_{i,3}(m_{t-1})(s_{t-1})\gamma_t \\ +\beta_{i,4}SIZE_{i,t-1}\gamma_t + \beta_{i,5}(s_{t-1})SIZE_{i,t-1}\gamma_t + \beta_{i,6}(m_{t-1})size_{i,t-1}\gamma_t \\ +\beta_{i,7}B/M_{i,t-1}\gamma_t + \beta_{i,8}(s_{t-1})B/M_{i,t-1}\gamma_t + \beta_{i,9}(m_{t-1})B/M_{i,t-1}\gamma_t + \epsilon_{i,t} \end{aligned} \tag{9}$$

where, R^*_{it} is excess return over and above the risk-free rate $(R_{it} - R_{ft})$, γ_t is excess market return at time t over and above the risk-free rate (market risk premium).

We implement Fama-Macbeth (1973) approach in estimating the precision of cross-sectional regression (CSR) estimates. To account for error-in-variable bias as a result of Fama-Macbeth CSR, we implement the corrections proposed by Shanken (1992).[13]

4 Data

4.1 Market Data

The main dataset consists of monthly equity data for all the equity shares listed on the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX). The data is sourced from the Center for Research for Security Prices (CRSP) and COMPUSTAT database. In our analysis, we only consider common shares (CRSP share code 10 and 11) for the period January 1980 through December 2014. Given the lack of sentiment data pre-1980 and the significant survivorship bias in pre-1980 COMPUSTAT data, our sample starts from 1980.[14] This gives us about 420 monthly observations. The common stock should satisfy

[13] We do not report the corrections of Jagannathan and Wang (1998) as they show that with the assumptions of conditional heteroskedasticy, Fama-MacBeth (1973) t-statistics calculation procedure does not necessarily understate the standard errors of the estimates. To follow conservative approach, we therefore report Shanken (1992) corrections, besides Fama-MacBeth estimates.

[14] It is widely acknowledged that survivorship-bias exists in COMPUSTAT's pre-1978 data. For example, Davis (1994) notes the 1963-1978 period to be a period where Compustat data is more suspectible to survivorship bias. Also see Kothari et al. (1995) who provide a detailed assessment of Compustat's selection procedure.

the following criteria in order to be included in our analysis. First, the returns data for the current month t and previous 36 months should be available from the CRSP. Second, sufficient data on stock price and common shares outstanding should be available in order to compute size, which is measured by market capitalization. Third, sufficient data on *t-2* trading volume should be available so as to compute turnover (T/O). Fourth, sufficient data should be available from COMPUSTAT for computing book-to-market (B/M) ratio as of December of previous calendar year. Following Fama and French (1992), the value of B/M for July of year t to June of year *t+1* is computed using accounting data at the end of calendar year *t-1*. The B/M ratio greater than 0.995 fractile or less than 0.005 fractile is set as 0.995 and 0.005 respectively. We drop all the firms that have negative B/M ratio.

After this screening process, we arrive at the total of 3,567 common stocks. In running cross-sectional regressions, we consider natural logarithmic transformation of all our monthly variables (except turnover and cumulative past return). For instance, size, which is measured by market capitalization (measured in billion of dollars), is the natural logarithm of the market capitalization of an individual firm. Similarly, B/M is the logarithmic transformation of the book-to-market ratio. Turnover, which is a measure of liquidity, is determined by dividing trading volume by number of shares outstanding. To proxy for momentum, we calculate Ret 2-3, Ret 4-6 and Ret 7-12, which is cumulative returns over the past second through past third months, past fourth through past sixth month and past seventh through the past twelfth months respectively. As a proxy for market returns, we consider CRSP value-weighted returns including distributions and one month T-Bill rate as a proxy for risk-free rate. The Fama-French factors, small-minus-big (SMB) and high-minus-low (HML), and momentum factor are sourced from Kenneth French data library.[15] The proxy of Pastor and Stambaugh's non-traded liquidity factor, which is the difference between value-weighted average return on stocks with high sensitivities to liquidity less the value-weighted average return on stocks with low sensitivities to liquidity, is sourced from Lubos Pastor's research homepage.[16]. We include default spread as a proxy for the macroeconomic variable. Default spread is measured by taking the differences in yield between Moody's BAA and AAA corporate bonds (data taken from the Board of Governors of the Federal Reserve System).

Table 1 reports the summary statistics of time-series averages of cross-sectional means

[15] Prof. French data library is available at, `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

[16] `http://faculty.chicagobooth.edu/lubos.pastor/research/`

and standard deviation for 3,567 NYSE-AMEX stocks for the period January 1980 to December 2014. The fourth and fifth column labeled coefficients and t-values are Fama Macbeth coefficients and t-values derived from running cross-sectional OLS regression of excess returns on the firm specific variables (size and B/M), turnover and cumulative prior returns. The negative and statistically significant coefficient for size and positive and statistically significant coefficient of B/M ratio indicate that small firms and the firms that have high B/M ratio earn higher excess returns, the finding consistent with the previous studies (Avramov and Chordia (2006), Brennan et al. (1998), etc). We get statistically significant negative coefficients for turnover, further indicating that firms with lower liquidity earn higher excess returns. Furthermore, we also obtain positive and significant coefficient estimates for cumulative prior returns suggesting that prior returns are positive related to excess returns, the finding which is in consistent with the momentum phenomenon highlighted by Jegadeesh and Titman (1993).

4.2 Investor Sentiment Data

We determine whether the eight different sentiment measures when included in the conditioning set can explain the predictive ability of size, book-to-market, turnover, and cumulative past return. The equity fund flow data (EFF) is obtained from the Investment Company Institute. Following Indro (2004), we compute equity fund flow as a percentage of total equity fund assets. We source Margin Debt data (MD) from NYSE Factbook and the equity options volume data from the Chicago Board of Options Exchange. Following Pan and Poteshman (2006), we calculate put-call ratio (PCR) as put volume divided by total equity options volume (put and call volume). IPO volume (IPOV) and IPO average first day returns (IPOR) are sourced from Jay Ritter's data library and dividend premium (DP) and closed-end fund discount data (CEFD) are sourced from from Prof Jeffery Wurgler web page.[17].

As each individual sentiment proxy may include both sentiment and non-sentiment, idiosyncratic component, we first use principal component analysis (PCA) to isolate the sentiment component. Before constructing a sentiment index, we remove business cycle variation from each of these proxies, where we regress each raw sentiment variable on five

[17]The data from Jeffery Wurgler webpage can be accessed at `http://people.stern.nyu.edu/jwurgler/`, whereas data library of Prof Jay Ritter can be accessed at `http://bear.warrington.ufl.edu/ritter/ipodata.htm`

macro-economic variables and use the residuals from the regression in the principal component analysis (PCA). These residuals can, therefore, be considered as a cleaner measure of investor sentiment.[18] The five macro-economic variables on which raw sentiment proxies are regressed on are the change in consumer durables, consumer non-durables, consumer services (data obtained from the U.S. Department of Commerce, Bureau Economic Analysis), dummy variable for NBER recession, and change in industrial production (data obtained from the Board of Governors of the Federal Reserve System).

The resulting index of the orthogonalized sentiment proxies using PCA is of the following form:

$$\begin{aligned} SENT_t &= 0.4399 FundFlow + 0.3332 IPOReturns + +0.4425 IPOVolume \\ &+0.4002 CEFD - 0.4312 PCR - 0.3114 DivPremium + 0.2380 MarginDebt \end{aligned} \tag{10}$$

where $SENT_t$ represents the composite sentiment index. The resulting sentiment index (IND, henceforth) is constructed after standardizing each sentiment proxies. This index constructed from the first principal component explains 42% of the total standardized variance of the orthogonalized proxies.

5 Empirical Results

In discussing the results for each model, we will look at the significance of Fama-Macbeth coefficient obtained from running the second pass cross-sectional OLS regression.[19] As noted before, the null hypothesis of exact pricing should successfully capture pricing anomalies in the first pass time series regression. Therefore, the coefficients obtained in the second pass cross-sectional OLS regression should be insignificant. However, if the obtained Fama-Macbeth coefficient in the second pass cross-sectional OLS regression is significant, it indicates that the pricing anomaly variables (size, value, liquidity and momentum) are related to the cross-section of risk adjusted returns. We also compare the magnitude of adjusted R^2 obtained in the unconditional case for all the models in our study with the conditional case. The lower adjusted R^2 and insignificant coefficient will indicate the efficacy of the model. Furthermore, if this holds true for conditional models, then it indicates

[18] The approach that we adopt is similar to Baker and Wurgler (2006). They construct their sentiment index using six sentiment variables, viz. CEFD, IPO first day returns, IPO volume, dividend premium, NYSE share turnover and the equity shares in new issues for the period 1961 to 2005.

[19] To account for error-in-variable bias from running the cross-sectional OLS regression, we also report Shanken (1992) corrected t-values, besides Fama-Macbeth t-values.

that the conditional models outperform unconditional models in capturing the firm pricing anomalies. We discuss our findings for unconditional models and each of the five conditional models in the following subsection.

5.1 Unconditional models

The results for each of the five unconditional asset pricing models are presented in table 2. In this table, we report Fama-Macbeth coefficients and its respective t-values from running the cross-sectional OLS regression of the monthly risk-adjusted returns of individual stocks on the variables representing firm characteristics (size and B/M), and liquidity (turnover) and momentum (cumulative past returns: Ret 2-3, Ret 4-6 and Ret 7-12) effects. The results of the conditional CAPM is reported in table 3.

In the case of unconditional CAPM, we find that the firms with small market capitalization, high B/M ratio, low T/O and high prior returns provide higher risk-adjusted excess returns. Our results suggest that the unconditional CAPM fails in capturing asset pricing anomalies. In the case of Fama-French three factor model, we again obtain significant coefficient estimates for all pricing anomalies. Although the coefficient estimates are qualitatively similar to that of unconditional CAPM, they are relatively lower in absolute terms (e.g. in the case of book-to-market ratio, it is 0.12 as opposed to 0.14). Our findings of the three factor model are consistent with the unconditional CAPM regarding the validity of the model. The findings, therefore, suggest the failure of three factor model in its ability to explain predictive power of equity characteristics. The addition of SMB and HML risk factors, in addition to excess market returns, however result in a marginal decrease in the adjusted R^2 from 4.11% of the unconditional CAPM to 4.06% of the unconditional FF model. This indicates that the FF model are slightly relatively better than the CAPM in explaining risk adjusted returns.

The similar findings were also observed in the case of the unconditional FFL model, where we add Pastor-Stambaugh (2003) liquidity factor.[20] We again obtain significant coefficient estimates. These estimates are qualitatively similar relative to that of the unconditional CAPM and FF model. However, the updated estimates are more significant at least in the case of turnover and prior returns. Furthermore, the overall explanatory

[20] We augment the three factor model with Pastor and Stambaugh's (2003) liquidity factor which is the difference between value-weighted average returns on stocks with high sensitivities to liquidity less value-weighted average returns on stocks with low sensitivities to liquidity.

power, adjusted R^2, of the unconditional FFL model is nearly the same as that of three factor model (i.e. 4.07% as oppose to 4.06%) indicating that the inclusion of liquidity factor does not contribute much in explaining the predictive power of equity characteristics.[21] Furthermore, we augment Fama-French three factor model with the momentum factor, commonly used factor on the basis of past returns, to determine its significance in explaining asset pricing anomalies. The momentum factor represents momentum strategy of buying winners and selling losers as shown by Jegadeesh and Titman (1993). The findings of the unconditional FFM model is again qualitatively similar to that of the earlier models discussed above. We again obtain significant coefficient estimates, however the coefficient estimates are relatively smaller in absolute values than that of the other three model discussed above (i.e. CAPM, FF and FFL). Furthermore, the adjusted R^2 of the unconditional FFM model is lower than the CAPM, FF and FFL model (i.e. 4.04%). The lower adjusted R^2 shows that the FFM model is relatively better than the unconditional versions of the CAPM, FF and FFL model in capturing predictive power of firm attributes. We also augment the FF model by including both liquidity and momentum factors (FFLM). The findings of the FFLM model is relatively similar to that of FFM model. Although there is a slight improvement in significance levels, coefficient estimates are relatively similar in absolute terms. Furthermore, the adjusted R^2 remains the same as that of FFM model (i.e. 4.04%). In all, it seems that by adding liquidity factor to the FFM model doesn't really add value in explaining cross-section of risk-adjusted returns, and it also fails in capturing any of the market anomalies.

5.2 Conditional capital asset pricing model (CAPM)

The results of the conditional CAPM is reported in table 3. All sentiment proxies including sentiment index are highlighted in the first column. The corresponding Fama-Macbeth coefficient estimates are determined for four anomalies (size, book-to market, turnover and prior returns) for four different specification (A, B, C and D), and are reported in the first row for each of the eight proxies for investor sentiment. For each coefficient estimates, we report both Fama-Macbeth t-values (fmb) and Shanken (1992) corrected t-values (shk) in the second and third row respectively. The adjusted R^2 for each sentiment proxy and for each specification is reported in the fourth row under size anomaly.

In our single factor conditional CAPM, we find that size effect is effectively captured

[21] Also see Avramov and Chordia (2006) who observe similar findings.

for all sentiment proxies (except PCR) when beta is scaled by investor sentiment and macro-economic variable (spec B). Furthermore, the size anomaly is captured for all specifications when IPOR and margin debt enters into beta conditioning process as we obtain insignificant coefficient estimates. We also observe that the conditional CAPM successfully captures the value effect for all sentiment measures except for equity fund flow. For instance, by conditioning beta on default spread and PCR (spec B) captures value effect on risk-adjusted returns of individual stocks. When we include sentiment measure along with firm-specific characteristics and default spread (spec D) into beta scaling process, we obtain insignificant coefficient estimates for all sentiment measures, except for EFF, CEFD and DP. Furthermore, we find that three sentiment proxies, viz. CEFD, PCR and dividend premium, play a significant role in capturing liquidity and momentum effect on risk-adjusted returns. For instance, when excess market returns are scaled by firm characteristics (size and B/M), default spread and CEFD (spec D), we obtain negative and insignificant estimates for turnover and positive and insignificant estimates for Ret 2-3 and Ret 7-12. We also obtain insignificant estimates for PCR for spec D and dividend premium for spec B. In all, we find that only CEFD and dividend premium play a significant role in capturing the impacts of all the market anomalies (i.e. size, value, liquidity and momentum).

Our findings are not consistent with that of Ho and Hung (2009) who observe that sentiment augmented conditional CAPM fails to capture the impacts of the value, liquidity and momentum effects on risk-adjusted returns of individual stocks. This difference is because they use direct measure of investor sentiment, investor survey, in beta conditioning process. It therefore seems that market based sentiment proxies do a better job in capturing pricing anomalies. Our findings are also not consistent with that of Avramov and Chrodia (2006) who find that the conditional CAPM fails to capture the impact of firm pricing attributes on risk-adjusted returns. We note that the difference in results is mainly due to the fact that Avramov and Chordia (2006) do not include investor sentiment as conditioning information in their asset pricing framework.

As noted earlier, we also look at the adjusted R^2 to determine the model efficacy in capturing the predictive power of firm attributes. The adjusted R^2 for specification B and C of sentiment augmented conditional CAPM is often relatively lower for most of sentiment proxies than that of unconditional CAPM (see table 2 and 3). Although the adjusted R^2 of specification B and C is marginally lower or similar for all sentiment proxies except for IPOR and IPOV, it is significantly lower for CEFD, PCR and dividend premium in the case of specification B (when beta is scaled by sentiment and default spread). For instance, the magnitude of the adjusted R^2 is significantly reduced from 4.11% for the unconditional CAPM (see table 2) to 2.45% for the CEFD (see spec B, table 3). Furthermore, when firm characteristics along with sentiment (spec A) and firm characteristics along with sentiment and default spread (spec D) enters into beta conditioning process, adjusted R^2 increases marginally for all sentiment proxies, except for PCR where we obtain marginally lower adjusted R^2 for specification (A and D). This finding might suggest that the inclusion of firm characteristics along with sentiment and default spread in the conditioning set do not add value in improving model efficiency, although it contributes in capturing market anomalies. Furthermore, the improvement in the adjusted R^2 for spec B and C suggest that the conditional models are relatively better than unconditional models in capturing the predictive power of firm attributes. In summary, we note that the inclusion of CEFD and dividend premium along with default spread (spec B) contributes in capturing size, value, liquidity and momentum effects on risk-adjusted returns of individual stocks.

5.3 Conditional Fama-French three factor model (FF)

The findings of the conditional FF model are reported in table 4. Our results show that the size effect is effectively captured when each of the eight sentiment measures enters into beta conditioning process. For instance, when beta is conditioned on either investor sentiment and default spread (spec B) or on only investor sentiment (spec C), size effect on risk-adjusted returns is explained for all sentiment variables except for PCR. In the case of PCR, the size effect is captured only when it enters into beta conditioning process along with the firm-specific characteristics and default spread (spec D). Furthermore, the value effect is captured when beta is conditioned on firm specific characteristics, default spread and sentiment (spec D) for EFF, IPOR and PCR.

The impact of the liquidity effect on the risk-adjusted returns is captured for all sentiment variables except for dividend premium and margin debt when beta is scaled by firm characteristics, default spread and sentiment (spec D). Interestingly CEFD is the only sentiment measure that explains liquidity effect for all specifications. Furthermore, we obtain insignificant coefficient estimates on prior returns for all of the eight sentiment proxies (except dividend premium) suggesting the fact that momentum effect is captured on the risk-adjusted returns of individual stocks. For instance, in the case of put-call ration for all specification (except spec A, Ret 4-6), we obtain insignificant estimates for prior returns. Our findings are not consistent with that of Avramov and Chordia (2006) who find that their conditional version of the FF model fails to capture the impact of the momentum effect on risk-adjusted returns. However, they do not include investor sentiment as conditioning variable in specifying time-varying beta. Our results, therefore, confirms the prominence of investor sentiment in capturing the momentum effect in the conditional FF model.

Previous findings on whether CEFD could be considered as as a measure of investor sentiment were mixed. For instance Lee et al. (1991) find that when CEFD is high (low), investors are pessimistic (optimistic) about the future returns.[22] However these findings were subsequently challenged by several studies.(e.g. Chen, Kan, and Miller 1993; Chordia and Swaminathan 1998; Elton et al. 1998). Given the fact that discount on closed-end funds continue to play a significant role in explaining size, value, liquidity and momentum effects on the risk-adjusted returns, we can safely assume that the discount on closed-end funds reflect the sentiment of investors.

We also find that the magnitude of the adjusted R^2 for both spec B and C decreases significantly to 2.16% and 2.34% respectively (in the case of CEFD) relative to 4.06% of the unconditional FF model (see table 2), therefore indicating the efficacy of the conditional FF models. This is true for all sentiment proxies (for spec B and spec C) except for the IPO volume in spec C. However, we observe marginal increase in the adjusted R^2 in the case of specification A and D for all sentiment proxies except for dividend premium. In all, we note the significance of equity fund flow, IPO first day returns and put-call ratio, when included as a conditioning variable, in capturing the impacts of the size, value, liquidity and momentum effects on risk-adjusted returns of individual stocks.

5.4 Conditional FF model augmented with the Pastor-Stambaugh liquidity factor (FFL)

Pastor and Stambaugh (2003) highlight that stocks with high liquidity betas earn higher average returns than stocks with low liquidity betas. We determine whether FF model augmented with liquidity factor contributes in capturing size, value, liquidity and momentum effects on risk-adjusted returns of individual stocks. The results of the FF model augmented with Pastor-Stambaugh's liquidity factor are reported in table 5. We find that conditioning beta on sentiment (spec C) captures the impact of the size for all sentiment

[22] Also see Neal and Wheatley (1998) who found that discount on closed-end funds to be positively related to small firm expected returns.

proxies. We observe the similar findings for all sentiment measures except for dividend premium when beta is conditioned on sentiment and default spread (spec B). We also find the prominence of the CEFD in capturing value effects on risk-adjusted returns as we obtain insignificant coefficient estimates for all specifications. However both CEFD as well as dividend premium fails to capture the turnover effect on risk-adjusted returns when included as a conditioning variable in the asset pricing specification. Our finding differs from that of Ho and Hung (2009) who find that their Fama-French three factor model augmented with Pastor and Stambaugh's (2003) liquidity factor fails to capture the liquidity effect on risk-adjusted returns. As noted earlier, this difference in finding is likely due to the fact that they use survey-based sentiment measure in their beta conditioning process. When beta is conditioned on firm-specific characteristics, sentiment and default spread (spec D), momentum effect is explained for sentiment proxies except for CEFD and dividend premium (see table 4, Ret 2-3 and Ret 4-6). However CEFD captures momentum effect in the case of specification C and D (see Ret 2-3).[23]

The adjusted R^2 reduces for all sentiment variables for spec B and C and all specifications in the case of PCR. When liquidity factor is conditioned only on PCR, the adjusted R^2 declines significantly to 2.54% as oppose to the unconditional case (i.e. 4.07%). However when beta is scaled on firm-specific characteristics and sentiment (spec A) and firm-specific characteristics, default spread and sentiment (spec D), we observe marginal increase in the adjusted R^2 for all sentiment proxies except for PCR and dividend premium. In all, we note that the EFF, IPOR, PCR and margin debt play a significant role in explaining pricing anomalies when included into beta conditioning process of FFL model.

5.5 Conditional FF model augmented with the momentum factor (FFM)

The results of the conditional FFM model are presented in table 6. We find that when EFF is included as a conditioning variable for all four specifications, it captures the impact of the size effect on risk-adjusted returns. However the inclusion of the IPOV and CEFD as conditioning variables do not contribute in explaining size effect as we obtain significant estimates. When conditioning beta on each of the eight sentiment variables except dividend premium along with firm-specific characteristics and default spread (spec D) does capture

[23]Avramov and Chordia (2006) find that their conditional FFL model fails to capture both liquidity and momentum effects on risk-adjusted returns of individual stocks.

the value effect on risk-adjusted returns. Similarly spec D captures liquidity effect for all sentiment proxies except CEFD. However when beta is conditioned by both CEFD and default spread (spec B) or by only CEFD (spec C), we obtain insignificant coefficient estimates for turnover, measure of liquidity. Furthermore, both CEFD and dividend premium, when included as a conditioning variable in all specifications, do not play any significant role in capturing momentum effect on risk-adjusted returns. However, put-call ratio is the only sentiment variable that captures the impact of past three-, six- and twelve month returns on the cross-section of returns. For all other sentiment variables, conditioning beta on firm-specific characteristics, default spread and sentiment (spec D) explain the predictive power of cumulative past returns.

We obtain lower adjusted R^2 for all sentiment variables for spec B and C, the finding similar to the conditional versions of CAPM, FF and FFL model. Although we see marginal increase in the adjusted R^2 for spec A and D for all sentiment proxies (except dividend premium) suggesting not so great improvement in conditional version of these two specifications, it indeed contributes in capturing most of the market anomalies.

5.6 Conditional FF model augmented with the liquidity and momentum factor (FFLM)

Finally, we add Pastor and Stambaugh (2003) liquidity factor and momentum factor to Fama-French three factor model (FFLM) to determine whether it captures the impact of size, value, liquidity and momentum effect on risk-adjusted returns. The FFLM is the most comprehensive model in our study, and it should capture most of the anomalies for the sentiment measures that failed to capture in the earlier models. The results of the conditional FFLM model are reported in table 7.

We find that the size effect is effectively captured for all sentiment proxies (except for dividend premium and IPOV). For instance, EFF, CEFD, PCR and margin debt play a significant role in capturing size effect for all specification. Furthermore, conditioning beta on firm-specific characteristics, default spread and sentiment (spec D) captures the impact of value effect for all sentiment proxies except EFF. For EFF, value effect is effectively explained by spec A and C. Similarly, the impact of liquidity effect on risk-adjusted returns is effectively captured by all sentiment proxies. Interesting, PCR continues to play a significant role over here. Its inclusion as a conditioning variable explains past two-three month returns, the finding similar to the FF and FFM model. Furthermore, beta spec D captures momentum effect for all sentiment measures (except CEFD and dividend premium). In the case of both CEFD and dividend premium, we obtain significant coefficient estimates for all asset pricing specification. These findings are similar to all the previous models studied except that of the conditional CAPM.[24] Could this be due to the fact that all sentiment proxies with the exception of dividend premium and CEFD are directly derived from market-based measure which represents collective behaviour of all investors. In the case of CEFD and dividend premium, their values are arrived at after taking into consideration both accounting measure as well as market-based measure. For instance, the discount on closed-end funds is calculated as a difference between fund's net asset value (NAV) and market price; whereas dividend premium takes into consideration both book-value as well as market value of dividend and non-dividend paying firms. The similar observation was also noted in the conditional versions of the FFL and FFM model. However it would be too premature to claim the above conclusively.

The adjusted R^2 declines marginally for specifications B and C for all sentiment proxies. The similar finding is observed across previous models suggesting that models where both sentiment and default spread (spec B) and only sentiment (spec C) are included as a conditioning variable successfully captures anomalies in most of the cases with relatively lower adjusted R^2. Furthermore, with the inclusion of firm-specific characteristics along with default spread and sentiment (spec D) contributes in capturing the impact of all anomalies in most of the case, however the adjusted R^2 increases marginally relative to unconditional models.

6 Conclusion

In this paper, we determine whether incorporating investor sentiment, as conditioning information, can help to capture the predictive ability of size, book-to-market ratio, turnover and cumulative past returns in explaining risk-adjusted returns of individual stocks. In assessing the predictive ability of these pricing attributes, we study the conditional case of the single factor CAPM, Fama-French three-factor (FF) model, FF model incorporated with Pastor and Stambaugh's liquidity factor, FF model incorporated with momentum factor, and FF model incorporated with liquidity and momentum factor. We adopt a single securities pricing framework, where in, we condition factor loadings in the first pass time

[24]The conditional CAPM successfully captures the impact of all the market anomalies when dividend premium along with default spread (spec B) is included in beta conditioning process.

series regression by incorporating investor sentiment along with the firm specific variables (size and book-to-market ratio) and macro-economic variable (default spread). To assess the efficacy of different asset pricing models, we regress risk-adjusted returns (the sum of alpha and residuals) obtained from the first pass time-series regression on the pricing attributes as measured by market capitalization, book-to-market ratio, turnover and past returns; variables representing size, value, liquidity and momentum effects respectively. We find that the conditional models outperform unconditional model in capturing the impacts of the size, value, liquidity and momentum effects on the risk-adjusted returns of individual stocks.

In particular, we observe that sentiment augmented conditional models often play a significant role in capturing predictive power of firm attributes. Specifically, conditioning beta on default spread and either CEFD or dividend premium in the case of CAPM explains predictive power of equity characteristics. The inclusion of EFF, IPOR and PCR as conditioning variable along with firm-specific characteristics and default spread contributes in capturing pricing anomalies in the case of FF, FFL, FFM and FFLM models. In addition to that, the inclusion of margin debt in specifying time-varying betas in FFL, FFM and FFLM model captures predictive power of equity characteristics. Furthermore, the significance of sentiment index in capturing the market anomalies is displayed in the conditional versions of both FFM and FFLM models.

As previous studies have shown that conditional models at its very least fail to capture the impact of turnover and momentum effects on the risk-adjusted returns (e.g. Avramov and Chordia (2006), etc), we find that sentiment-augmented conditional asset pricing models play a significant role in capturing the impacts of the size, value, liquidity and momentum effects on the risk-adjusted returns of individual stocks. In all, the conditional role of investor sentiment should not be ignored in explaining pricing anomalies as they certainly play a significant role in augmenting the performance of the asset pricing models.

References

[1] Ahoniemi, K., 2008. Modeling and Forecasting the VIX Index. Working Paper. Helsinki Centre of Economic Research.

[2] Antoniou, C., Doukas, J., and Subrahmanyam, A., 2016. Investor sentiment, Beta, and the Cost of equity capital. Management Science 62. 347-367.

[3] Avramov, D., and Chordia, T., 2006. Asset Pricing Models and financial markets anomalies. Review of financial studies 19. 1001-1040.

[4] Baker, M., and Wurgler, J., 2004. A Catering theory of Dividends. Journal of Finance 59. 1125-1166.

[5] Baker, M., and Wurgler, J., 2006. Investor Sentiment and the Cross-Section of Stock Returns. Journal of Finance 61. 1645-1680.

[6] Baker, M., and Wurgler, J., 2007. Investor Sentiment in the Stock Market. Journal of Economic Perspectives 21. 129-151.

[7] Baker, M., and Wurgler, J., and Yuan, Y., 2012. Global, Local, and Contagious Investor Sentiment, Journal of Financial Economics 104. 272287.

[8] Ball, R., 1978. Anomalies in relationships between securities' yields yield-surrogates. Journal of Financial Economics 6. 103-126.

[9] Banz, R., 1981. The relationship between returns and market value of common stocks. Journal of Financial Economics 9. 3-18.

[10] Barberis, N., Shleifer, A., and Vishny, R., 1998. A model of investor sentiment. Journal of Financial Economics 49. 307-343.

[11] Basu, S., 1977. Investment performance of cormnon stocks in relation to their price earnings ratios: A test of the efficient market hypothesis. Journal of Finance 32. 663-682.

[12] Bathia, D., and Bredin, D., 2013. An examination of investor sentiment effect on G7 stock market returns. European Journal of Finance 19. 909-937.

[13] Bhandari, L., 1988. Debt-Equity ratio and expected common stock returns: Empirical evidence. Journal of Finance 43. 507-528.

[14] Black, F., 1986. Noise. Journal of Finance 41. 529-543.

[15] Brennan, M., Chordia, T., and Subrahmanyam, A., 1998. Alternative factor specification, security characteristics, and the cross-section of expected stock returns. Journal of Financial Economics 49. 345-373.

[16] Brown, G., and Cliff, M., 2004. Investor Sentiment and the near term stock market. Journal of Empirical Finance 11. 1-27.

[17] Brown, G., and Cliff, M., 2005. Investor Sentiment and Asset Valuation. Journal of Business 78. 405-440.

[18] Brown, S., Goetzmann, W., Hiraki, T., Shiraishi, N., and Watanabe, N., 2003. Investor Sentiment in Japanese and US Daily Mutual Fund Flows. Working Paper. NBER 9470.

[19] Chan, K., Chen, N., and Hsieh, D., 1985. An exploratory investigation of the firm size effect. Journal of Financial Economics 14. 451-471.

[20] Chan, K., and Chen, N., 1988. An unconditional asset pricing test and the role of firm size as an instrument variable for risk. Journal of Finance 43. 309-325.

[21] Chan, L., Hamao, Y., and Lakonishok, J., 1991. Fundamentals and stock returns in Japan. Journal of Finance 46. 1739-1789.

[22] Chen, N., Kan, R., and Miller, M., 1993. Are the discounts on closed-end funds a sentiment index?. Journal of Finance 58. 795-800.

[23] Davis, J., 1994, The cross-section of stock returns and survivorship bias: Evidence from delisted stocks. Quarterly Review of Economics and Finance 36. 365-375.

[24] De Bondt, W., and Thaler, R., 1985. Does the stock market overreact?. Journal of Finance 40. 793-805.

[25] DeBondt, W., and Thaler, R. H., 1987. Further evidence on investor overreaction and stock market seasonality. Journal of Finance 42. 557-581

[26] De Long, J.B., Shleifer, A., Summers, L. and Waldmann, R., 1990. Noise Trader Risk in Financial Markets. Journal of Political Economy 98. 703-738.

[27] Easley, D., O'Hara, M., and Srinivas, P., 1998. Option volume and stock prices: Evidence on where informed traders trade. Journal of Finance 53. 431-465.

[28] Edelen, R., and Warner, J., 2001. Aggregate price effects of institutional trading: A study of mutual fund flow and market returns. Journal of Financial Economics 59. 195-220.

[29] Elton, E., Gruber, M., and Busse, J., 1998. Do investors care about sentiment?. Journal of Business 71. 477-500.

[30] Fama, E., and French, K., 1992. The cross-section of expected stock returns. Journal of Finance 47. 427-465.

[31] Fama, E., and French, K., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33. 3-56.

[32] Fama, E., and French, K., 1996. Multi factor explanations of asset pricing anomalies. Journal of Finance 51. 55-84.

[33] Fama, E., and French, K., 1997. Industry costs of equity. Journal of Financial Economics 43. 153-193.

[34] Fama, E., and Macbeth, J., 1973. Risk, Return and Equilibrium: Empirical Tests. Journal of Political Economy 81. 609-636.

[35] Ferson, W., Kandel, S., and Stambaugh, R., 1987. Test of asset pricing with time varying expected risk premiums and market betas. Journal of Finance 42. 201-220.

[36] Ferson, W., and Harvey, C., 1999. Conditioning variables and the cross-section of stock returns. Journal of Finance 54. 1325-1360.

[37] Fisher K., and Statman, M.. 2000. Investor sentiment and stock returns. Financial Analysts Journal 56. 1623.

[38] Frazzini, A., and Lamont, O., 2006. ‘Dumb Money: Mutual Fund Flows and the Cross Section of Stock Returns. Journal of Financial Economics 88. 299-322.

[39] Gomes, J., Kogan, L., and Zhang, L., 2003. Equilibrium cross-section of returns. Journal of Political Economy 111. 693-732.

[40] Grundy, B., and Martin, S., 2001. Understanding the nature of the risks and source of the rewards to momentum investing. Review of Financial Studies 14. 29-78.

[41] Guo, H., 2006. Time-varying risk premia and the cross-section of stock returns. Journal of Banking and Finance 31. 2087-2107.

[42] Hansen, L., and Richard, P., 1987. The Role of Conditioning Information in Deducing Testable Restrictions Implied by Dynamic Asset Pricing Models. Econometrica: Journal of the Econometric Society 55. 587-613.

[43] He, J., Kan, R., Ng, L., and Zhang, C., 1996. Tests of the relations among market-wide factors, firm-specific variables, and stock returns using conditional asset pricing model. Journal of Finance 60. 1891-1908.

[44] Ho, C., and Hung, C., 2009. Investor Sentiment as conditioning information in asset pricing. Journal of Banking and Finance 33. 892-903.

[45] Ibottson, R., Ritter, J., 1995. Initial public offerings. North-Holland Handbooks of Operations Research and Management Science: Finance. North-Holland, Amsterdam. 993-1016.

[46] Indro, D., 2004. Does Mutual Fund Flow Reflect Investor Sentiment?. Journal of Behavioural Finance 5. 105-115.

[47] Jagannathan, R., and Wang, Z., 1996. The conditional CAPM and the cross-section of expected returns. Journal of Finance 51. 3-53.

[48] Jagannathan, R., and Wang, Z., 1998. An asymptotic theory for estimating beta-pricing models using cross-sectional regression. Journal of Finance 53. 12851309.

[49] Jegadeesh, N., and Titman, S., 1993. Returns to buying winners and selling losers:Implications for stock market efficiency. Journal of Finance 48. 65-91.

[50] Jegadeesh, N., and Titman, S., 2001. Profitability of momentum strategies: An evaluation of alternative explanations. Journal of Finance 56. 699-720.

[51] Kothari, S., Shanken, J., and Sloan, R., 1995. Another Look at the Cross-section of Expected Stock Returns. Journal of Finance 50. 185-224.

[52] Lee, C., Shleifer, A., and Thaler, R., 1991. Investor Sentiment and the Closed End Puzzle. Journal of Finance 46. 75-109.

[53] Lemmon, M., and Portniaguina, E., 2006. Consumer confidence and Asset Prices: Some Empirical Evidence. Review of Financial Studies 19. 1499-1529.

[54] Lettau, M., and Ludvigson, S., 2001. Resurrecting the (C)CAPM: A cross-sectional test when risk premia are time varying. Journal of Political Economy. 109. 1238-1287.

[55] Lewellen, J., 1999. The time-series relations among expected return, risk, and book-to-market. Journal of Financial Economics 54. 543

[56] Li, G., 2007. Time-varying risk aversion and asset prices. Journal of Banking and Finance 31. 243-257.

[57] 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 47. 13-37.

[58] Litzenberger, R. and Ramaswamy, K., 1979. The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence. Journal of Financial Economics 7. 163-195.

[59] Ljungqvist, A., 2006. IPO Underpricing. Handbook of Corporate Finance: Empirical Corporate Finance Chapter 7. Elsevier/North-Holland Publication.

[60] Pan, J., and Poteshman, A., 2006. The Information in Option Volume for Future Stock Prices. Review of Financial Studies 19. 871-908.

[61] Pastor, L., and Stambaugh, R., 2003. Liquidity risks and expected stock returns. Journal of Political Economy 111. 642-685.

[62] Post, T., and Vliet, P., 2006. Downside risk and asset pricing. Journal of Banking and Finance 30. 823-849.

[63] Poti, V., and Shefrin, H., 2014. The signature of sentiment in conditional consumption CAPM estimates: A note. Journal of Behavioural and Experimental Finance 2. 1-9.

[64] Ritter, J., 1991. The Long-Run Performance of Initial Public Offerings, Journal of Finance 46. 3-27.

[65] Ritter, J., 2003. Investment Banking and Securities Issuance. Handbook of the Economics of Finance Chapter 5. Elsevier Science Publication.

[66] Rosenberg, B., Reid, K., and Lanstein, R., 1985. Persuasive evidence of market inefficiency. Journal of Portfolio Management 11. 9-17.

[67] Schmeling, M., 2009. Investor sentiment and stock returns: Some international evidence. Journal of Empirical Finance 16. 394-408.

[68] Shanken, J., 1992. On the estimation of beta-pricing models. Review of Financial Studies 5. 1-33.

[69] Sharpe, W., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. Journal of Finance 19. 425-442.

[70] Stambaugh, R., Yu, J., and Yuan, Y., 2012. The short of it: Investor sentiment and anomalies. Journal of Financial Economics 104. 288-302.

[71] Wang, K., 2003. Asset Pricing with Conditioning Information: A New Test. Journal of Finance 58. 161-196.

[72] Warther, V., 1995. Aggregate mutual fund flows and security returns. Journal of Financial Economics 39. 209-235.

[73] Weiss, K., 1989. The post-offering price performance of closed-end funds. Financial Management 18. 57-57.

Table 1: Summary Statistics (3567 firms for the period Jan 1980 to Dec 2014)

	Mean	**Std Dev**	**Coefficient (%)**	**T-statistics**
Excess Returns (%)	0.82	1.99		
Size ($ billion)	2.18	8.31	-0.11	-3.02
B/M	0.75	0.43	0.07	2.23
T/O	0.09	0.08	-0.02	-1.94
Ret 2-3	1.69	3.32	0.59	1.73
Ret 4-6	2.45	4.78	0.74	2.71
Ret 7-12	4.98	10.22	0.46	2.26
Adj R^2 (%)	3.97			

The above table presents the time-series averages of cross-sectional means and standard deviations for 3567 NYSE-AMEX common stocks for the period January 1980 to December 2014. The fourth and fifth column labeled 'coefficient' and 'T-statistics' respectively represents Fama-Mcbeth coefficients and t-values derived from running regression of excess returns on the firm characteristics of size, book-to-market ratio, turnover as well as cumulative returns. Adj R^2 is the average of the adjusted R-square from running the cross-sectional OLS regression. SIZE represents market capitalization, the product of share price and shares outstanding, measured in billion of dollars. B/M represents book-to market ratio of equity. T/O is share turnover, which is monthly trading volume divided by shares outstanding. Ret 2-3, Ret 4-6, and Ret 7-12 are the cumulative returns over the second through third, fourth to sixth and seventh to twelfth months defore the current month respectively. A common stock must meet following criteria in order to be included in the analysis: a) the returns data for the current month t and previous 36 months should be available from the CRSP. b) Sufficient data on stock price and common shares outstanding should be available so as to compute SIZE, which is measured by the market capitalization. c) Sufficient data on t-2 trading volume should be available so as to compute TURNOVER, which is measured by the ratio of trading volume to the number of common shares outstanding. d) Sufficient data should be available from COMPUSTAT for computing book-to-market (B/M) ratio as of December of previous calendar year. The value of B/M for July of year t to June of year t+1 is computed using accounting data at the end of calendar year t-1. The B/M ratio greater that 0.995 fractile or less than 0.005 fractile is set as 0.995 and 0.005 respectively. The firms with negative B/M is dropped from our analysis.

Table 2: Unconditional Case (CAPM, FF, FFL, FFM and FFLM)

	CAPM	**FF**	**FFL**	**FFM**	**FFLM**
SIZE	-0.07	-0.06	-0.06	-0.07	-0.07
fmb	-2.39	-2.12	-2.09	-2.43	-2.39
shk	-2.31	-2.06	-2.03	-2.35	-2.32
B/M	0.14	0.12	0.12	0.12	0.11
fmb	4.06	3.61	3.53	3.43	3.40
shk	3.71	3.32	3.26	3.17	3.15
T/O	-0.02	-0.02	-0.02	-0.02	-0.02
fmb	-2.82	-2.42	-2.45	-1.97	-2.00
shk	-2.64	-2.29	-2.31	-1.88	-1.91
RET 2-3	1.39	1.34	1.34	1.29	1.29
fmb	4.06	3.91	3.93	3.76	3.78
shk	3.70	3.58	3.60	3.46	3.47
RET 4-6	1.49	1.44	1.44	1.40	1.41
fmb	5.47	5.30	5.32	5.16	5.18
shk	4.85	4.72	4.73	4.60	4.62
RET 7-12	1.13	1.08	1.08	1.05	1.05
fmb	5.58	5.38	5.38	5.23	5.22
shk	4.94	4.78	4.78	4.66	4.65
Adj R^2	4.11	4.06	4.07	4.04	4.04

The above table presents the averages of the coefficient estimates derived from running the second pass cross-sectional OLS regression for the NYSE-AMEX common stocks over 420 months from January 1980 through December 2014. The dependent variable is the excess risk adjusted return using excess market return as the risk factor for the CAPM, excess market returns, SMB,and HML as risk factors for the FF, fama french three factors augmented with Pastor Stambaugh liquidity factor as risk factors for the FFL, fama fremch three factors augmented with momentum factor as risk factors for the FFM and fama fremch three factors augmented with Pastor Stambaugh liquidity factor and momentum factor as risk factors for the FFLM. The independent variables are SIZE, B/M, T/O, RET 2-3, RET 4-6 and RET 7-12 as defined in the methodology section. Values against 'fmb' and 'shk' are Fama-Macbeth t-values and Shanken (1992) corrected t-values. Adj R^2 is the average of the adjusted R-square from running the second pass cross-sectional OLS regression.

Table 3: Fama-Macbeth estimates with excess market return as the risk factor (the CAPM)

	SIZE				B/M				T/O				RET 2-3				RET 4-6				RET 7-12			
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
EFF	0.07	-0.02	-0.02	0.07	-0.03	0.14	0.14	-0.08	-0.03	-0.02	-0.01	-0.02	0.96	1.24	1.20	1.14	1.29	1.41	1.41	1.06	1.11	1.19	1.16	1.23
fmb	2.12	-0.48	-0.51	1.69	-2.11	4.32	4.39	-2.23	-3.42	-2.29	-2.15	-2.36	2.43	3.70	3.61	2.54	3.78	5.32	5.32	2.95	5.40	6.19	6.04	5.68
shk	2.02	-0.47	-0.51	1.62	-2.01	3.92	3.98	-2.11	-3.17	-2.17	-2.05	-2.23	2.29	3.40	3.33	2.39	3.47	4.73	4.73	2.75	4.79	5.41	5.30	5.02
Adj R^2	4.29	3.91	3.89	4.36																				
IPOR	0.00	-0.06	-0.06	0.02	-0.04	0.13	0.13	-0.02	-0.02	-0.02	-0.02	-0.03	1.53	1.54	1.52	1.51	1.59	1.64	1.62	1.51	1.03	1.18	1.16	1.03
fmb	0.25	-1.63	-1.70	1.22	-1.43	3.92	3.77	-0.88	-2.90	-3.04	-3.04	-3.25	4.59	4.79	4.72	4.41	6.11	6.50	6.43	5.63	5.21	6.19	6.10	5.20
shk	0.24	-1.57	-1.63	1.18	-1.39	3.59	3.46	-0.86	-2.71	-2.83	-2.83	-3.01	4.14	4.31	4.25	3.99	5.35	5.65	5.60	4.98	4.65	5.42	5.34	4.64
Adj R^2	4.15	4.18	4.14	4.35																				
IPOV	0.05	-0.07	-0.07	0.05	-0.04	0.14	0.13	-0.01	-0.03	-0.02	-0.02	-0.03	1.08	1.42	1.38	1.12	1.42	1.54	1.51	1.40	1.01	1.17	1.15	1.03
fmb	2.36	-1.79	-1.79	3.25	-1.24	4.04	3.87	-0.29	-3.56	-2.91	-2.98	-3.88	2.98	4.16	4.05	3.06	4.77	5.68	5.57	4.73	5.00	5.93	5.81	4.91
shk	2.23	-1.71	-1.72	3.01	-1.20	3.69	3.55	-0.29	-3.28	-2.72	-2.78	-3.55	2.78	3.79	3.69	2.85	4.29	5.02	4.93	4.26	4.48	5.21	5.12	4.41
Adj R^2	4.38	4.18	4.18	4.41																				
CEFD	0.01	0.03	-0.08	0.01	-0.23	-0.26	0.13	-0.23	-0.01	0.02	-0.02	-0.01	0.37	3.35	1.36	0.42	2.31	1.23	1.42	2.37	1.18	2.04	0.93	1.25
fmb	0.10	0.18	-2.10	0.10	-2.31	-0.93	4.12	-2.31	-0.59	0.60	-2.47	-0.61	0.33	1.81	4.19	0.37	2.70	1.07	5.40	2.77	1.86	2.48	5.00	1.96
shk	0.09	0.18	-2.00	0.10	-2.19	-0.91	3.75	-2.19	-0.58	0.59	-2.33	-0.60	0.33	1.73	3.81	0.37	2.53	1.05	4.79	2.60	1.78	2.34	4.47	1.87
Adj R^2	4.46	2.45	4.05	4.46																				
PCR	0.06	-0.16	-0.12	0.06	0.05	0.01	-0.04	0.01	0.05	0.14	0.01	0.01	-0.19	0.30	0.88	0.30	0.69	0.69	1.11	0.65	0.68	0.37	0.80	0.60
fmb	2.42	-5.10	-4.02	2.78	2.26	0.15	-1.33	0.27	4.79	7.85	1.55	1.86	-0.38	0.61	2.69	0.76	1.82	1.75	4.14	2.35	2.54	1.27	4.17	2.95
shk	2.28	-4.56	-3.67	2.60	2.14	0.15	-1.29	0.26	4.31	6.66	1.49	1.78	-0.38	0.60	2.53	0.75	1.74	1.68	3.77	2.22	2.39	1.23	3.80	2.76
Adj R^2	3.82	2.73	2.58	3.89																				
DP	0.07	-0.07	-0.08	0.07	0.01	-0.02	0.12	0.01	-0.03	-0.01	-0.02	-0.03	0.56	2.03	1.34	0.86	0.87	1.00	1.42	1.11	0.48	0.52	0.91	0.61
fmb	2.27	-1.26	-2.28	2.27	2.62	-0.20	3.75	2.64	-3.83	-0.96	-2.39	-3.61	1.26	3.53	4.15	2.13	2.41	2.12	5.41	3.32	1.98	1.46	4.90	2.68
shk	2.15	-1.22	-2.16	2.15	2.46	-0.20	3.44	2.49	-3.51	-0.94	-2.26	-3.33	1.23	3.26	3.78	2.03	2.28	2.01	4.80	3.08	1.89	1.41	4.39	2.52
Adj R^2	4.40	3.06	3.86	4.40																				
MD	0.03	-0.07	-0.07	0.04	0.00	0.14	0.14	-0.04	-0.02	-0.02	-0.02	-0.02	1.11	1.42	1.40	1.16	1.28	1.51	1.49	1.15	1.04	1.15	1.13	1.06
fmb	1.62	-1.88	-1.85	1.90	-0.34	4.26	4.17	-1.36	-2.68	-2.85	-2.82	-2.64	2.88	4.16	4.07	2.91	4.21	5.57	5.50	3.56	4.99	5.70	5.59	4.99
shk	1.56	-1.79	-1.77	1.82	-0.34	3.87	3.80	-1.31	-2.52	-2.66	-2.64	-2.48	2.69	3.79	3.72	2.72	3.83	4.93	4.87	3.29	4.46	5.03	4.94	4.46
Adj R^2	4.24	4.11	4.10	4.39																				
IND	0.04	-0.07	-0.07	0.04	-0.05	0.14	0.14	0.00	-0.03	-0.02	-0.02	-0.03	0.90	1.42	1.39	1.28	1.29	1.52	1.49	1.41	0.97	1.14	1.13	1.05
fmb	1.30	-1.77	-1.74	3.09	-1.04	4.13	4.03	0.06	-3.37	-2.83	-2.85	-3.76	2.26	4.13	4.06	3.47	4.02	5.60	5.47	4.69	4.32	5.64	5.57	4.78
shk	1.26	-1.70	-1.67	2.88	-1.01	3.76	3.68	0.06	-3.12	-2.65	-2.67	-3.45	2.14	3.77	3.70	3.21	3.67	4.95	4.85	4.22	3.92	4.98	4.93	4.29
Adj R^2	4.35	4.11	4.11	4.43																				

The above table presents the averages of the coefficient estimates derived from running the second pass cross-sectional OLS regression for the NYSE-AMEX common stocks over 420 months from January 1980 through December 2014. The dependent variable is the excess risk adjusted return using excess market return as the risk factor. The independent variables are SIZE, B/M, T/O, RET 2-3, RET 4-6 and RET 7-12 as defined in the methodology section. A, B, C and D denotes four different conditional specifications, as also discussed in the methodology section. The conditional variables considered in the study are various sentiment measures, firm characteristics (SIZE and B/M) and default spread. Different sentiment measures considered in our conditional asset pricing study are equity fund flow (EFF), IPO first day returns (IPOR), IPO volume (IPOV), closed-end fund discount (CEFD), equity put-call ratio (PCR), dividend premium (DP), change in margin debt (MD) and composite sentiment index (IND) constructed using the first principal component analysis. Values against 'fmb' and 'shk' are Fama-Macbeth t-values and Shanken (1992) corrected t-values. Adj R^2 is the average of the adjusted R-square from running the second pass cross-sectional OLS regression.

Table 4: Fama Macbeth estimates with the Fama-French three factors

	SIZE				B/M				T/O				RET 2-3				RET 4-6				RET 7-12			
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
EFF	-0.05	-0.03	-0.03	-0.01	-0.12	0.18	0.11	-0.22	-0.06	-0.02	-0.01	-0.12	2.60	1.22	1.14	2.30	2.21	1.35	1.33	0.73	1.04	1.16	1.11	-0.32
fmb	-0.43	-0.75	-0.74	-0.04	-2.69	5.36	3.67	-0.53	-1.95	-2.28	-1.86	-1.57	2.53	3.56	3.44	0.90	3.07	5.03	5.03	0.36	2.77	5.88	5.76	-0.29
shk	-0.42	-0.73	-0.73	-0.04	-2.52	4.76	3.38	-0.52	-1.86	-2.16	-1.78	-1.51	2.39	3.28	3.18	0.88	2.86	4.50	4.50	0.36	2.60	5.17	5.08	-0.29
Adj R^2	4.45	3.66	3.73	4.49																				
IPOR	0.05	-0.06	-0.06	0.08	-0.13	0.10	0.11	-0.08	-0.03	-0.02	-0.02	-0.02	1.04	1.50	1.49	1.69	1.67	1.58	1.59	0.77	1.15	1.12	1.13	1.63
fmb	1.08	-1.62	-1.71	0.59	-0.65	2.96	3.41	-0.48	-2.69	-2.39	-2.54	-0.96	2.42	4.65	4.66	2.06	5.49	6.22	6.27	1.23	3.26	5.94	5.97	3.35
shk	1.05	-1.56	-1.65	0.58	-0.64	2.77	3.16	-0.47	-2.53	-2.26	-2.39	-0.94	2.28	4.19	4.20	1.96	4.86	5.44	5.48	1.20	3.03	5.22	5.24	3.10
Adj R^2	4.38	3.99	4.02	4.54																				
IPOV	0.38	-0.07	-0.07	0.41	-0.69	0.12	0.12	-1.01	-0.02	-0.01	-0.02	-0.01	0.84	1.38	1.32	1.00	1.45	1.49	1.46	1.94	1.37	1.06	1.09	1.39
fmb	4.51	-2.01	-1.81	4.25	-4.16	3.57	3.43	-2.90	-1.26	-1.93	-2.50	-0.37	1.27	4.05	3.89	1.11	2.04	5.50	5.38	2.08	2.85	5.40	5.52	2.08
shk	4.08	-1.92	-1.73	3.86	-3.78	3.29	3.17	-2.71	-1.22	-1.84	-2.36	-0.37	1.23	3.69	3.56	1.08	1.94	4.88	4.78	1.98	2.67	4.79	4.89	1.98
Adj R^2	4.52	3.97	4.10	4.54																				
CEFD	0.14	-0.00	0.00	0.14	-0.23	0.00	0.01	-0.23	-0.01	-0.03	-0.03	-0.01	0.65	1.85	1.85	0.56	1.65	1.60	1.61	1.55	1.07	0.78	0.80	0.94
fmb	3.65	-0.01	0.05	3.64	-2.98	0.04	0.13	-2.98	-1.40	-1.22	-1.21	-1.56	1.33	2.46	2.46	1.15	4.27	2.56	2.57	4.02	3.94	2.28	2.35	3.45
shk	3.36	-0.01	0.05	3.35	-2.78	0.04	0.13	-2.78	-1.36	-1.19	-1.18	-1.51	1.29	2.32	2.32	1.12	3.87	2.41	2.42	3.67	3.60	2.16	2.23	3.19
Adj R^2	4.43	2.16	2.34	4.43																				
PCR	0.12	-0.13	-0.13	0.31	-0.18	0.24	0.21	0.18	-0.01	0.04	0.05	-0.03	-0.35	0.16	0.18	-2.62	0.87	0.43	0.43	-0.74	0.48	0.12	0.13	0.34
fmb	2.56	-3.71	-3.87	1.86	-2.09	3.88	3.52	0.53	-0.65	5.24	5.75	-1.34	-0.65	0.35	0.41	-1.34	2.26	1.16	1.16	-0.76	1.66	0.47	0.51	0.57
shk	2.41	-3.41	-3.54	1.78	-1.99	3.55	3.25	0.52	-0.64	4.67	5.07	-1.30	-0.64	0.35	0.40	-1.30	2.14	1.13	1.13	-0.75	1.60	0.46	0.51	0.56
Adj R^2	4.00	2.57	2.55	4.05																				
DP	0.01	-0.05	-0.06	0.01	0.00	0.11	0.09	0.00	-0.02	-0.02	-0.02	-0.02	1.31	1.36	1.28	1.26	1.39	1.49	1.42	1.37	0.90	1.00	0.93	0.90
fmb	1.63	-1.31	-1.56	1.64	3.30	3.21	2.77	2.52	-2.32	-2.42	-2.40	-2.40	4.01	4.20	3.95	3.82	5.20	5.60	5.34	5.14	4.86	5.42	5.07	4.84
shk	1.56	-1.27	-1.50	1.58	3.06	2.98	2.59	2.37	-2.20	-2.28	-2.27	-2.27	3.66	3.82	3.61	3.50	4.64	4.96	4.75	4.59	4.36	4.81	4.53	4.35
Adj R^2	3.78	3.55	3.55	3.77																				
MD	0.06	-0.06	-0.06	0.12	-0.06	0.12	0.12	-0.28	-0.02	-0.02	-0.02	-0.03	0.88	1.29	1.34	0.94	1.36	1.47	1.45	0.32	0.97	1.10	1.08	0.97
fmb	2.71	-1.52	-1.49	1.63	-0.75	3.36	3.70	-2.60	-2.34	-2.55	-2.58	-2.74	2.07	3.74	3.93	1.06	4.06	5.38	5.34	0.49	4.24	5.32	5.38	2.74
shk	2.55	-1.46	-1.43	1.56	-0.74	3.11	3.40	-2.45	-2.21	-2.40	-2.43	-2.57	1.97	3.43	3.59	1.03	3.71	4.78	4.75	0.48	3.86	4.73	4.78	2.57
Adj R^2	4.52	4.03	4.06	4.55																				
IND	0.08	-0.06	-0.06	0.33	-0.41	0.12	0.12	-0.88	-0.02	-0.02	-0.02	-0.02	0.52	1.38	1.36	2.10	1.65	1.49	1.45	2.15	1.17	1.08	1.09	1.94
fmb	1.81	-1.61	-1.53	2.76	-3.77	3.64	3.64	-2.85	-1.74	-2.27	-2.42	-0.97	1.12	4.04	3.96	2.22	4.22	5.49	5.35	2.12	3.93	5.33	5.37	2.73
shk	1.74	-1.55	-1.48	2.59	-3.46	3.35	3.35	-2.66	-1.67	-2.15	-2.29	-0.95	1.09	3.69	3.62	2.11	3.84	4.87	4.75	2.02	3.60	4.74	4.77	2.56
Adj R^2	4.54	4.02	4.06	4.56																				

The above table presents the averages of the coefficient estimates derived from running the second pass cross-sectional OLS regression for the NYSE-AMEX common stocks over 420 months from January 1980 through December 2014. The dependent variable is the excess risk adjusted return using excess market return, SMB and HML as the risk factors. The independent variables are SIZE, B/M, T/O, RET 2-3, RET 4-6 and RET 7-12 as defined in the methodology section. A, B, C and D denotes four different conditional specifications, as also discussed in the methodology section. The conditional variables considered in the study are various sentiment measures, firm characteristics (SIZE and B/M) and default spread. Different sentiment measures considered in our conditional asset pricing study are equity fund flow (EFF), IPO first day returns (IPOR), IPO volume (IPOV), closed-end fund discount (CEFD), equity put-call ratio (PCR), dividend premium (DP), change in margin debt (MD) and composite sentiment index (IND) constructed using the first principal component analysis. Values against 'fmb' and 'shk' are Fama-Macbeth t-values and Shanken (1992) corrected t-values. Adj R^2 is the average of the adjusted R-square from running the second pass cross-sectional OLS regression.

Table 5: Fama Macbeth estimates with the Fama-French risk factors augmented with Pastor Staumbagh Liquidity Factor

	SIZE				B/M				T/O				RET 2-3				RET 4-6				RET 7-12			
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
EFF	-0.03	0.01	-0.03	0.12	-0.15	0.12	0.14	-0.19	-0.04	-0.02	-0.01	-0.06	1.49	1.34	1.16	-1.17	2.05	1.44	1.37	0.52	1.17	1.20	1.12	1.08
fmb	-0.29	0.29	-0.76	0.62	-2.11	3.72	4.50	-0.40	-1.74	-2.66	-1.58	-2.16	1.66	3.89	3.50	-0.39	2.33	5.19	5.15	0.33	2.80	6.05	5.81	1.54
shk	-0.29	0.29	-0.74	0.61	-2.00	3.42	4.07	-0.39	-1.67	-2.50	-1.52	-2.05	1.59	3.56	3.23	-0.39	2.20	4.63	4.60	0.33	2.62	5.31	5.12	1.49
Adj R^2	4.45	3.65	3.75	4.49																				
IPOR	0.04	-0.06	-0.06	0.35	-0.12	0.08	0.11	-0.15	-0.03	-0.02	-0.02	-0.03	1.32	1.54	1.49	-0.57	1.88	1.60	1.59	0.60	0.46	1.13	1.13	1.88
fmb	0.45	-1.60	-1.68	1.52	-0.51	2.53	3.18	-0.50	-2.14	-2.30	-2.61	-0.99	2.11	4.75	4.65	-0.36	4.64	6.32	6.28	0.53	0.93	5.92	5.96	2.51
shk	0.45	-1.54	-1.61	1.47	-0.51	2.38	2.95	-0.49	-2.03	-2.18	-2.45	-0.96	2.01	4.27	4.19	-0.35	4.18	5.51	5.48	0.52	0.91	5.21	5.23	2.37
Adj R^2	4.50	4.02	4.03	4.56																				
IPOV	0.30	-0.07	-0.07	0.51	-0.76	0.12	0.12	-1.36	-0.03	-0.02	-0.02	0.00	0.56	1.37	1.33	-1.91	1.41	1.48	1.45	2.47	1.34	1.06	1.09	1.26
fmb	3.36	-2.05	-1.81	2.76	-3.69	3.60	3.44	-2.54	-1.47	-2.08	-2.54	-0.06	0.73	4.03	3.90	-0.77	1.87	5.43	5.32	1.67	2.65	5.38	5.50	1.29
shk	3.11	-1.95	-1.74	2.59	-3.39	3.32	3.18	-2.39	-1.42	-1.98	-2.39	-0.06	0.71	3.68	3.57	-0.75	1.79	4.82	4.73	1.61	2.49	4.78	4.88	1.25
Adj R^2	4.54	3.99	4.10	4.55																				
CEFD	0.00	0.02	0.02	0.00	-0.01	0.05	0.05	-0.01	-0.02	-0.04	-0.04	-0.03	1.39	0.78	0.82	1.50	1.30	1.57	1.58	1.35	0.79	1.18	1.16	0.91
fmb	-0.13	0.53	0.44	-0.10	-0.77	1.06	1.18	-0.67	-2.75	-3.42	-3.38	-3.60	3.85	1.80	1.90	4.07	4.52	4.59	4.64	4.57	4.02	5.10	5.07	4.59
shk	-0.13	0.52	0.44	-0.10	-0.75	1.03	1.15	-0.66	-2.58	-3.16	-3.13	-3.31	3.53	1.72	1.81	3.71	4.08	4.14	4.19	4.12	3.67	4.55	4.53	4.14
Adj R^2	4.28	2.92	3.10	4.27																				
PCR	0.12	-0.05	-0.05	0.20	-0.45	-0.05	-0.03	-0.06	0.01	0.00	0.00	0.00	-0.21	0.70	0.71	-1.80	0.96	0.97	0.95	0.07	0.52	0.62	0.63	0.35
fmb	2.16	-1.69	-1.67	1.10	-1.84	-2.08	-1.15	-0.11	0.59	0.11	0.03	0.06	-0.33	2.37	2.48	-0.73	1.91	4.06	4.03	0.06	0.92	3.75	3.84	0.39
shk	2.05	-1.63	-1.60	1.07	-1.76	-1.98	-1.12	-0.11	0.58	0.11	0.03	0.06	-0.32	2.24	2.34	-0.72	1.82	3.71	3.68	0.06	0.90	3.44	3.52	0.39
Adj R^2	4.02	2.58	2.54	4.05																				
DP	0.01	-0.08	-0.07	0.01	0.00	0.08	0.08	0.00	-0.02	-0.02	-0.02	-0.02	1.22	1.14	1.24	1.29	1.34	1.27	1.37	1.39	0.86	0.77	0.90	0.94
fmb	2.18	-2.27	-1.93	2.20	3.47	2.54	2.47	5.16	-2.22	-2.28	-2.19	-2.24	3.73	3.51	3.82	3.87	5.02	4.80	5.21	5.11	4.64	4.13	4.87	5.01
shk	2.07	-2.15	-1.84	2.09	3.21	2.39	2.33	4.60	-2.10	-2.16	-2.08	-2.12	3.43	3.24	3.50	3.55	4.49	4.31	4.64	4.56	4.18	3.76	4.37	4.48
Adj R^2	3.70	3.76	3.68	3.68																				
MD	0.01	-0.06	-0.05	0.18	-0.10	0.11	0.12	-0.14	-0.02	-0.02	-0.02	-0.04	1.56	1.38	1.35	1.10	1.63	1.53	1.46	0.36	1.19	1.12	1.08	1.42
fmb	0.21	-1.49	-1.41	1.46	-0.94	3.34	3.61	-0.79	-1.95	-2.48	-2.58	-2.91	2.46	4.02	3.95	0.75	4.00	5.57	5.39	0.49	4.16	5.44	5.39	3.05
shk	0.21	-1.44	-1.36	1.41	-0.92	3.09	3.33	-0.77	-1.86	-2.34	-2.43	-2.72	2.32	3.67	3.61	0.74	3.66	4.93	4.79	0.48	3.79	4.83	4.79	2.84
Adj R^2	4.55	4.04	4.06	4.57																				
IND	0.16	-0.06	-0.05	0.52	-0.55	0.12	0.12	-1.48	-0.04	-0.02	-0.02	-0.03	1.10	1.40	1.36	0.93	1.30	1.47	1.45	2.68	1.37	1.09	1.09	2.52
fmb	1.39	-1.51	-1.48	2.52	-3.37	3.60	3.62	-2.50	-1.91	-2.46	-2.43	-0.77	1.34	4.10	3.99	0.33	1.68	5.42	5.33	1.27	2.76	5.38	5.37	1.88
shk	1.34	-1.45	-1.43	2.37	-3.12	3.32	3.34	-2.36	-1.83	-2.33	-2.29	-0.75	1.30	3.74	3.64	0.33	1.61	4.81	4.74	1.23	2.59	4.78	4.77	1.79
Adj R^2	4.56	4.01	4.06	4.58																				

The above table presents the averages of the coefficient estimates derived from running the second pass cross-sectional OLS regression for the NYSE-AMEX common stocks over 420 months from January 1980 through December 2014. The dependent variable is the excess risk adjusted return using excess market return, SMB, HML, and Pastor STambaugh liquidity factor as the risk factors. The independent variables are SIZE, B/M, T/O, RET 2-3, RET 4-6 and RET 7-12 as defined in the methodology section. A, B, C and D denotes four different conditional specifications, as also discussed in the methodology section. The conditional variables considered in the study are various sentiment measures, firm characteristics (SIZE and B/M) and default spread. Different sentiment measures considered in our conditional asset pricing study are equity fund flow (EFF), IPO first day returns (IPOR), IPO volume (IPOV), closed-end fund discount (CEFD), equity put-call ratio (PCR), dividend premium (DP), change in margin debt (MD) and composite sentiment index (IND) constructed using the first principal component analysis. Values against 'fmb' and 'shk' are Fama-Macbeth t-values and Shanken (1992) corrected t-values. Adj R^2 is the average of the adjusted R-square from running the second pass cross-sectional OLS regression.

Table 6: Fama Macbeth estimates with the Fama-French risk factors augmented with Momentum Factor

	SIZE				**B/M**				**T/O**				**RET 2-3**				**RET 4-6**				**RET 7-12**			
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
EFF	0.01	-0.03	-0.04	-0.34	-0.18	0.10	0.07	-0.54	-0.06	-0.02	-0.01	-0.06	2.21	1.20	1.07	5.87	2.67	1.30	1.29	3.92	1.21	1.17	1.06	-0.21
fmb	0.10	-0.89	-1.20	-0.78	-3.24	3.23	2.13	-0.94	-1.98	-2.17	-1.38	-0.75	2.18	3.55	3.23	1.71	3.77	4.83	4.85	1.58	3.01	6.08	5.53	-0.12
shk	0.10	-0.87	-1.16	-0.76	-3.00	3.00	2.03	-0.92	-1.89	-2.07	-1.33	-0.73	2.07	3.28	3.00	1.65	3.46	4.34	4.35	1.53	2.81	5.33	4.90	-0.12
Adj R^2	4.48	3.52	3.59	4.49																				
IPOR	0.28	-0.07	-0.08	0.33	-0.08	0.10	0.11	0.10	-0.08	-0.02	-0.02	-0.10	0.07	1.47	1.43	-1.16	1.70	1.55	1.52	0.69	1.70	1.09	1.07	3.68
fmb	1.60	-1.85	-2.14	1.31	-0.38	3.01	3.20	0.16	-3.12	-2.17	-2.16	-1.95	0.10	4.51	4.43	-0.67	2.14	6.09	6.00	0.32	2.66	5.80	5.68	1.89
shk	1.54	-1.77	-2.03	1.27	-0.38	2.81	2.97	0.16	-2.90	-2.06	-2.05	-1.86	0.10	4.08	4.01	-0.66	2.04	5.34	5.26	0.32	2.50	5.11	5.02	1.81
Adj R^2	4.52	3.88	3.91	4.55																				
IPOV	0.74	-0.09	-0.09	1.04	-1.28	0.12	0.11	-0.60	-0.02	-0.01	-0.02	-0.09	0.42	1.36	1.27	0.86	1.72	1.48	1.43	1.06	1.57	1.07	1.06	2.30
fmb	5.48	-2.32	-2.35	3.31	-3.77	3.45	3.22	-0.81	-0.85	-1.64	-2.10	-1.30	0.39	4.01	3.73	0.31	1.52	5.44	5.27	0.49	2.04	5.40	5.37	1.31
shk	4.86	-2.20	-2.22	3.07	-3.46	3.18	2.99	-0.80	-0.84	-1.58	-1.99	-1.26	0.39	3.66	3.43	0.31	1.46	4.82	4.69	0.48	1.94	4.80	4.77	1.27
Adj R^2	4.54	3.90	4.04	4.57																				
CEFD	-0.04	-0.08	-0.08	-0.04	0.01	0.13	0.14	0.01	-0.02	-0.01	-0.01	-0.02	1.59	1.34	1.29	1.67	1.34	1.28	1.22	1.40	0.93	0.83	0.79	1.09
fmb	-3.83	-2.15	-2.11	-3.85	0.98	4.02	4.13	0.88	-2.07	-1.72	-1.61	-2.08	4.72	4.08	3.92	4.71	4.71	4.80	4.59	4.78	4.54	4.31	4.14	5.13
shk	-3.51	-2.04	-2.01	-3.53	0.95	3.67	3.76	0.86	-1.97	-1.65	-1.55	-1.98	4.25	3.72	3.59	4.24	4.24	4.31	4.14	4.30	4.10	3.91	3.77	4.58
Adj R^2	4.18	3.61	3.82	4.15																				
PCR	0.21	-0.59	-0.68	0.16	-0.31	0.78	0.74	0.63	0.02	0.01	0.04	0.03	-0.66	0.48	-0.16	0.47	0.74	0.94	0.55	-0.58	0.15	0.30	0.01	0.86
fmb	1.71	-10.79	-11.39	0.73	-1.77	6.76	7.81	0.90	1.10	0.74	3.67	0.76	-0.61	0.70	-0.23	0.27	0.77	1.73	0.99	-0.32	0.19	0.94	0.04	0.83
shk	1.64	-8.71	-9.11	0.71	-1.70	5.85	6.63	0.88	1.07	0.72	3.37	0.75	-0.60	0.69	-0.23	0.27	0.75	1.66	0.97	-0.31	0.19	0.92	0.04	0.81
Adj R^2	4.04	2.63	2.64	4.06																				
DP	0.01	-0.07	-0.10	0.01	0.00	0.12	0.09	0.00	-0.02	-0.02	-0.01	-0.01	1.29	1.34	1.29	1.27	1.34	1.17	1.14	1.38	0.86	0.80	0.79	0.87
fmb	1.62	-1.73	-2.61	1.70	3.58	3.56	2.70	3.11	-2.36	-1.86	-1.48	-1.48	3.94	4.05	3.97	3.78	5.07	4.25	4.17	5.14	4.65	4.02	4.09	4.57
shk	1.55	-1.66	-2.45	1.63	3.30	3.28	2.54	2.90	-2.23	-1.78	-1.43	-1.42	3.60	3.70	3.63	3.47	4.53	3.87	3.80	4.59	4.19	3.67	3.73	4.13
Adj R^2	3.78	3.32	3.61	3.76																				
MD	0.18	-0.06	-0.06	-0.17	-0.11	0.12	0.12	-0.41	-0.02	-0.02	-0.02	0.01	0.55	1.31	1.28	4.26	1.40	1.46	1.41	0.80	0.93	1.09	1.04	1.73
fmb	5.03	-1.55	-1.60	-0.38	-1.81	3.39	3.54	-1.13	-2.29	-2.29	-2.21	0.20	1.36	3.84	3.73	1.51	4.36	5.37	5.19	0.45	4.04	5.33	5.18	1.05
shk	4.50	-1.50	-1.54	-0.38	-1.73	3.14	3.27	-1.10	-2.17	-2.17	-2.10	0.20	1.32	3.52	3.43	1.46	3.95	4.77	4.63	0.45	3.69	4.74	4.62	1.03
Adj R^2	4.53	4.02	4.03	4.59																				
IND	0.60	-0.06	-0.07	0.97	-0.83	0.13	0.11	-0.55	-0.04	-0.01	-0.02	-0.07	0.70	1.40	1.31	-0.78	1.54	1.49	1.42	-0.04	1.75	1.06	1.05	1.99
fmb	4.29	-1.72	-1.80	4.36	-3.48	3.67	3.39	-1.56	-1.48	-1.91	-1.97	-1.78	0.68	4.07	3.81	-0.44	1.47	5.48	5.23	-0.02	2.61	5.25	5.21	2.03
shk	3.89	-1.65	-1.73	3.95	-3.22	3.37	3.13	-1.51	-1.42	-1.82	-1.88	-1.71	0.67	3.72	3.49	-0.44	1.42	4.86	4.66	-0.02	2.46	4.68	4.64	1.94
Adj R^2	4.57	4.00	4.03	4.58																				

The above table presents the averages of the coefficient estimates derived from running the second pass cross-sectional OLS regression for the NYSE-AMEX common stocks over 420 months from January 1980 through December 2014. The dependent variable is the excess risk adjusted return using excess market return, SMB, HML, and WML as the risk factors. The independent variables are SIZE, B/M, T/O, RET 2-3, RET 4-6 and RET 7-12 as defined in the methodology section. A, B, C and D denotes four different conditional specifications, as also discussed in the methodology section. The conditional variables considered in the study are various sentiment measures, firm characteristics (SIZE and B/M) and default spread. Different sentiment measures considered in our conditional asset pricing study are equity fund flow (EFF), IPO first day returns (IPOR), IPO volume (IPOV), closed-end fund discount (CEFD), equity put-call ratio (PCR), dividend premium (DP), change in margin debt (MD) and composite sentiment index (IND) constructed using the first principal component analysis. Values against 'fmb' and 'shk' are Fama-Macbeth t-values and Shanken (1992) corrected t-values. Adj R^2 is the average of the adjusted R-square from running the second pass cross-sectional OLS regression.

Table 7: Fama Macbeth estimates with the Fama-French risk factors augmented with Liquidity factor and Momentum Factor

	SIZE				**B/M**				**T/O**				**RET 2-3**				**RET 4-6**				**RET 7-12**			
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
EFF	-0.04	0.01	-0.03	0.31	-0.18	0.09	0.02	2.87	-0.06	-0.01	-0.01	-0.27	2.44	1.43	1.33	7.86	2.56	1.45	1.52	1.50	1.41	1.25	1.29	2.99
fmb	-0.34	0.15	-0.78	0.43	-1.81	2.82	0.61	2.19	-2.25	-1.67	-1.49	-2.35	2.36	4.15	3.91	0.68	4.05	5.19	5.57	0.23	3.45	6.48	6.52	1.00
shk	-0.34	0.15	-0.77	0.42	-1.73	2.64	0.60	2.08	-2.13	-1.60	-1.44	-2.22	2.23	3.78	3.58	0.67	3.69	4.63	4.93	0.23	3.19	5.64	5.67	0.97
Adj R^2	4.48	3.63	3.74	4.50																				
IPOR	0.20	-0.07	-0.08	-0.71	0.00	0.09	0.10	-1.86	-0.08	-0.02	-0.02	-0.03	1.12	1.52	1.42	17.67	2.40	1.57	1.52	9.00	1.20	1.09	1.07	-0.95
fmb	1.19	-1.86	-2.11	-0.73	0.01	2.62	3.01	-2.05	-3.28	-2.15	-2.25	-0.30	1.16	4.62	4.42	1.50	2.65	6.18	6.00	1.68	1.21	5.77	5.66	-0.35
shk	1.15	-1.78	-2.01	-0.71	0.01	2.46	2.81	-1.95	-3.04	-2.04	-2.14	-0.29	1.12	4.17	4.00	1.45	2.49	5.41	5.27	1.62	1.18	5.09	5.00	-0.35
Adj R^2	4.55	3.88	3.91	4.57																				
IPOV	0.55	-0.09	-0.09	2.00	-1.34	0.12	0.11	-0.23	-0.02	-0.01	-0.02	-0.08	0.22	1.34	1.28	0.16	1.16	1.46	1.41	1.35	1.27	1.06	1.06	4.23
fmb	5.03	-2.36	-2.33	2.66	-4.43	3.44	3.27	-0.16	-0.96	-1.84	-2.13	-0.64	0.24	3.95	3.74	0.03	1.24	5.36	5.19	0.31	2.23	5.36	5.35	1.00
shk	4.50	-2.24	-2.20	2.50	-4.01	3.18	3.04	-0.16	-0.94	-1.76	-2.03	-0.63	0.24	3.61	3.44	0.03	1.20	4.77	4.63	0.31	2.12	4.76	4.76	0.97
Adj R^2	4.54	3.93	4.02	4.58																				
CEFD	-0.02	-0.07	-0.06	-0.02	0.00	0.10	0.11	0.00	-0.02	-0.02	-0.02	-0.01	1.46	1.42	1.37	1.51	1.30	1.36	1.31	1.27	0.80	0.93	0.88	0.77
fmb	-2.02	-1.86	-1.77	-2.02	2.17	3.12	3.52	0.84	-2.45	-2.15	-2.07	-1.81	4.28	4.45	4.30	4.28	4.62	5.13	4.96	4.38	4.06	4.92	4.67	3.87
shk	-1.93	-1.78	-1.70	-1.92	2.06	2.90	3.25	0.82	-2.31	-2.05	-1.97	-1.74	3.89	4.03	3.90	3.89	4.17	4.58	4.44	3.97	3.70	4.41	4.21	3.55
Adj R^2	4.09	3.71	3.80	4.07																				
PCR	0.17	-0.06	-0.05	3.13	-0.46	-0.02	0.00	-0.98	-0.03	0.00	0.01	0.12	-0.79	0.40	0.33	-11.80	-0.24	0.61	0.56	-23.72	-0.38	0.36	0.35	-3.42
fmb	1.40	-2.06	-1.79	1.77	-2.19	-0.77	0.11	-0.28	-1.23	0.22	1.46	1.01	-0.65	1.30	1.11	-0.54	-0.26	2.45	2.33	-1.24	-0.46	2.08	2.08	-0.47
shk	1.35	-1.95	-1.71	1.69	-2.08	-0.76	0.11	-0.28	-1.19	0.22	1.41	0.98	-0.64	1.26	1.08	-0.53	-0.26	2.32	2.21	-1.20	-0.46	1.98	1.98	-0.47
Adj R^2	4.05	2.47	2.49	4.07																				
DP	0.01	-0.08	-0.08	0.01	0.00	0.10	0.09	0.00	-0.02	-0.02	-0.01	-0.03	1.24	1.32	1.26	1.40	1.34	1.44	1.39	1.41	0.84	0.96	0.93	0.86
fmb	2.15	-2.13	-2.24	2.16	3.00	3.18	2.74	1.19	-2.01	-2.03	-1.83	-3.49	3.73	4.08	3.89	4.18	4.94	5.51	5.29	5.09	4.47	5.21	5.03	4.43
shk	2.04	-2.02	-2.13	2.06	2.80	2.95	2.57	1.16	-1.91	-1.93	-1.75	-3.22	3.43	3.72	3.56	3.80	4.43	4.88	4.71	4.55	4.04	4.64	4.50	4.01
Adj R^2	3.70	3.72	3.73	3.65																				
MD	0.05	-0.05	-0.06	-0.09	-0.25	0.11	0.12	2.15	-0.01	-0.02	-0.02	0.15	1.58	1.35	1.28	-3.85	1.62	1.49	1.42	6.28	1.19	1.07	1.04	7.76
fmb	0.49	-1.35	-1.54	-0.08	-1.94	3.08	3.46	0.81	-1.10	-2.26	-2.20	0.76	1.41	3.92	3.73	-0.32	2.40	5.42	5.23	0.84	2.93	5.25	5.16	1.71
shk	0.48	-1.31	-1.48	-0.08	-1.85	2.87	3.19	0.80	-1.07	-2.14	-2.09	0.74	1.36	3.59	3.43	-0.32	2.27	4.81	4.66	0.82	2.74	4.68	4.61	1.64
Adj R^2	4.57	4.04	4.03	4.60																				
IND	0.38	-0.06	-0.06	0.25	-0.87	0.13	0.12	0.72	-0.03	-0.02	-0.02	-0.12	1.02	1.37	1.31	-5.70	1.27	1.42	1.42	0.45	1.66	1.04	1.05	3.72
fmb	3.17	-1.70	-1.75	0.46	-4.08	3.88	3.41	0.72	-1.53	-2.17	-1.98	-1.82	1.12	4.00	3.83	-1.02	1.44	5.22	5.21	0.12	3.18	5.18	5.21	1.64
shk	2.95	-1.63	-1.68	0.46	-3.72	3.55	3.15	0.71	-1.47	-2.06	-1.89	-1.74	1.09	3.65	3.51	-1.00	1.39	4.65	4.64	0.12	2.95	4.62	4.65	1.57
Adj R^2	4.57	3.94	4.04	4.60																				

]

The above table presents the averages of the coefficient estimates derived from running the second pass cross-sectional OLS regression for the NYSE-AMEX common stocks over 420 months from January 1980 through December 2014. The dependent variable is the excess risk adjusted return using excess market return, SMB, HML, Pastor Stambaugh liquidity factor, and WML as the risk factors. The independent variables are SIZE, B/M, T/O, RET 2-3, RET 4-6 and RET 7-12 as defined in the methodology section. A, B, C and D denotes four different conditional specifications, as also discussed in the methodology section. The conditional variables considered in the study are various sentiment measures, firm characteristics (SIZE and B/M) and default spread. Different sentiment measures considered in our conditional asset pricing study are equity fund flow (EFF), IPO first day returns (IPOR), IPO volume (IPOV), closed-end fund discount (CEFD), equity put-call ratio (PCR), dividend premium (DP), change in margin debt (MD) and composite sentiment index (IND) constructed using the first principal component analysis. Values against 'fmb' and 'shk' are Fama-Macbeth t-values and Shanken (1992) corrected t-values. Adj R^2 is the adjusted R-square from running the second pass cross-sectional OLS regression.