Investor Sentiment as Conditioning Information in Asset Pricing

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Abstract

This paper extends the conditional asset pricing framework of Avramov and Chordia (2006) by allowing factors loadings to vary with various measures of investor sentiment in addition to the default spread and firm-specific characteristics. We evaluate the relative performance of various empirical specifications of the CAPM and multifactor models in respect of how well they capture the well-documented size, value, liquidity, and momentum effects at the firm level. We find that our framework of incorporating investor sentiment as conditioning information can improve the overall explanatory power of the asset pricing models and that investor sentiment conveys more information than the default spread. We provide empirical evidence that different sentiment indices reflect distinct information about investor sentiment of the stock markets.

JEL classification: G12; G14

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1. Introduction

The Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) theoretically contends that systematic risk is measured by the exposure to the single market factor. Prior literature has shown, however, that the CAPM cannot explain the returns on stocks with certain firm-characteristics or price histories such as the size effect (Banz, 1981), the value effect (e.g., Chan, Hamao, and Lakonishok, 1991) and the momentum effect (Jegadeesh and Titman, 1993). In the attempt to capture the dimensions of risk other than the exposure to the market factor, Fama and French (1993) further include size and value factors and Pastor and Stambaugh (2003) consider a liquidity factor. Gibbons and Ferson (1985) and Ferson, Kandel, and Stambaugh (1987) argue that, as opposed to the static nature of unconditional models, conditional models provide better performance in explaining stock returns since factor loadings are time-varying. Harvey (1989) also shows that the factor loadings of both the CAPM and multifactor models change over time. In this paper, we ask an important question that whether incorporating investor sentiment as conditioning information can improve the performance of asset pricing models if investors’ demand for risky assets is affected by their sentiments.

In specifying time-varying betas many studies have considered macroeconomic variables such as the term premium, default spread, or consumption-wealth ratio as conditioning variables (e.g., Shanken, 1990; Ferson and Harvey, 1991; Braun, Nelson and Sunier, 1995; Ferson and Schadt, 1996; Jagannathan and Wang, 1996; and Lettau and Ludvigson, 2001). Others scale factor loadings by firm-specific
characteristics such as dividend-to-price ratio (D/P), book-to-market ratio (B/M), or market capitalization of equity (size) (Cochrane, 1996; Lewellen, 1999; Gomes, Kogan, and Zhang, 2003; and Avramov and Chordia, 2006).

While the rational trader, as is traditionally hypothesized, fully takes into account of all publicly available information related to macroeconomic news and firm-specific variables, the sentiment measures of economic agents in the aggregate level may provide incremental information related to the prospects of the economy and financial markets. Recent studies suggest that, instead of focusing on the macroeconomic or firm level variables, investor sentiment and trading activities of noise investors influence stock prices. This is so because the smart-money investors, who are risk averse, trade quickly on the basis of fundamental information in an unbiased manner (Shleifer and Summers, 1990; De Long, Shleifer, Summers, and Waldman (DSSW), 1990; Campbell and Kyle, 1993; Kelly, 1997). Chan, Hameed, and Tong (2000) show that higher trading volume and investor sentiment leads to subsequently larger momentum return. Baker and Stein (2004) argue that an increase in trading volume as a result of higher market participation by irrational traders reflects a risk related to investor sentiment. In a similar vein, Glushkov (2006) shows that an increase in the proportion of irrationally sentimental traders in a stock increases the correlation of the stock with the common sentiment factors and thus leads to a higher sentiment beta. Liu (2006) find a liquidity effect in that high sentiment induces high market turnover.

We extend the conditional asset pricing framework of Avramov and Chordia
(2006) by allowing factor loadings to vary with measures of investor sentiment in addition to the default spread (a measure of macroeconomic condition), and firm-specific characteristics such as size and B/M. We use three survey measures of investor sentiment: the Conference Board Consumer Confidence Index (CCI), the Investors’ Intelligence Survey Index (II) and the University of Michigan Consumer Sentiment Index (MS). We further construct a composite sentiment measure which extracts the principle component of the three survey measures, going beyond the analysis of Baker and Wurgler (2006) and Lemmon and Portniaguina (2006) who consider measures of investor or consumer sentiment as conditioning information.

We examine our empirical specifications by evaluating the relative performance of asset pricing models in respect of how well they capture the well-documented size, value, liquidity, and momentum effects. We consider the following asset pricing models: (i) the CAPM, (ii) the Fama-French (1993) three-factor model (FF), (iii) FF augmented by the Pastor-Stambaugh (2003) liquidity factor (FFP), (iv) FF augmented by the winners-minus-losers (WML) portfolio to proxy for momentum (FFW), and (v) FF augmented by the liquidity and momentum factors (FFPW). Our stock sample covers a total of 3,918 the common stocks listed on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) over the period of July 1964 to December 2005.

We use the two-pass regression framework of Avramov and Chordia (2006) where in the first-pass time-series regression, we regress monthly stock returns on the risk factors, while allowing the factor loadings of each model under
consideration to vary with the conditioning variables. In the second-pass, we regress cross-sectionally the risk-adjusted return—the sum of the pricing error and the residual in the first-pass regression for each stock—on the size, value, liquidity, and momentum variables. The conditional pricing models are deemed to be capable of capturing the empirically documented price effects if the coefficient estimates on the corresponding variables in the second-pass regression are insignificantly different from zero. The overall explanatory power of the asset pricing model is measured by the average adjusted $R^2$ in the cross-sectional regression. A smaller value of $\bar{R}^2$ is an indicator of larger overall explanatory power of the asset pricing model in depicting stock price behavior.

This paper contributes to the literature in the following areas. First, our framework is able to capture liquidity, momentum, size and value effects. The findings show that incorporating investor sentiment as conditioning information can improve the overall power of the asset pricing models in depicting the stock price behavior. Second, we find empirical evidence that investor sentiment, as a conditioning variable, conveys more information than the default spread in the sense that it enhances the overall explanatory power of the conditional CAPM and multifactor models. Moreover, the conditional CAPM in our study successfully explains the size effect which Avramov and Chordia (2006) fail to capture in their conditional CAPM specification. Third, our conditional model specification appropriately captures the dynamic of factor loadings and thus outperforms the unconditional ones, in line with the prediction of Hansen and Richard (1987) and
Ghysels (1998). In our analysis, the conditional models have lower $R^2$ than those of the unconditional models, indicating the superiority of conditional models in describing stock price.

Finally, since different sentiment indices measure different groups of agents about their anticipations or perceptions of the stock market or economic condition, our framework provides a platform where various proxies of investor sentiment can be compared in terms of the performance in explaining stock price behavior. Our results indicate that, among the direct sentiment measures, the Conference Board Consumer Confidence Index outperforms Investors’ Intelligence Survey Index and University of Michigan Consumer Sentiment Index, whereas MS yields the lowest overall performance in the conditional versions of the CAPM and Fama-French three-factor models. We find the composite sentiment measure outperforms all direct sentiment indices in the conditional CAPM and Fama-French models. The composite sentiment seems to represent a cleaner measure of investor sentiment and exploits as much information as possible from these three sentiment indices (Brown and Cliff, 2004; Baker and Wurgler, 2006).

The rest of the paper proceeds as follows. The next section describes the sentiment indices and the stock trading data used in the analyses. Section 3 details the two-pass regression methodology where various specifications of asset pricing models are examined. Section 4 presents the empirical results. Section 5 concludes.

2. Data
2.1. Sentiment Indices

Despite a number of studies have documented that investor sentiment are associated with the price and liquidity of stocks, there is no consensus on which direct measure better proxy the investor sentiment in the literature. To circumvent this problem, we use three direct sentiment indices, MS, CCI and II as well as the composite sentiment index compiled from these three sentiment indices, respectively, to proxy for investor sentiment in our test framework. Among these, II directly measures the opinions of the market professionals about the future movements of the stock market. MS and CCI have been frequently examined and used in the literature although they are measures of consumer confidence and are more concentrated on the consumers’ expectations about the overall prospects of the economy rather than the stock market. Fisher and Statman, (2002), Lee, Jiang, and Indro (2002), Brown and Cliff (2004, 2005), Lemmon and Portniagunia (2006) and Liu (2006) show that these indices exhibit predictive power for the behavior of stock price. Fisher and Statman (2002) further demonstrate that consumer confidence move stock prices. We use all three indices to examine whether different sentiment proxies lead to significantly different results.

Finally, we choose these three investor sentiment indices because they have longer-standing history than other indices, for example, those compiled by American Association of Individual Investors (AAII) or UBS/Gallup. They have been available since the 1960s or earlier, which are more parallel to the sampling period of the stock trading data from Center for Research in Security Prices (CRSP) and COMPUSTAT.
in our study.

When the sentiment indices are released at a weekly or bi-monthly frequency rather than monthly frequency, the values of investor sentiment indices are adjusted in order to obtain time series data with monthly frequency that matches the monthly stock returns. In particular, since the MS prior to January of 1978 was released every quarter, we use the most recently available data for the current month. For example, the index published in February is used as the values for those of the following March and April until the new index is released in May. A similar adjustment method is used for CCI to convert its bi-monthly data into monthly ones prior to January of 1977. For II, the monthly values of the index are obtained by averaging the weekly data available in the month.

Panel A of Table 1 shows the descriptive statistics of the various survey sentiment indices. Since the total score for each sentiment index is calculated using different formulae, using the coefficient of variation—the ratio of standard deviation to mean—rather than the standard deviation can better describe the variation of each sentiment index over the sample period. We find that the variations of CCI and II are very close with the coefficients of variation of 23.45% and 22.81%, respectively. In contrast, the coefficient of variation of MS of 13.97% is almost half of those of CCI and II, indicating that the variation in MS is much less than those of the other two sentiment measures.

Panel B of Table 1 shows the correlations between the various survey sentiment indices. In our sample, the correlation coefficient of the two measures of consumer
confidence–MS and CCI–is statistically significant and as high as 0.76, which reflects the nature that both two indices reflect the opinions of general households. In contrast, the correlation coefficient is 0.27 (statistically significant) between MS and II, and is as low as 0.04 (statistically insignificant) between CCI and II. It is apparent that these three sentiment indices may each measure different aspect of the expectations about the economy or the stock market of certain group of investors or consumers. Hence, each individual index may not completely reflect the common views of investors and is likely to have its idiosyncratic nature. Following Brown and Cliff (2004), Baker and Wurgler (2006), and Glushkov (2006), we construct a composite sentiment index using principal component analysis to extract the common component contained in the three sentiment proxies. The selected first principal component gives a parsimonious composite index as

\[ COMP_t = 0.521MS_t + 0.493CCI_t + 0.192II_t \]  

(1)

where each of the index components has been standardized. The \( COMP_t \) represents the composite sentiment index and captures high common variation in the three index components because it explains 60.53% of the total (standardized) sample variance.

2.2. Trading Data

We use the monthly equity data of the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) from the CRSP and COMPUSTAT datasets for the period from July 1964 to December 2005. A common stock must meet the
following criteria in order to be included in the analyses: First, the returns of these stocks must be available in the current month, \( t \), and over the past 36 months in the CRSP. Second, information on stock prices and shares outstanding for calculating the size of a firm and the month \( t - 2 \) trading volume for calculating the turnover must be available. Third, the B/M as of December of the previous calendar year has to be available from the COMPUSTAT dataset. We only include stocks with positive B/M as in Fama and French (1992). We drop the first two years of COMPUSTAT data for every firm to control for the COMPUSTAT survival bias as in Fama and French (1992) and Kothari, Shanken, and Sloan (1995). The total number of the common stocks is 3,918 in our sample. As in Fama and French (1992), the value of B/M for July of year \( t \) to June of year \( t + 1 \) was computed using accounting data at the end of year \( t - 1 \), and B/M values greater than the 0.995 fractile or less than the 0.005 fractile are set to the 0.995 and 0.005 fractile values, respectively, as in Avramov and Chordia (2006). We use the CRSP value-weighted return to proxy for the market return in the model. For each stock the following variables are calculated in each month as follows:

**MS:** the level of the Consumer Confidence Index of the Michigan Survey.

**CCI:** the level of the Consumer Confidence Index of the Conference Board.\(^1\)

**II:** the percentage of newsletters classified as optimism by Investors’ Intelligence.

**SIZE:** the natural logarithm of the market value of the stock measured in billions of dollars.

\(^1\) We thank Lynn Franco, the director of the Consumer Research Center of the Conference Board, for providing the data.
B/M: the natural logarithm of the book-to-market ratio.

TURNOVER: the ratio of trading volume to the number of shares outstanding.

RET2-3(%): the cumulative return over the past second through the past third months.

RET4-6(%): the cumulative return over the past fourth through the past sixth months

RET7-12(%): the cumulative return over the past seventh through the past twelfth months

z: the default spread, the difference between Baa bond returns and Aaa bond returns.

Since the literature has found that the default spread and investor sentiment exhibit predictability for the stock markets and both variables are market-wide conditioning variables used in our models, we also report the correlation coefficients of the default spread with each of the survey sentiment indices in panel B of Table 1. The correlation coefficients of the default spread with MS and CCI are both around -0.5 and are statistically significant at the 1% level, while the correlation coefficient of the default spread with II is -0.02, which is much weaker and statistically insignificant. The larger coefficient of variation of the default spread, 39.62%, than those of sentiment indices indicates that the default spread is more variable than the sentiment indicators.

3. Methodology

3.1. Theoretical Framework
We use the two-pass framework of Avramov and Chordia (2006). The conditional framework can be summarized in a generic form as:

\[
R^*_j \equiv R_j - [R_{ft} + \beta(t; S_{t-1}, z_{t-1}, X_{t-1})' F_t] = c_{jt} + c_t Z_{jt-1} + e_{jt}
\]  

(2)

where \( R^*_j \) is the vector of the estimated risk-adjusted return on stock \( j \) for time \( t \), \( R_j \) denotes the raw stock return and \( R_{ft} \) is the risk-free rate. \( \theta \) denotes the set of parameters that captures the dependence of \( \beta \) on the investor sentiment (\( S_{t-1} \)), the macroeconomic variables (\( z_{t-1} \)), and the firm characteristics (\( X_{jt-1} \)) for time \( t-1 \). \( F_t \) is the vector of risk factors specified in the asset pricing models of interest. The vector of the conditional beta is estimated by a first-pass time-series regression over the entire sample period as per the specification of the empirical model given in Section 3.2. The left-hand side of (2) is equal to the sum of the intercept and the residual obtained from a first-pass time-series regression. \( Z_{jt-1} \) denotes the vector of the financial market anomalies—the size, value, liquidity, and momentum effects—that we intend to capture. \( c_t \) is the vector of characteristic rewards.

Equation (2) is a second-pass cross-sectional regression where we run the risk-adjusted stock return on the financial market anomalies to examine whether the anomalies can be captured by the conditional asset pricing models specified in the first-pass regression. The null hypothesis of the test is 

\[
\hat{c}_c = (Z_{t-1}' Z_{t-1})^{-1} Z_{t-1}' R^*_j = 0.
\]

A decision that we accept (not reject) the null hypothesis indicates that the relevant size, value, liquidity, and momentum effects cannot provide any explanatory power for individual stock return, and hence, the conditional asset pricing model specified in
the first-pass regression successfully captures the relevant financial market anomalies.

### 3.2. Empirical Models

The asset pricing models examined in this paper are: (i) the CAPM, (ii) the Fama-French three-factor model (FF), (iii) the FF model plus the Pastor-Stambaugh liquidity factor (FFP), (iv) the FF model plus a momentum factor (FFW), and (v) the FF model plus both the liquidity and the momentum factors (FFPW). The most comprehensive model in our study that contains all the risk factors considered is the FFPW model as:

\[
    r_{jt} = \alpha_j + \beta_{jm} r_{mt} + \beta_{jSMB} SMB_t + \beta_{jHML} HML_t + \beta_{jPS} PS_t + \beta_{jWML} WML_t + \epsilon_{jt} \tag{3}
\]

where \( r_{jt} \) and \( r_{mt} \) are, respectively, the excess return on stock \( j \) and the (CRSP value-weighted) market at time \( t \). \( \epsilon_{jt} \) is the error term. \( SMB \) denotes the monthly return difference between the average return on the three small size portfolios minus the average return on the three big size portfolios. \( HML \) denotes the monthly return difference between the average return on the two value portfolios minus the average return on the two growth portfolios. \( PS \) is the Pastor-Stambaugh (2003) liquidity factor obtained by the return difference between the value-weighted return on the high liquidity sensitive portfolios and the value-weighted return on the low liquidity sensitive portfolios. \( WML \) is the momentum factor that represents the return difference between the return on the winner portfolio and the return on the loser portfolio based on the momentum strategy as depicted by Jegadeesh and Titman.
We obtain all the risk factors from Ken French’s website. The most parsimonious asset pricing model examined in our study is the CAPM that contains the single risk factor—the excess market return.

To further illustrate how the theoretical framework described in the previous section can be tested in its empirical form, we use the single-factor CAPM as an example to describe the empirical specification that the factors loadings may vary with investor sentiment, the default spread, and (SIZE+B/M).

The beta of the excess market return, $\beta_{j,t-1}$, can be expressed as a function of investor sentiment, the default spread, and (SIZE+B/M) as

$$
\beta_{j,t-1} = \beta_{j1} + \beta_{j2}z_{t-1} + \beta_{j3}S_{t-1} + \beta_{j4}z_{t-1}S_{t-1} + (\beta_{j5} + \beta_{j6}z_{t-1} + \beta_{j7}z_{t-1}S_{t-1})SIZE_{j,t-1} + (\beta_{j8} + \beta_{j9}z_{t-1} + \beta_{j10}z_{t-1}S_{t-1})(B/M)_{j,t-1}
$$

(4)

The one period lag variables are used to emphasize that the beta is one period lagged as compared to the stock returns and the risk factors in the asset pricing models. When the beta is not a function of $S_{t-1}$, $z_{t-1}$, and $(SIZE_{j,t-1} + BM_{j,t-1})$, i.e., all $\beta$'s except $\beta_{j1}$ are set to be zeros, the model becomes a standard unconditional model. In contrast, if the beta is set to be a function of these conditioning variables, the conditional version of the CAPM becomes

$$
r_{j,t} = \alpha_j + \beta_{j1}r_{mt} + \beta_{j2}z_{t-1}r_{mt} + \beta_{j3}S_{t-1}r_{mt} + \beta_{j4}z_{t-1}S_{t-1}r_{mt} + \beta_{j5}SIZE_{j,t-1}r_{mt} + \beta_{j6}S_{t-1}SIZE_{j,t-1}r_{mt} + \beta_{j7}z_{t-1}SIZE_{j,t-1}r_{mt} + \beta_{j8}BM_{j,t-1}r_{mt} + \beta_{j9}S_{t-1}BM_{j,t-1}r_{mt} + \beta_{j10}z_{t-1}BM_{j,t-1}r_{mt} + u_{j,t}
$$

(5)

The specification in (5) is the conditional model that incorporates all

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2 [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)
conditioning information. The other versions of the model can be derived by restricting the values of betas in (5) to be zeros. Therefore, the various versions of the conditional beta specification are:

Model A: Function of \((\text{SIZE} + \text{BM})\) and \(S\): (i.e., \(\beta_{12} = \beta_{14} = \beta_{17} = \beta_{110} = 0\))

Model B: Function of \((\text{SIZE} + \text{BM})\) and \(z\): (i.e., \(\beta_{13} = \beta_{15} = \beta_{16} = \beta_{19} = 0\))

Model C: Function of \(z, S\): (i.e., \(\beta_{15} = \beta_{16} = \beta_{17} = \beta_{19} = \beta_{110} = 0\))

Model D: Function of \((\text{SIZE} + \text{BM})\): (i.e., \(\beta_{12} = \beta_{13} = \beta_{14} = \beta_{16} = \beta_{17} = \beta_{19} = \beta_{110} = 0\))

Model E: Function of \(S\): (i.e., \(\beta_{12} = \beta_{14} = \beta_{15} = \beta_{16} = \beta_{17} = \beta_{18} = \beta_{19} = \beta_{110} = 0\))

Model F: Function of \(z\): (i.e., \(\beta_{13} = \beta_{14} = \beta_{15} = \beta_{16} = \beta_{17} = \beta_{18} = \beta_{19} = \beta_{110} = 0\))

Model G: Function of all \(z, S, \text{SIZE}, \text{BM}\): (i.e., all \(\beta_s \neq 0\))

The market adjusted return is obtained from the first-pass time-series regression as \(R^*_\mu = \alpha_j + u_\mu\) and then becomes the dependent variable in the second-pass regressions on the independent variable of size, B/M, liquidity, and momentum measures. The adjusted-R squared (\(R^2\)) of each model for the second-pass regression serves as an indicator for comparing the relative performance of the conditional Models A through G for the same asset pricing model. The lower value of the corresponding \(R^2\) indicates that the conditional model specified in the first-pass regression has a superior overall ability to capture the financial market anomalies. The significance of the estimates on the individual anomaly is used to detect whether the corresponding anomaly is successfully captured by the asset pricing model in the first stage. For example, if the coefficient on size is insignificantly different from zero, it indicates that the asset pricing model specified in the first-pass regression is able to capture the size effect.

Following Brennan, Chordia, and Subrahmanyam (1998) and Avramov and
Chordia (2006), in the cross-sectional regressions, all of the firm characteristics variables for a given month are deviations from the cross-sectional means for that month rather than the raw values of the firm characteristics variables. This implies that the average stock will have zero values for each non-risk firm characteristics, so only its risk characteristics can determine its expected return. The firm characteristics variables are also lagged one more period to get around the possibility that the biased estimate of risk-adjusted return may arise because of bid-ask effects and thin trading.

4. Empirical Results

4.1. Descriptive Statistics

Before formally testing whether the conditional asset pricing model can capture the market anomalies, we first obtain the Fama-MacBeth coefficients from the regression of excess stock returns on firm characteristics in order to examine whether traditionally documented market anomalies exist over the sample period. Table 2 shows the existence of the size (value) effect that small size (high B/M) firms earn higher returns than large (low B/M) firms, in line with the findings of Brennan, Chordia, and Subrahmanyam (1998), Chordia, Subrahmanyam, and Anshuman (2001), and Avramov and Chordia (2006). The negative sign on the turnover is also consistent with the argument of Amihud and Mendelson (1986) that investors would demand higher expected returns for holding less-liquid stocks since the trading of less-liquid stocks involves higher transaction costs. The momentum
effect (Jegadeesh and Titman, 1993) is also present in that the cumulative returns over the past short-term horizons affect excess stock returns and that the impact of the return performance in the past six months or earlier has a larger impact than the most recent return performance. The average $R^2$ is 5.76% for all NYSE-AMEX stocks, a magnitude that is very close to that of Avramov and Chordia (2006) which used a shorter sample period than our study.

4.2. The CAPM

Table 3 presents the Fama-MacBeth coefficient estimates for the cross-sectional regressions where the dependent variable is the monthly risk-adjusted return of the CAPM. The first column lists the unconditional model and the various time-varying beta specifications as described in (6) for conditional models. For conditional models with the sentiment indicator as conditioning variable in the beta specification, we present the results for each of the four proxies of investor sentiment. The last four columns present the average $R^2$ of the cross-sectional regressions for the various beta specifications.

The first row of Table 3 shows that all the coefficients on the anomaly variables are significantly different from zeros. All anomaly variables exhibit expected sign that small, value firms, and stocks with low turnover and high past returns earn higher risk-adjusted returns. These results indicate that the CAPM with a constant beta fails to capture any of the CAPM anomalies. In Model C where the market beta in the first pass is allowed to vary with both the sentiment indicator and default
spread or in Model G where the firm characteristics of SIZE and B/M are further allowed to enter the beta specification, the conditional CAPM marginally captures the size effect using either CCI or COMP as sentiment indicator. There exhibits a decline in the average $\bar{R}^2$ from 4.84% in the unconditional model to 4.44% in Model G that use either CCI or COMP as sentiment indicator. This pattern of a decreased power of the anomaly variables in explaining the cross-sectional variability of risk-adjusted returns indicates an improved beta specification in the first-pass time-series regression.

Table 3 also provides evidence that using the sentiment indicator as a conditioning variable yields a higher overall model explanatory power (i.e., a smaller $\bar{R}^2$) than using only the default spread or the firm characteristics in the conditional version of the CAPM. In particular, Model E, in which the beta is conditioned by the sentiment indicator of either CCI or COMP, has a smaller $\bar{R}^2$ than Models F and D where the former uses the default spread and the later uses the firm characteristics as conditioning variables. Furthermore, in the specifications with two conditioning variables, Model A where the sentiment indicator of either CCI or COMP is paired with the firm characteristics outperforms Model B where the default spread is paired with the firm characteristics as conditioning variables. Similarly, Model C where the sentiment indicator is paired with the default spread also outperforms Model B. In other words, substituting the sentiment indicator of either CCI or COMP for either the default spread or the firm characteristics as the conditioning variables in Model B can enhance the overall model explanatory power.
The $R^2$ can also serve as a measure of comparing the usefulness of the various proxies of investor sentiment in yielding a better overall model explanatory power. Table 3 shows that, among the three surveyed sentiment indices, CCI performs best, which is followed by II and then MS. The composite sentiment index, COMP, in general, outperforms CCI, II, and MS, as can be seen by the pattern: $R^2_{\text{COMP}} < R^2_{\text{CCI}} < R^2_{\text{II}} < R^2_{\text{MS}}$.

4.3. The Fama-French Three-Factor Model (FF)

Table 4 presents the results of the unconditional and conditional versions of FF model. The unconditional FF, which includes two additional risk factors $SMB$ and $HML$, has a much lower $R^2$ of 2.79% compared with 4.84% of the unconditional CAPM (Table 3), and thus shows higher overall explanatory power than the CAPM. Compared to the unconditional CAPM which does not capture any anomalies, the unconditional FF model marginally captures the size effect. For the conditional FF models A, B, and G where the factor loadings are conditioned by the sentiment, default spread, and firm characteristics, the variables of both size and the B/M ratio are no longer important in explaining the cross-section of risk-adjusted returns. This can be seen from the dramatically reduced $t$-values of the estimates on both the SIZE and B/M variables. The results are robust regardless of which indicator is used to proxy for investor sentiment.

When the factor loadings are conditioned by the sentiment indicator of COMP and the default spread as in Model C, the variables of SIZE and RET2-3 are no
longer significant in explaining the cross-section of risk-adjusted returns. Replacing the sentiment indicator by CCI in Model C leads to a greatly reduced $t$-value for the SIZE variable and a slightly less significant coefficient estimate for RET2-3. Avramov and Chordia (2006) do not consider sentiment as conditioning information and find that the conditional FF model fails to explain the impact of the momentum effect on the cross-section of risk-adjusted returns. In contrast, our results suggest that investor sentiment plays a crucial role in explaining the momentum effect. This is because we allow the sensitivities of risky asset returns on risk factors to take into account of the variation in the interaction between the sentiment of market participants and the default spread.

The results in Table 4 also suggest that the investor sentiment might be more useful than the default spread in being specified as a conditioning variable in the conditional FF. Consider Models E and F, where there is only one conditioning variable, the sentiment and default spread, respectively, we find that Model E has a slightly lower $R^2$ than that of Model F. Similarly, Models A, which has the sentiment paired with the firm characteristics as conditioning variables, has a slightly lower $R^2$ than that of Model B which has the default spread paired with the firm characteristics as conditioning variables. Unlike in the conditional CAPM, in the conditional FF the sentiment indicator does not lead to a better overall model performance than that using the firm characteristics as conditioning variables.

Similar to what we have found in Section 4.2 for the CAPM, among the sentiment indices used in the model, the composite sentiment index has the smallest
in all of the conditional FF models (Models A, C, E, and G) that involve sentiment as conditioning variable. Moreover, the composite sentiment index further demonstrates its superiority by the capability to capture RET2-3 when working with the default spread as conditioning variables. Among the survey sentiment indices, CCI outperforms II and MS as its $R^2$ is smaller than the others.

4.4. The FF Model plus the Pastor-Stambaugh Liquidity Factor (FFP)

We augment the FF model by the Pastor-Stambaugh liquidity factor because Pastor and Stambaugh (2003) report that high liquidity-beta stocks earn higher average return than low liquidity-beta stocks by 7.5% annually. The liquidity factor is the difference between the value-weighted return on the stocks with high sensitivities to liquidity and the value-weighted return on the stocks with low sensitivities to liquidity.

Table 5 presents the results for the FFP model. The inclusion of the liquidity factor improves the FF model in the following ways. First, in the unconditional model, the size effect is better captured (becomes less significant) by including the liquidity factor since the $t$-value of the coefficient estimate of the size effect drops to -1.59 in the FFP model from -1.91 in the FF model. Second, RET2-3, along with the SIZE variable, can now be fully captured in Model C regardless of the sentiment proxies. The FF model (Table 4) can successfully capture RET2-3 only when the composite sentiment index is used as the proxy for investor sentiment; however, all

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3 We thank Lubos Pastor for providing this factor.
sentiment indices exhibit such capability after adding the liquidity factor to the FF model. Third, Model F where factor loadings are scaled by the default spread alone can also capture RET2-3. For Model G, however, apart from using COMP as the sentiment proxy, the FFP model can not capture the value effect.

As in the FF model, the use of the sentiment as a conditioning variable in the FFP model leads to higher overall explanatory power of the model than does the default spread. This can be seen from the lower $R^2$ in Model E (where the risk factors are scaled by the sentiment only) compared with that in Model F (where the risk factors are scaled by the default spread only). Similarly, Model A (where the risk factors are scaled by the sentiment paired with firm characteristics) shows a lower $R^2$ than that in Model B (where the risk factors are scaled by the default spread paired with firm characteristics). Interestingly for the conditional FFP model, although the conditional models outperform the unconditional model, there is no consistent pattern in the ordering of $R^2$ from using different proxies for investor sentiment.

4.5. The FF Model plus the Winners-minus-Losers Factor (FFW)

Table 6 presents the results of a model (FFW) that includes an extra risk factor, WML, as along with the FF three factors. In general, the coefficient estimates in the FFW are qualitatively similar to those in the FFP. Using MS, CCI, and II as the sentiment proxy, Model G of the FFW where the factor loadings are allowed to vary with all conditioning variables can successfully capture TURNOVER. In addition, Model G
can also capture RET2-3 when MS and II are used to proxy for investor sentiment. The finding that the conditional FFW can successfully explain the liquidity effect on the cross-section of the stock return supports the view that investor sentiment is related to stock liquidity. This is in line with the argument of Baker and Stein (2004) that high liquidity (e.g., high trading volume) is a sign of high irrational investor sentiment. Liu (2006) also documents that the stock market is more liquid when sentiment is higher.

4.6. The FF Model plus the Liquidity and WML Factors (FFPW)

Table 7 reports the results of a model that augments the FF model by both the liquidity and the momentum factors. It is clear that considering the liquidity and momentum factors together with the FF model does not improve the explanatory power of the model. The outcomes of the FFPW appear much closer to those of the FFP. For example, RET2-3 is captured by Model C and F regardless of the sentiment proxy. The noticeable exception is that TURNOVER is captured in the FFPW using MS as the sentiment proxy while the FFP does not capture TURNOVER at all.

Comparing the results in the FFPW to those in the FFW, we find two critical differences. First, in FFPW, CCI and II no longer exert any influence in Model G in explaining the cross-section of risk-adjusted return. Second, Model G of FFPW completely fails to capture RET2-3. The most noticeable benefit from the FFPW probably is that Model G of FFPW can successfully capture the size effect which Model G of FFW fails to capture.
4.7. Discussions

Overall, we find that when comparing all versions of the conditional models that involve investor sentiment as conditioning information, the size effect can often be explained by the conditional FF-based models (FF, FFP, FFW and FFPW) which allow the factor loadings to be scaled by the sentiment measures alone (Model E). Furthermore, when the sentiment measure is paired with firm-specific characteristics as conditional variables (Model A) in the FF-based models, most of these models can successfully capture both the size and value effects. In particular, the FFP model, which augments the FF with the liquidity factor, can dramatically increase its explanatory power for both size and value effects. The FFW model however, which augments the FF with the momentum factor, almost loses its power in capturing the value effect.

In model C, where the factor loadings of the FF-based models are conditioned on both the investor sentiment and default spread, the performance of all the FF-based models are significantly improved in two ways. First, all the FF-based models successfully capture the momentum effect (RET2-3) in addition to the size effect regardless of the sentiment measures. Second, the (absolute) values of $t$-statistics of the captured size and momentum effects in the FF-based models are much smaller than those in the FF 3 factor model. This result implies that the impacts of both captured anomalies of stock returns are reduced once the additional risk factor(s) are added to the FF model.
5. Conclusions

We examine various specifications of the conditional CAPM and multifactor asset pricing models in an attempt to explain the well-documented CAPM anomalies—size, value, liquidity, and momentum effects. Previous studies claim that the systematic risk or factor loadings of the asset pricing models are associated with business-cycle and firm-specific financial variables. The literature also provides evidence that investor sentiment exhibit time-series and cross-sectional impacts on stock returns and liquidity. In this paper, we posit that a conditional pricing model that allows the factor loadings to vary with investor sentiment, the default spread, and firm-specific characteristics variables may successfully capture the financial market anomalies.

We find that our conditional models not only successfully capture both the size and value effects, but also explain the impacts of liquidity and momentum factors on the cross-section of stock return. The evidence suggests that adding the investor sentiment to the default spread and firm-specific characteristics variables as conditioning variables improves the overall explanatory power of the conditional asset pricing model.

Second, we find that investor sentiment, as a conditioning variable, conveys more information than the default spread since (i) it enhances the overall explanatory power of the asset pricing models in depicting the stock prices; (ii) the conditional CAPM can successfully capture the size effect. Third, using $R^2$ as a measure of the overall explanatory power of the asset pricing model, we find that conditional models outperform unconditional models in all asset pricing model under
consideration. Finally, in the conditional versions of the CAPM and the Fama-French model, using the composite investor sentiment index, followed by the Conference Board Consumer Confidence Index, to proxy for investor sentiment yields the highest overall model explanatory power. The sentiment indices compiled by Investors’ Intelligence and the University of Michigan do not seem to provide significantly incremental information content in enhancing the performance of the asset pricing models.
Appendix: Investor Sentiment Indices

In this section, we discuss the investor sentiment indices that we use in our study.

University of Michigan Consumer Sentiment Survey (MS)

The historical data for the MS are publicly available at the website of the University of Michigan Survey Research Center. The detailed procedure used to calculate the Index can be found in Howrey (2001) and Charoenrook (2005). To collect the data in order to measure the optimism of consumers, prior to 1978, the Research Center revealed the data in February, May, August, and November of each year. The index became available on a monthly basis after 1978. The data are obtained by polling 500 US households who are asked to respond to the following five questions: (i) We are interested in how people are getting along financially these days. Would you say that you are better off or worse off financially than you were a year ago? (ii) Now, looking ahead – do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now? (iii) Now, turning to business conditions in the country as a whole – do you think that during the next twelve months, we’ll have good times financially, or bad time, or what? (iv) Looking ahead, which would you say is more likely – that we’ll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what? (v) About the big things people buy for their homes – such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good time or a bad time for people to buy major household items?
The center of each question can be restated in a shorter form as follows: (i) A rating of household financial conditions, (ii) a rating of expected household financial conditions a year from now, (iii) a rating of expected business conditions a year from now, (iv) expectations for the economy for the next five years, (v) buying plans. The overall score of the index is consisted of the relative score of each question which is calculated as the difference of favorable replies and unfavorable, plus 100, rounded to the nearest whole number. The index of the first quarter of 1966 serves as the base index of the time series data.

**The Conference Board Consumer Confidence Index (CCI)**

The Conference Board has published this data by mailing questionnaires to a representative sample of 5,000 U.S. households. A different group of 5,000 households is surveyed in each month. Samples feature representative key demographics and geographic as defined by the U.S. Census Bureau. The data frequency was changed from bi-monthly since its inception to monthly after June 1977, although the questions remained unchanged throughout the entire history of time series.

Similarly to MS, CCI also asks the household respondents to answer five questions: (i) How would you rate present general business conditions in your area? (ii) What would you say about available jobs in your area right now? (iii) Six months from now, do you think business conditions in your area will be better, same, or worse? (iv) Six months from now, do you think there will be more, same, or fewer
jobs available in your area? (v) Would you guess your total family income to be higher, same, or lower six months from now? Likewise, these questions can be summarized as the following short statements to inquire the respondents’: (i) Appraisal of current business conditions. (ii) Expectations regarding business conditions six months hence. (iii) Appraisal of current employment conditions. (iv) Expectations regarding employment conditions six months hence. (v) Expectations regarding their total family income six months hence. The respondents have three response options: positive, negative, and neutral. The relative score of each question is obtained by dividing the total number of “positive” responses by the sum of the “positive” and “negative” responses. The average of the five relative scores, which are indexed using the 1985 data, composes the overall index of CCI.

**Investors’ Intelligence Survey (II)**

The II index is compiled by Chartcraft, Inc., based on stock market newsletters. Investors’ Intelligence differs from MS and CCI in two ways. First, II measures the sentiment of “investors” of the stock market, while MS and CCI gauge the confidence of “consumers” regarding the whole economy. Second, II collects the opinions of retired or current market professionals, while MS and CCI primarily focus on retail investors. Each weekend, the Investors’ Intelligence reads about 150 newsletters and marks the opinions of newsletter writers into one of the three labels – bullish, bearish, or neutral – based on the advisory services recommendation of transactions. “Bullish” are labeled when the advisory services recommend stock for
purchase or predict that the market will rise. “Bearish” are marked when they recommend closing long position or opening short ones because the market is predicted to decline. The data have been available since 1964 on a weekly basis. II has long been considered a contrarian indicator by the practitioners since extreme in either direction signals reversal of the market’s current trend.
References


Table 1: Summary statistics and correlations of survey investor sentiment indicators and the default spread

Panel A: Descriptive Statistics of survey investor sentiment indicators and the default spread

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>C.V. (%)</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>MS</td>
<td>86.61</td>
<td>12.10</td>
<td>13.97</td>
<td>51.70</td>
<td>112.00</td>
</tr>
<tr>
<td>CCI</td>
<td>98.17</td>
<td>23.02</td>
<td>23.45</td>
<td>43.20</td>
<td>144.71</td>
</tr>
<tr>
<td>II</td>
<td>44.19</td>
<td>10.08</td>
<td>22.81</td>
<td>10.30</td>
<td>76.66</td>
</tr>
<tr>
<td>DEF (%)</td>
<td>1.06</td>
<td>0.42</td>
<td>39.62</td>
<td>0.55</td>
<td>2.69</td>
</tr>
</tbody>
</table>

Panels B: Correlations between survey investor sentiment indicators and the default spread

<table>
<thead>
<tr>
<th></th>
<th>MS</th>
<th>CCI</th>
<th>II</th>
<th>DEF</th>
</tr>
</thead>
<tbody>
<tr>
<td>MS</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCI</td>
<td>0.76*</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>II</td>
<td>0.27*</td>
<td>0.04</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>DEF</td>
<td>-0.50*</td>
<td>-0.53*</td>
<td>-0.02</td>
<td>1.00</td>
</tr>
</tbody>
</table>

*: significant at the 1% level.

MS, CCI, and II are the investor/consumer sentiment indices compiled by the University of Michigan, Consumer Conference Board, and Investor’s Intelligence, respectively. DEF is the default spread which measures the yield difference between Baa and Aaa bonds. C.V. is the coefficient of variation calculated as the ratio of standard deviation to mean.
Table 2: Summary statistics (3,918 firms: 07/1964 - 12/2005)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Coefficient (%)</th>
<th>$t$-value</th>
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<tbody>
<tr>
<td>EXCESS RETURN (%)</td>
<td>0.84</td>
<td>0.86</td>
<td>5.47</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SIZE ($ billions)</td>
<td>1.97</td>
<td>0.84</td>
<td>2.10</td>
<td>-0.12</td>
<td>-2.73</td>
</tr>
<tr>
<td>B/M ratio</td>
<td>0.89</td>
<td>0.83</td>
<td>0.35</td>
<td>0.26</td>
<td>4.69</td>
</tr>
<tr>
<td>TURNOVER</td>
<td>0.05</td>
<td>0.04</td>
<td>0.03</td>
<td>-0.09</td>
<td>-1.63</td>
</tr>
<tr>
<td>RET2-3 (%)</td>
<td>2.61</td>
<td>3.18</td>
<td>8.38</td>
<td>0.65</td>
<td>2.23</td>
</tr>
<tr>
<td>RET4-6 (%)</td>
<td>3.93</td>
<td>4.12</td>
<td>10.58</td>
<td>0.82</td>
<td>3.13</td>
</tr>
<tr>
<td>RET7-12 (%)</td>
<td>7.94</td>
<td>7.75</td>
<td>15.44</td>
<td>0.96</td>
<td>6.15</td>
</tr>
<tr>
<td>$\bar{R}^2$ (%)</td>
<td></td>
<td></td>
<td></td>
<td>5.76</td>
<td></td>
</tr>
</tbody>
</table>

This table presents the time-series averages of the cross-sectional means, medians, and standard deviation for 3,918 NYSE-AMEX stocks over firms over 498 months from July 1964 through December 2005. The “Reg. Coefficient” column represents the time-series averages of slope coefficients in cross-sectional OLS regressions of excess return on various equity characteristics. The $t$-value for each equity characteristic is listed in the last column. $\bar{R}^2$ denotes the adjusted R square. SIZE represents the market capitalization in billions of dollars. B/M denotes the book-to-market ratio. TURNOVER is the monthly share trading volume divided by shares outstanding. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seven through twelfth months before the current month, respectively. A common stock must meet the following criteria in order to be included in the analysis: (i) the returns of these stocks must be available in the current month, $t$, and over the past 36 months in the CRSP, (ii) information on stock prices and shares outstanding for calculating the size of a firm and the month $t–2$ trading volume for calculating the turnover must be available, (iii) the B/M as of December of the previous calendar year has to be available from the COMPUSTAT dataset, (iv) the B/M must be positive, and (v) the B/M values greater than the 0.995 fractile or less than the 0.005 fractile are set to the 0.995 and 0.005 fractile values, respectively.
**Table 3: Fama-MacBeth regression estimates with excess market return as the risk factor (CAPM)**

<table>
<thead>
<tr>
<th>MODEL</th>
<th>SIZE</th>
<th>B/M</th>
<th>TURNOVER</th>
<th>RET2-3</th>
<th>RET4-6</th>
<th>RET7-12</th>
<th>Adj. R^2 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MS</td>
<td>CCI</td>
<td>II</td>
<td>MS</td>
<td>CCI</td>
<td>II</td>
<td>MS</td>
</tr>
<tr>
<td>UNCOND</td>
<td>-0.099</td>
<td>--</td>
<td></td>
<td>-0.161</td>
<td>--</td>
<td></td>
<td>0.764</td>
</tr>
<tr>
<td>A</td>
<td>-0.093</td>
<td>-0.087</td>
<td>-0.010</td>
<td>-0.085</td>
<td>0.253</td>
<td>0.260</td>
<td>0.234</td>
</tr>
<tr>
<td>B</td>
<td>-0.087</td>
<td>--</td>
<td></td>
<td>-0.152</td>
<td>--</td>
<td></td>
<td>0.936</td>
</tr>
<tr>
<td>C</td>
<td>-0.142</td>
<td>-0.099</td>
<td>-0.172</td>
<td>-0.167</td>
<td>0.257</td>
<td>0.271</td>
<td>0.256</td>
</tr>
<tr>
<td>D</td>
<td>-0.093</td>
<td>--</td>
<td></td>
<td>-0.159</td>
<td>--</td>
<td></td>
<td>0.852</td>
</tr>
<tr>
<td>E</td>
<td>-0.097</td>
<td>-0.088</td>
<td>-0.100</td>
<td>-0.087</td>
<td>0.268</td>
<td>0.290</td>
<td>0.260</td>
</tr>
<tr>
<td>F</td>
<td>-0.095</td>
<td>--</td>
<td></td>
<td>-0.150</td>
<td>--</td>
<td></td>
<td>0.726</td>
</tr>
<tr>
<td>G</td>
<td>-0.148</td>
<td>-0.074</td>
<td>-0.093</td>
<td>-0.076</td>
<td>0.231</td>
<td>0.238</td>
<td>0.215</td>
</tr>
<tr>
<td>H</td>
<td>-0.231</td>
<td>-0.182</td>
<td>-0.237</td>
<td>-0.186</td>
<td>0.452</td>
<td>0.471</td>
<td>0.439</td>
</tr>
</tbody>
</table>

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates for NYSE-AMEX stocks over 498 months from July 1964 through December 2005. The dependent variable is the excess return risk-adjusted using the excess market return as the risk factor. The factor loading (i.e., beta) is scaled by investor sentiment index, the default spread, as well as SIZE and B/M. The row of “UNCOND” is the estimated coefficients on financial market anomalies under consideration when the market beta in the first-pass pricing model is constant. The rows for models A – G are the results for the conditional versions of the asset pricing model as per the specification described in equation (6). SIZE represents the logarithm of market capitalization in billions of dollars. B/M denotes the logarithm of the book-to-market ratio with the exception that B/M greater than 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. TURNOVER is the monthly share trading volume divided by shares outstanding. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seven through twelfth months before the current month, respectively. A d j. R^2 denotes the time-series average of the monthly adjusted R square. MS, CCI, and II are the investor/consumer sentiment indices compiled by the University of Michigan, Consumer Conference Board, and Investor’s Intelligence, respectively. COMP is the composite sentiment index derived from principal component analysis using the above three sentiment indices. All coefficients are multiplied by 100.

****: t ≤ 1.85; **: t ≤ 2.00.
Table 4: Fama-MacBeth regression estimates with Fama-French three factors as the risk factors (FF)

| MODEL | SIZE | B/M | TURNOVER | RET2-3 | RET4-6 | RET7-12 | Adj. R² (%)
|-------|------|-----|----------|--------|--------|---------|-------------
| UNCOND | -0.040* | MS | -0.166 | (4.04) | 0.728 | 0.846 | 0.954 | 2.79
| A | -0.029** -0.019** -0.026** -0.025** | (1.43) (0.92) (1.29) (1.22) | 0.034** 0.034** 0.060** 0.040** | (-4.84) (-5.13) (-5.01) (-4.94) | 0.812 0.773 0.992 0.774 | 0.991 0.986 1.116 0.982 | 1.025 1.080 1.031 1.073 | 2.45 2.36 2.39 2.35
| B | -0.026 | MS | 0.022** | (-1.10) | 0.781 | 1.009 | 1.025 | 2.46
| C | -0.040** -0.026** -0.041** -0.035** | (-1.79) (-1.17) (-1.84) (-1.56) | 0.105 0.105 0.107 0.111 | (-1.51) (-1.60) (-1.52) (-1.67) | 0.522 0.482* 0.583 0.432** | 0.781 0.801 0.893 0.792 | 0.902 0.918 0.899 0.937 | 2.65 2.58 2.66 2.56
| D | -0.020** | MS | 0.003 | -0.156 | 0.856 | 1.003 | 1.004 | 2.68
| E | -0.044** -0.037** -0.047 -0.041** | (-1.70) (2.43) (4.38) (4.35) | 0.144 0.147 0.148 0.156 | (-0.159) (-0.171) (-0.161) (-0.178) | 0.688 0.595 0.757 0.596 | 0.847 0.847 0.880 0.834 | 0.918 0.952 0.951 0.954 | 2.70 2.60 2.70 2.58
| F | -0.040** | MS | 0.135 | -0.154 | 0.542 | 1.002 | 0.907 | 2.74
| G | -0.022** -0.007** -0.014** -0.016** | (-1.17) (-0.37) (-0.76) (-0.88) | 0.010** 0.015** 0.022** 0.018** | (-0.148) (-0.157) (-0.154) (-0.154) | 0.806 0.770 0.882 0.765 | 0.988 0.974 1.100 1.013 | 0.961 0.985 0.954 1.008 | 2.43 2.33 2.41 2.34

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates for NYSE-AMEX stocks over 498 months from July 1964 through December 2005. The dependent variable is the excess return risk-adjusted using the Fama-French three factors as the risk factors. The factor loadings are scaled by investor sentiment index, the default spread, as well as SIZE and B/M. The row of “UNCOND” is the estimated coefficients on financial market anomalies under consideration when the market beta in the first-pass pricing model is constant. The rows for models A – G are the results for the conditional versions of the asset pricing model as per the specification described in equation (6). SIZE represents the logarithm of market capitalization in billions of dollars. B/M denotes the logarithm of the book-to-market ratio with the exception that B/M greater than 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. TURNOVER is the monthly share trading volume divided by shares outstanding. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seven through twelfth months before the current month, respectively. A d j. R ² denotes the time-series average of the monthly adjusted R square. MS, CCI, and II are the investor/consumer sentiment indices compiled by the University of Michigan, Consumer Conference Board, and Investor’s Intelligence, respectively. COMP is the composite sentiment index derived from principal component analysis using the above three sentiment indices. All coefficients are multiplied by 100.

**: t ≤ 1.85; *: t ≤ 2.00.
This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates for NYSE-AMEX stocks over 498 months from July 1964 through December 2005. The dependent variable is the excess return risk-adjusted using the Fama-French three factors and Pastor and Stambaugh liquidity factor as the risk factors. The factor loadings are scaled by investor sentiment index, the default spread, as well as SIZE and B/M. The row of “UNCOND” is the estimated coefficients on financial market anomalies under consideration when the market beta in the first-pass pricing model is constant. The rows for models A – G are the results for the conditional versions of the asset pricing model as per the specification described in equation (6). SIZE represents the logarithm of market capitalization in billions of dollars. B/M denotes the logarithm of the book-to-market ratio with the exception that B/M greater than 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. TURNOVER is the monthly share trading volume divided by shares outstanding. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month, respectively. Adj. $R^2$ denotes the time-series average of the monthly adjusted $R^2$ square. MS, CCI, and II are the investor/consumer sentiment indices compiled by the University of Michigan, Consumer Conference Board, and Investor’s Intelligence, respectively. COMP is the composite sentiment index derived from principal component analysis using the above three sentiment indices. All coefficients are multiplied by 100.

** denotes $t \leq 1.85$; * denotes $t \leq 2.00$.
Table 6: Fama-MacBeth regression estimates with Fama-French three factors plus WML as the risk factors (FFW)

<table>
<thead>
<tr>
<th>MODEL</th>
<th>SIZE</th>
<th>B/M</th>
<th>TURNOVER</th>
<th>RET2-3</th>
<th>RET4-6</th>
<th>RET7-12</th>
<th>Adj. R²(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MS</td>
<td>CCI</td>
<td>II</td>
<td>COMP</td>
<td>MS</td>
<td>CCI</td>
<td>II</td>
</tr>
<tr>
<td>UNCOND</td>
<td>-0.046**</td>
<td>0.182</td>
<td>0.125</td>
<td>0.080</td>
<td>0.033</td>
<td>0.027</td>
<td>2.73</td>
</tr>
<tr>
<td>A</td>
<td>-0.017**</td>
<td>-0.004**</td>
<td>-0.012**</td>
<td>-0.131</td>
<td>-0.676</td>
<td>2.15</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>-0.004**</td>
<td>0.041**</td>
<td>-0.132</td>
<td>0.699</td>
<td>0.934</td>
<td>2.14</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>-0.031**</td>
<td>-0.017**</td>
<td>-0.028**</td>
<td>-0.119</td>
<td>0.333**</td>
<td>2.21</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>-0.023**</td>
<td>0.064</td>
<td>-0.133</td>
<td>0.796</td>
<td>0.976</td>
<td>2.24</td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>-0.046**</td>
<td>-0.034**</td>
<td>-0.130</td>
<td>0.485**</td>
<td>2.29</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>-0.034**</td>
<td>0.164</td>
<td>-0.123</td>
<td>0.458**</td>
<td>2.31</td>
<td></td>
<td></td>
</tr>
<tr>
<td>G</td>
<td>0.049</td>
<td>0.034**</td>
<td>0.112</td>
<td>0.076</td>
<td>0.057</td>
<td>2.32</td>
<td></td>
</tr>
</tbody>
</table>

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates for NYSE-AMEX stocks over 498 months from July 1964 through December 2005. The dependent variable is the excess return risk-adjusted using the Fama-French three factors and momentum factor as the risk factors. The factor loadings are scaled by investor sentiment index, the default spread, as well as SIZE and B/M. The row of “UNCOND” is the estimated coefficients on financial market anomalies under consideration when the market beta in the first-pass pricing model is constant. The rows for models A – G are the results for the conditional versions of the asset pricing model as per the specification described in equation (6). SIZE represents the logarithm of market capitalization in billions of dollars. B/M denotes the logarithm of the book-to-market ratio with the exception that B/M greater than 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. TURNOVER is the monthly share trading volume divided by shares outstanding. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seven through twelfth months before the current month, respectively. Adj. R² denotes the time-series average of the monthly adjusted R square. MS, CCI, and II are the investor/consumer sentiment indices compiled by the University of Michigan, Consumer Conference Board, and Investor’s Intelligence, respectively. COMP is the composite sentiment index derived from principal component analysis using the above three sentiment indices. All coefficients are multiplied by 100.

**: t ≤ 1.85; *: t ≤ 2.00.
Table 7: Fama-MacBeth regression estimates with Fama-French three factors plus (PS Liquidity + WML) as the risk factors (FFPW)

<table>
<thead>
<tr>
<th>MODEL</th>
<th>SIZE</th>
<th>B/M</th>
<th>TURNOVER</th>
<th>RET2-3</th>
<th>RET4-6</th>
<th>RET7-12</th>
<th>Adj. R² (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>UNCOND</td>
<td>MS CCI II COMP</td>
<td>MS CCI II COMP</td>
<td>MS CCI II COMP</td>
<td>MS CCI II COMP</td>
<td>MS CCI II COMP</td>
<td>MS CCI II COMP</td>
<td>MS CCI II COMP</td>
</tr>
<tr>
<td>A (SIZE-B/M)</td>
<td>-0.015** (-1.85)</td>
<td>-0.003** (-0.81)</td>
<td>0.004** (1.53)</td>
<td>-0.122 (-4.30)</td>
<td>0.063 (0.06)</td>
<td>0.941 (5.79)</td>
<td>0.879 (5.35)</td>
</tr>
<tr>
<td>B (SIZE-B/M)</td>
<td>-0.007** (-0.38)</td>
<td>0.004** (1.19)</td>
<td>-0.112 (-4.47)</td>
<td>0.069 (2.89)</td>
<td>0.941 (2.16)</td>
<td>0.879 (6.18)</td>
<td>0.941 (3.91)</td>
</tr>
<tr>
<td>C (SIZE-B/M)</td>
<td>-0.007** (-0.26)</td>
<td>-0.003** (-0.17)</td>
<td>-0.111 (-3.40)</td>
<td>0.069 (3.23)</td>
<td>0.941 (2.16)</td>
<td>0.879 (6.18)</td>
<td>0.941 (3.91)</td>
</tr>
<tr>
<td>D (SIZE-B/M)</td>
<td>-0.007** (-1.46)</td>
<td>-0.007** (-1.00)</td>
<td>-0.116 (-3.63)</td>
<td>0.069 (3.23)</td>
<td>0.941 (2.16)</td>
<td>0.879 (6.18)</td>
<td>0.941 (3.91)</td>
</tr>
<tr>
<td>E (SIZE-B/M)</td>
<td>-0.007** (-1.46)</td>
<td>-0.007** (-1.00)</td>
<td>-0.116 (-3.63)</td>
<td>0.069 (3.23)</td>
<td>0.941 (2.16)</td>
<td>0.879 (6.18)</td>
<td>0.941 (3.91)</td>
</tr>
<tr>
<td>F (SIZE-B/M)</td>
<td>-0.007** (-1.46)</td>
<td>-0.007** (-1.00)</td>
<td>-0.116 (-3.63)</td>
<td>0.069 (3.23)</td>
<td>0.941 (2.16)</td>
<td>0.879 (6.18)</td>
<td>0.941 (3.91)</td>
</tr>
<tr>
<td>G (SIZE-B/M)</td>
<td>-0.007** (-1.46)</td>
<td>-0.007** (-1.00)</td>
<td>-0.116 (-3.63)</td>
<td>0.069 (3.23)</td>
<td>0.941 (2.16)</td>
<td>0.879 (6.18)</td>
<td>0.941 (3.91)</td>
</tr>
</tbody>
</table>

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates for NYSE-AMEX stocks over 498 months from July 1964 through December 2005. The dependent variable is the excess return risk-adjusted using the Fama-French three factors, Pastor and Stambaugh, and momentum factor as the risk factors. The factor loadings are scaled by investor sentiment index, the default spread, as well as SIZE and B/M. The row of “UNCOND” is the estimated coefficients on financial market anomalies under consideration when the market beta in the first-pass pricing model is constant. The rows for models A – G are the results for the conditional versions of the asset pricing model as per the specification described in equation (6). SIZE represents the logarithm of market capitalization in billions of dollars. B/M denotes the logarithm of the book-to-market ratio with the exception that B/M greater than 0.995 fractile or less than the 0.005 fractile are set equal to the 0.995 and the 0.005 fractile values, respectively. TURNOVER is the monthly share trading volume divided by shares outstanding. RET2-3, RET4-6, and RET7-12 are the cumulative returns over the second through third, fourth through sixth, and seven through twelfth months before the current month, respectively. Adj. R² denotes the time-series average of the monthly adjusted R square. MS, CCI, and II are the investor/consumer sentiment indices compiled by the University of Michigan, Consumer Conference Board, and Investor’s Intelligence, respectively. COMP is the composite sentiment index derived from principal component analysis using the above three sentiment indices. All coefficients are multiplied by 100.

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