Investor Sentiment, Regimes and Stock Returns

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Abstract

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Keywords: Investor Sentiment, Return Predictability, Mispricing, Markov-Switching Vector Autoregressive Model, Bootstrap.

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Abstract

In this study, we empirically examine the relationship between return predictability and sentiment while the stock fundamentals perform regime shifts. This study is motivated by the realization that while we examine the predictive power of sentiment, we may not be able to separately identify the price change as a correction pattern for a mispricing or a adjustment dynamic in relation to the regime-switching stock fundamentals. We proposed a simple way to explore this issue within the conventional predictive regression framework and a testing procedure to tackle the potential econometric problems in this study. Our main empirical findings are: (1) the effects of sentiment on predicting the cross-section of future stock returns are conditional on the state of regime. The magnitude of coefficient estimates associated with sentiment increases while regimes are controlled; (2) dividend- and earning-oriented portfolios perform strong conditional predictability patterns only after conditioning on sentiment and regimes; (3) the appearance of the size and value effects are also conditional on sentiment and the state of regime; (4) the cross-sectional predictability patterns associated with sentiment reflect the mispricing, not the compensation for systematic risk.

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"We simply attempt to be fearful when others are greedy and to be greedy when others are fearful." -Warren Buffett

1 Introduction

Traditional financial theory advocates that an equilibrium stock price equals the discounted value of a stream of expected cash flows and any co-movement in stock returns reflects the common movements in systematic risks. Shifts in investor sentiment are not expected to affect stock prices since such shocks are supposed to be offset in no time by the actions of rational arbitrageurs. Since the seminal works of De Long, Shleifer, Summers and Waldman (1990), and Lee, Shleifer and Thaler (1991), the effects of "the actions of rational arbitrageurs" have been doubted in that arbitrage is risky and costly[1]. For example, while a speculative position on a stock is created in response to a shock to the sentiment of noise traders, the noise trader risk, a risk of a further change of noise traders'opinion away from its fundamentals, poses a significant threat in arbitrage and in turn precludes rational arbitrageurs aggressively exploiting this lucrative investment chance, leading to the market price of the stock departing from its fundamentals. This mispricing would eventually be corrected as sentiment waning and hence the market price of the stock reverts back to its fundamentals. It is apparent that, given the limits of arbitrage, sentiment may affect stock prices and is therefore negatively correlated with future returns of stocks.

To test the theoretical prediction, the effects of sentiment on predicting stock returns have been largely investigated in empirical finance literature, see for example, Swaminathan (1996), Brown and Cliff (2004), Qiu and Welch (2004), Baker and Wurgler (2006, 2007), Glushkov (2006), Kumar and Lee (2006), Lemmon and Portniaguina (2006). Empirical evidence has uncovered that investor (or consumer) sentiment performs predictive power for the cross-section of stock returns, in particular for stocks with some sorts of firm characteristics,

[1]In reality, many professional arbitrageurs, such as institutional investors and mutual fund managers, would borrow money and securities from financial intermediaries and individual investors to execute their trades. They must face to the risk of liquidation by the lenders if prices move against them and the value of collateral tumbles. This is particular true when the liquidation criterion for the lenders is based on past performance, see Shleifer (2000) and Shleifer and Vishny (1997).

such as small stocks, unprofitable stocks, growth stocks or non-dividend-paying stocks.

In this paper, we attempt to further explore the predictive power of sentiment while the stock fundamentals have a regime-shift feature. Our study is motivated by the following realizations. First, equilibrium asset pricing under a regime-switching fundamental process, such as the regime-switching consumption/dividend process, has long advocated by the financial literature to reconcile the unconditional moments of stock returns, the intertemporal relation between stock returns and market volatility and the market volatility dynamics, see for example, Hung (1994), Veronesi (1999), Whitelaw (2000) and Lettau, Ludvigson and Wachter (2008). Second, a number of recent empirical articles in the financial literature suggests that the distributions of stock returns are in the presence of regime shifts. Regime is an unobserved state variable driving the levels, volatility or correlations of the distributions of stock returns, see for example, Gray (1996), Maheu and McCurdy (2000), Perez-Quirors and Timmermann (2000), Guidolin and Timmermann (2008). Third, according to the behavioral finance theory (or hypothesis) proposed by Baker and Wurgler (2006, 2007) and Glushkov (2006), the cross-sectional effect of sentiment is associated with firm characteristics. Small stocks, unprofitable stocks, non-dividend-paying stocks and growth stocks not only have the high *propensity to speculate*[2] in response to the shocks of sentiment on stock demands, but also pose a significant difficulty in arbitrage. Those stocks do not have a long enough earning history to remove the subjectivity in valuation by individual investors. Plus, lack of collaterals for them may deteriorate the execution of arbitrage.

Since the sentiment-driven mispricing would be hard to identify directly, Baker and Wurgler (2006) examined whether the patterns of mispricing correction depend on investor sentiment. As shown in the top panel of Figure 1, they tested the negative relationship between the price changes of stocks and previous investor sentiment. However, while the stock fundamentals have a regime-switching feature, an identification may happen. That is, we are not able to separately identify the price changes as a correction pattern for a mispricing or an adjustment dynamic for the regime-shift stock fundamentals. For example, during a bubble period in the bull market, bullish sentiment gives rise to a mispricing. Then the bubble burst

[2]Baker and Wurgler (2006) adopted this typical term to explain investor sentiment.

brings down the stock prices and may potentially trigger the bear Regime. The decreased stock prices might reflect either a correction pattern for a mispricing as sentiment wanes, or a mean-reverting process as the state of regime switches to a bear/crash market, expressed by low levels and high volatility for stock returns. The bottom panel of Figure 1 illustrates this identification problem. Therefore, it poses a significant methodological challenge to identify the causality of the return predictability in this regard.

In order to examine the effects of sentiment on predicting the cross-section of stock returns and tackle the above potential identification problem, we extend the empirical approach used by Baker and Wurgler (2006) in several dimensions. First, the effects of regime shifts have been considered. Controlling the state of regime while we test the predictive power of sentiment is a simple and straightforward way to isolate the effects of regime shifts in stock fundamentals. We launch the three-pass sort–firm characteristics, the state of regime and the level of sentiment proxy–to look for how the cross-section of subsequent equal-weighted portfolio average returns[3] varies with the level of the previous month's sentiment proxy and the state of regime. Second, we then perform predictive regressions (including a conditional CAPM model), which control four characteristics factors–size, book-to-market, market, and momentum–and use the previous month's level of the sentiment proxy to forecast the returns of various long-short (zero-investment) portfolios, based on the regime-sorted observations[4]. In robustness checks, we perform a generic predictive regression model that simultaneously control for characteristic factors, sentiment and the sates of regimes (or regime dummy variables) to confirm the findings from the three-pass sort and predictive regressions. Third, in order to deal with the non-normality for the joint distribution of the cross-sectional stock returns and small sample size for some regime-sorted observations that may invalidate the standard critical values of the normal distribution for t statistics, we proposed the bootstrapped testing procedure to calculate the empirical distribution of t-statistic through re-

[3]The theory predicts that large firms will be less affected by sentiment, and hence value-weighted average returns may obscure the relevant pattern.

[4]Unlike the regime switching models in the econometric literature, our predictive regressions based on regime-sorted observations treat the state variable of regime as an exogenous input. Note that in this study we look for how the state of regime affects return predictability associated with sentiment, not how to use sentiment to identify regimes. Our approach turns out to be an appropriate one in this regard.

sampling and then computing the bootstrapped p-values for the realistic t statistic computed by real sample observations.

Investigating the interplay between the regime-shift stock fundamentals, investor sentiment and the dynamic patterns of stock returns is not new. Barberis, Shleifer and Vishny (1998), for example, proposed a model of investor sentiment which is characterized by distorted predictions about the regime-shift stock fundamentals. The short/long run patterns of stock returns can be linked to the shifts in distorted beliefs. Cecchetti, Lam and Mark (2000) performed a similar model to link distorted beliefs with equity premium puzzle and excessive volatility, both of which have been long advocated in financial literature. Although these studies sought to fix the problematic assumption of constant stock fundamentals in conventional behavioral finance theory, they didn't explore the interplay between regime shifts, mispricing and return predictability. We empirically address this issue. Our main empirical findings are: (1) the effects of sentiment on predicting the cross-section of future stock returns are conditional on the state of regime. The magnitude of coefficient estimates associated with sentiment increases while regimes are controlled; (2) dividend- and earning-oriented portfolios perform strong conditional predictability patterns only after conditioning on sentiment and regimes; (3) the appearance of the size and value effects are also conditional on sentiment and the state of regime; (4) the cross-sectional predictability patterns associated with sentiment reflect the mispricing, not the compensation for systematic risk.

The reminder of this paper is organized as follows. Section 2 lays out the hypotheses. Section 3 introduces the test procedure and the model we use in characterizing regimes. The data and test results are given in Section 4. Several robustness checks are reported in Section 5. Section 6 concludes the paper.

2 The Theoretical Hypotheses for Sentiment

According to the behavioral finance theory, the prices of stocks which are held predominately by noise traders will be affected by the sentiment of noise traders as long as arbitrage is risky and costly, see for example, De Long, Shleifer, Summers and Waldman (1990), and

Lee, Shleifer and Thaler (1991). It predicts that the sentiment of noise traders is negatively correlated with future returns of stocks. To illustrate, interpret sentiment as the market-wide expectation of investors for the aggregate stock market relative to a norm: bullish (bearish) investors would predict a higher (lower) return than its mean. A speculative stock demand is created because of a misvalued stock price. The noise trader risk, a risk of a further change of noise traders' opinion away from its mean, put up the uncertainty in arbitrage and hence precludes the arbitrageurs aggressively exploiting this attractive and lucrative investment chance leading to the market price of the stock departing from its fundamentals. Then the mispricing is ultimately corrected as sentiment waning and the stock price in turn reverts to reflect its fundamentals. It turns out that the return predictability related to sentiment is associated with a systematic correction pattern of a mispricing. Noise traders are usually meant to be individual investors in practice. The prior literature primarily focuses on small stocks which are disproportionately held by individual investors as opposed to institutions.

Sentiment is expected to have a wide impact on the cross-section of stock returns. De Long, Shleifer, Summers and Waldman (1990), and Lee, Shleifer and Thaler (1991) advocated that the noise trader risk is systematic so that the sentiment risk will be compensated by a risk premium[5]. Thus, the corresponding cost of equity, or the discount rates of expected cash flows, in turn contains a risk premium for sentiment. If the cash flows of a stock are fixed, a shock to sentiment will produce a cross-sectional effect on stocks through the various sentiment-compensated costs of equities. However, Baker and Wurgler (2006, 2007) and Glushkov (2006) proposed an alternative theoretical explanation for the cross-sectional effect of sentiment without imposing a strong and controversial assumption on the risk for sentiment. They pointed out that the cross-sectional effect of sentiment is associated with the firm characteristics. Small stocks, unprofitable stocks, non-dividend-paying stocks and growth stocks not only have the high propensity to speculate in response to the shocks of sentiment on stock demands, but also pose a significant mechanical difficulty in arbitrage.

[5]The equilibrium stock price function in De Long *et. al.* (1990) contains a specific term representing the uncertainty of the next period's stock price, which is decided by the next period's sentiment of noise traders. It drives price down and return up, and thus can be interpreted as a compensation for sentiment risk, see Shleifer (2000).

It is known that those stocks do not have a long enough earning history to alleviate the subjectivity in valuation by individual investors. Moreover, lack of collaterals for those stocks deteriorates the execution of arbitrage. In short, it is called a *hard-to-value, difficult-to-arbitrage hypothesis* (or theory).

Many recent empirical articles in the financial literature unveiled that the distributions of stock returns have a regime switching feature. Regime is an unobserved state variable driving the levels, volatility or correlations of the distributions of stock returns. Although market regimes may change over time, the conditional predictability patterns associated with sentiment are expected to be irrelevant to regime shifts, in accordance with the hard-to-value, difficult-to-arbitrage hypothesis. For example, when the regimes are bearish, the assessment for small stocks, unprofitable stocks, or non-dividend-paying stocks becomes a difficult task since their values of collaterals sharply decline and liquidity rapidly worsens. The risk of arbitrage increases. In contrast, when the regimes are bullish, small stocks, unprofitable stocks, or non-dividend-paying stocks perform high propensity to speculate. Optimism would cause severe trend-chase behavior for these stocks. It turns out that the theoretical predictions of the hard-to-value, difficult-to-arbitrage hypothesis remain valid even if market regimes are changing.

The three testable hypotheses based on the above behavioral finance theories are formulized as follows:

- **Hypothesis 1:** Investor sentiment has predictive power for the future returns of small stocks, growth stock, unprofitable stocks and non-dividend-paying stocks. High (low) sentiment value will drive down (up) the subsequent stock returns.

- **Hypothesis 2:** The predictive power of investor sentiment is irrelevant to the state of regime.

- **Hypothesis 3:** The predictability patterns associated with sentiment would reflect a mispricing/correction pattern, rather than a compensation for systematic risk materialized by time variation in risk loading of market beta.

Hypothesis 1 and 2 attempts to test the predictive ability of sentiment to cross-section of future stock returns while the effects of regime shifts are/ain't invoked. Hypothesis 3 tests if the sentiment risk is systematic or not. It identifies the effects of sentiment on return predictability as a mispricing correction pattern or a co-movement by a common risk factor associated with sentiment.

3 Empirical Approaches

3.1 A Multivariate Markov Switching Model for Stock Returns

We need to characterize the regimes implied by the joint distribution of the cross-section of stock returns before proceeding to test the conditional predictability patterns associated with sentiment. To this end, we perform a formal econometric model, the Markov switching model, in this paper.

Many empirical articles in recent financial literature unveiled that the expected returns, volatility and correlations for stocks vary in bull and bear markets, see Gray (1996), Ang and Chen (2002) and Perez-Quirors and Timmermann (2000). To the end of characterizing the realistic patterns, a Markov switching vector autoregressive (MSVAR) model can be used to capture those empirical characteristics implied by the time series of stock returns. As advocated by Timmermann (2000), the Markov switching specification is capable of capturing the heteroskedasticity, skews and fat tails of the stock return distribution. The VAR specification conveniently captures the predictability of the expected returns by lagged returns and predictors. This model specification typically allows different means, variances and correlations across stocks on different regimes. Since the state of regime varies with time, the expected returns, volatility, correlations and predictability are in turn time-varying. In sum, the MSVAR model is able to generate consistent features implied by realistic observations of stock returns.

Denote the vector of n stock returns by $\mathbf{r}_{t+1} = (r_{1t+1}, r_{2t+1}, \ldots, r_{nt+1})$. Suppose that a multivariate Markov switching process is driven by a common discrete regime variable s_t with integer values from 1 to J. Thus, the specification of the Markov switching model for is expressed as:

$$\mathbf{r}_{t+1} = \mu_{s_{t+1}} + \sum_{j=1}^{p} \mathbf{\Phi}_{j,s_{t+1}} \mathbf{r}_t + \varepsilon_{t+1}, \tag{1}$$

where $\mu_{s_{t+1}}$ is an $n \times 1$ vector of the regime-dependent mean returns, $\mathbf{\Phi}_{j,s_{t+1}}$ is an $n \times n$ matrix of regime-dependent autoregressive coefficients at lag j, and the return innovations $\varepsilon_{t+1} = (\varepsilon_{1t+1}, \varepsilon_{2t+1}, \ldots, \varepsilon_{nt+1})$ is assumed to follow a multivariate normal distribution with zero means and regime-specific variance-covariance matrix $\mathbf{\Omega_{s_{t+1}}}$.

The discrete regime variable s_{t+1} is assumed to follow a $J-$state first-order Markov chain whose $J \times J$ transition probability matrix $\mathbf{P}$ with time-invariant elements $\Pr(s_{t+1} = i|s_t = j) = p_{ji},\ i, j = 1, \ldots, J$. Following the literature the regime variable s_t is assumed to be hidden but able to be statistically inferred from realistic observations. The possibilities of regimes at each time point can be characterized by the filtered probabilities $\Pr(s_{t+1} = j|\mathbf{Y}^{t+1})$ and the smoothed probabilities $\Pr(s_{t+1}|\mathbf{Y}^T)$, where $\mathbf{Y}^{t+1}$ is the information set at time $t+1$ and $\mathbf{Y}^T$ is the complete information set.

3.2 Predictive Regressions

To test our hypotheses, we follow Baker and Wurgler (2006) and perform a conditional characteristics regression model and a conditional CAPM model, which allows a time-varying risk loading of market beta. In the former case, we use the last period's level of the sentiment proxy to forecast equal-weighted average returns of long-short portfolios that are long on stocks with high values of a characteristic and short on stock with low values, controlling the generic effect of characteristics. We seeks to assess the predictive ability of sentiment on the cross-section of future portfolio returns. In the latter case, we test whether the conditional predictability pattern by sentiment is explained by the time variation in the pattern of the risk loading of market beta or a correction pattern for a mispricing. To achieve isolating the effects of regime shifts, we will perform the above models using the regime-sorted observations in estimation. In comparison to the regime switching models in the econometric literature, our predictive regressions treat the state variable of regime as an exogenous input. Note that in this study we look for how the state of regime affects the predictive ability of sentiment, rather than how to use sentiment to identify regimes. Our approach turns out to be an appropriate one in this regard.

We proceed with examining the hypothesis that sentiment can predict the next period's excess returns of the long-short portfolios conditional on firm characteristics, like size, profitability or dividend policy. Specifically, we perform the following conditional characteristics regression model:

$$\begin{aligned} r_{it,high} - r_{it,low} &= \alpha_i + \gamma_{i,1}\mathrm{SENTIMENT}^{\perp}_{t-1} + \beta_{i,\circ}\mathrm{RMRF}_t \\ &\quad + \gamma_{i,2}\mathrm{SMB}_t + \gamma_{i,3}\mathrm{HML}_t + \gamma_{i,4}\mathrm{UMD}_t + \epsilon_{i,t}, \end{aligned} \tag{2}$$

where $r_{it,high}$ and $r_{it,low}$ are the equal-weighted portfolio returns with high and low values of a characteristic, respectively; $\mathrm{SENTIMENT}^{\perp}_{t-1}$ is a time $t-1$ sentiment proxy orthogonalized to macroeconomic conditions; $\mathrm{RMRF}_t, \mathrm{SMB}_t, \mathrm{HML}_t$ and UMD_t are the time t return spreads on zero-investment factor-mimicking portfolios for aggregate market proxy, size, book-to-market equity, and one-year momentum in stock returns, respectively. Note that using $\mathrm{SENTIMENT}^{\perp}$ attempts to isolate the effects of macroeconomic fluctuation on predicting the future returns of long-short portfolios. The sign of the coefficient parameter $\gamma_{i,1}$ is expected to be positive in accordance with the theoretical prediction of hypotheses, whereas it doesn't identify the causality of the conditional predictability patterns related to sentiment as a mispricing or a compensation for systematic risk.

The subsequent issue is how do we identify sentiment-driven changes in cross-sectional predictability patterns a mispricing or a compensation for the sentiment risk? A systematic risk explanation for sentiment is associated with the time-variant risk loading of market beta varying with the sentiment proxies. It is natural to perform the following conditional CAPM model:

$$\begin{aligned} r_{it,high} - r_{it,low} &= \alpha_i + \gamma_{i,1}\mathrm{SENTIMENT}^{\perp}_{t-1} + (\beta_{i,\circ} + \beta_{i,1}\mathrm{SENTIMENT}^{\perp}_{t-1})\mathrm{RMRF}_t \\ &\quad + \gamma_{i,2}\mathrm{SMB}_t + \gamma_{i,3}\mathrm{HML}_t + \gamma_{i,4}\mathrm{UMD}_t + \epsilon_{i,t}, \end{aligned} \tag{3}$$

where the specification $(\beta_{i,\circ} + \beta_{i,1}\mathrm{SENTIMENT}^{\perp}_{t-1})$ captures the time-varying market beta driven by sentiment. The value of the coefficient parameter $\beta_{i,1}$ is zero under the null hypothesis and any nonzero estimate of the coefficient parameter $\beta_{i,1}$ captures the risk compensation for sentiment. According to the hypothesis prediction, the sign of the coefficient parameter $\beta_{i,1}$ is the same as the estimate of coefficient parameter $\gamma_{i,1}$, expected to be positive.

3.3 A Simple Bootstrapped Testing Procedure

Several empirical issues need to be sorted out before we proceed to conduct hypotheses testing. There are several reasons invalidating the standard critical values of the normal distribution in testing the predictability patterns for the cross-section of stock returns. First, the distributions of the cross-sectional stock portfolios conditional on a specific stock characteristic, like size, profitability or dividend policy, are not drawn from a multivariate normal distribution (see panel A of Table 1). One might argue that invoking the central limit theorem can resolve the non-normality problem. However, insufficient sample sizes may substantially lead the asymptotic distribution departing from the finite sample one. Second, variations in risk-taking across the cross-sectional stock portfolios will generate the nonzero cross-sectional correlations in regression residuals in the tail, if extreme stock portfolios load some nonpriced factors. Plus, there may be co-skewness in the cross-sectional stock returns. Thus, normality may be a poor approximation in practice. Third, the parameter estimation error leads to a bias. As pointed out by Baker and Wurgler (2006), while the sentiment index with an autocorrelated pattern has innovations that are correlated with innovations of portfolio returns, it may give rise to a bias in parameter estimates. In sum, all the above issues suggest that a bootstrapped testing procedure is necessary for proper statistical inference[6].

We use the conditional characteristics model to illustrate our testing procedure. The implementation is as follows:

- **Step 1:** we compute and save OLS-estimated risk loadings $\{\hat{\alpha}_i, \hat{\beta}_{i,\circ}, \hat{\gamma}_{i,1}, \hat{\gamma}_{i,2}, \hat{\gamma}_{i,3}, \hat{\gamma}_{i,4}\}$, residuals $\{\hat{\epsilon}_{it}, t = T_{i0}, \ldots, T_{in}\}$ and t-statistic of $\hat{\gamma}_{i,1}$ for all stock portfolio $i = 1, \ldots, N$, where T_{i0} and T_{in} are the dates of the first and last observations.

- **Step 2:** Denote the cross-section of residuals at time t $(\hat{\epsilon}_{1,t}, \ldots, \hat{\epsilon}_{N,t})'$ by $\hat{\mathbf{\Upsilon}}_t$. We draw

[6]Kosowski, Timmermann, Wermers and White (2006) proposed a similar bootstrap procedure to assess the performance of mutual funds based on Fama-French four factor model.

a sequence of resampled residual vectors, $\{\hat{\boldsymbol{\Upsilon}}_{t_\epsilon}, t_\epsilon = s^b_{T_0}, \ldots, s^b_{T_n}\}$, where b is the index for the bootstrap sample and the time indices $s^b_{T_0}, \ldots, s^b_{T_n}$ are drawn randomly from $[T_0, \ldots, T_n]$.

- **Step 3:** The pseudo portfolio returns are constructed under the null hypothesis $\gamma_{i,1} = 0$, $\forall i = 1, \ldots, N$ and $t_\epsilon = s^b_{T_0}, \ldots, s^b_{T_n}$:

$$r^b_{it_\epsilon} = \hat{\alpha}_i + \hat{\beta}_{i,\circ}\mathrm{RMRF}_{t_\varepsilon} + \hat{\gamma}_{i,2}\mathrm{SMB}_{t_\varepsilon} + \hat{\gamma}_{i,3}\mathrm{HML}_{t_\epsilon} + \hat{\gamma}_{i,4}\mathrm{UMD}_{t_\epsilon} + \hat{\epsilon}^b_{t_\epsilon}. \quad (4)$$

- **Step 4:** we run the regression model of the conditional characteristics model (2) using the bootstrapped data made by Step 3, and compute the bootstrapped t-statistic of $\gamma^b_{i,1}$. Repeating Step 2 and 3 for M times, a empirical distribution of t-statistic of $\gamma^b_{i,1}$ under the null ($\gamma_{i,1} = 0$) is available.

- **Step 5:** we compute the p-value associated with t-statistic by comparing $\sqrt{T} \cdot t(\hat{\gamma}_{i,1})$ to the quantiles of $\sqrt{T} \cdot [t^b_j(\hat{\gamma}_{i,1}) - t(\hat{\gamma}_{i,1})]$ to obtain the p-value, where T is the total sample size, $t(\hat{\gamma}_{i,1})$ and $t^b_j(\hat{\gamma}_{i,1})$ are the t-statistics computed by real data sample and the b-th resampled data, respectively. The bootstrap p-value may be defined as the probability in favor of the null hypothesis

$$\mathrm{Prob}\Big(\sqrt{T}[t^b_j(\hat{\gamma}_{i,1}) - t(\hat{\gamma}_{i,1})] > \sqrt{T}t(\hat{\gamma}_{i,1})\Big).$$

  The readers can refer to Sullivan, Timmermann and White (1999) and Wang (2005) for the details of implementing bootstrap.

4 Empirical Analysis

4.1 Data Description

Several datasets are used in this study. A brief description of each is as follows. First, monthly stock returns that have been sorted based on firm characteristics, such as market equity (ME), book-to-market equity ratio (BE/ME), dividend-to-market equity ratio (D/ME) and earning-to-market equity ratio (E/ME). The range for sorting covers all NYSE, AMEX, and NASDAQ stocks. The sorted stock returns is classified into ten or eleven deciles and the equal-weighted average monthly returns are calculated. Further details about portfolio formation and calculation of market equity, book equity, dividend yield and earnings are available from the web-page of Kenneth French. Except for earning-oriented portfolios[7], the sample period of the portfolio returns is from January 1928 to December 2007[8].

For the implementation of the MSVAR model, we use the following portfolio returns: market, growth, value, small caps and large caps. Note that the four firm-characteristic portfolio returns are the equal-weighted average returns calculated by the stocks belonging to top 30% and bottom 30% of the size (or market equity) and book-to-market sorted groups. It would lessen the impacts from the firms falling into the extreme tails. The total length of data sample covers 960 months (or 80 years) that make parameter estimates of the MSVAR more efficient.

Table 1 reports summary statistics. Panel A reports the sample mean, standard deviations, skewness, kurtosis, maximum and minimum for the data used in estimating the MSVAR model. It is seen that four firm-characteristic portfolios perform higher returns and volatility than market portfolio. The size and value premiums appear in terms of sample mean. In addition, except for market portfolio, the other four portfolios display positive skewness. However, if we compute summary statistics using the sample after 1930, all portfolios perform negative skewness. Excess kurtosis turns out to be an universal features for five portfolios.

Panel B reports the same statistics for the equal-weighted average monthly returns over ten or eleven deciles conditional on firm characteristics: size, book-to-market, dividend policy and earning. The sample period for these statistics starts from January 1966 to December 2007. Since we use this dataset in three-pass sorting and predictive regressions, this sample period is identical to the sentiment proxy provides by Baker and Wurgler (2006, 2007)[9]. It is apparent that the first and last deciles may display positive skewness and the middle

[7] The sample period for the portfolios sorted by E/ME begins with January 1953.

[8] From Ken French's web-page (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/) the return data used in this study is available.

[9] The series of the sentiment proxy used in Baker and Wurgler (2006, 2007) begins with January 1966.

deciles have negative one by far. The excess kurtosis is positive in all cases. The results of panel B are strongly rejected the normality property in the cross-section of stock returns. In addition, the size and value premiums turn out to be solid in terms of the sample mean.

We employ several macroeconomic variables drawn from the literature as controls: the short-term nominal yield, measured by the log yield on the 90-day Treasury bill rate in CRSP risk-free rate file[10]; term spread, measured by the difference between yields to maturity on 10 years and 1 year bonds; default spread, measured by the yield spread between Moody's Baa-rated and Aaa-rated corporate bonds. These macroeconomic variables will be used to orthogonalize macroeconomic conditions on some sentiment proxies.

We use the following investor sentiment proxies in this study: (1) Baker and Wurgler's orthogonal sentiment index; (2) consumer confidence level; and (3) the VXO index (the old VIX index). The sentiment index of Baker and Wurgler (2006) is made by the first principal component analysis of six major proxies for the investor sentiment from the literature, including the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. It in turn summarizes most of the sentiment information contained in these six proxies. Consumer confidence level is the University of Michigan survey of consumer sentiment. This data is available from the web-page of Federal Reserve at St. Louis. The sample period of consumer confidence data is from January 1978 to December 2007. Qiu and Welch (2004) and Lemmon and Portniaguina (2006) have shown that consumer sentiment characterized by consumer confidence level can predict the future returns. The VXO index (the old VIX index) is regarded as an investor fear gauge since VXO is based on real-time option prices and thus reflects investors' consensus view of future expected stock market volatility. It is observed that during periods of financial stress, which are often accompanied by steep market declines, option prices and VXO tend to increase. Thus high VXO value reflects low investor sentiment in the financial market. We obtain monthly VXO data from CBOE's web-page with the sample period from January 1986 to December 2007. Following Baker and Wurgler (2006), consumer confidence level and VXO need to be orthogonalized to macroeconomic

[10]Following Campbell (1991), the short rate is adjusted by subtracting a backward moving average.

Table 1:
Summary Statistics

	Mean	Standard Deviation	Skewness	Kurtosis	Maximum	Minimum
Panel A (Period: 1928.1–2007.12)						
Market	0.42	3.98	-0.68	3.36	14.88	-26.30
Growth	0.89	6.91	0.14	4.55	37.98	-31.24
Value	1.78	8.99	2.95	27.09	93.39	-32.86
Small Caps	1.60	9.54	3.14	29.03	100.71	-31.32
Large Caps	0.99	5.93	0.56	9.66	43.85	-30.20

Table 1-Continued

	< 0	1	2	3	4	5	6	7	8	9	10
Panel B (Period: 1966.1–2007.12)											
Size											
Mean		1.43	1.09	1.13	1.09	1.13	1.06	1.11	1.04	1.01	0.89
Standard Deviation		6.72	6.46	6.23	6.01	5.81	5.48	5.31	5.18	4.76	4.58
Skewness		0.33	-0.06	-0.19	-0.32	-0.35	-0.38	-0.29	-0.30	-0.22	-0.22
Excess Kurtosis		2.83	2.83	2.39	2.26	2.51	1.94	2.23	1.67	1.56	1.87
Maximum		32.88	32.52	29.90	26.41	27.54	23.02	24.81	21.13	19.06	20.92
Minimum		-27.68	-30.31	-28.87	-29.43	-28.12	-25.87	-25.90	-24.07	-22.09	-20.38
Book-to-Market											
Mean		0.65	1.00	1.11	1.24	1.28	1.39	1.48	1.50	1.65	1.86
Standard Deviation		7.59	6.48	6.08	5.78	5.45	5.27	5.13	5.17	5.49	6.30
Skewness		0.02	-0.22	-0.30	-0.30	-0.24	-0.18	-0.08	0.14	0.08	0.61
Excess Kurtosis		2.76	1.85	2.51	3.08	3.54	3.58	3.90	4.26	4.47	4.93
Maximum		41.42	25.69	27.23	29.71	30.02	29.24	29.75	32.05	33.10	40.77
Minimum		-32.62	-29.34	-30.10	-29.21	-27.88	-26.18	-25.25	-24.06	-27.01	-25.54
Dividend											
Mean	1.30	1.18	1.28	1.25	1.31	1.28	1.36	1.34	1.38	1.29	1.18
Standard Deviation	7.59	5.80	5.35	5.13	4.95	4.72	4.57	4.32	4.19	3.84	4.07
Skewness	0.20	-0.53	-0.52	-0.36	-0.49	-0.39	-0.48	-0.41	-0.22	0.10	1.07
Excess Kurtosis	2.31	2.33	3.22	3.70	3.74	3.80	3.82	4.49	4.59	4.42	8.45
Maximum	35.35	19.92	25.70	27.40	24.63	24.83	23.30	24.24	25.53	25.06	33.20
Minimum	-30.29	-28.64	-26.95	-25.74	-26.24	-25.14	-24.80	-23.98	-22.09	-17.13	-12.40
Earning											
Mean	1.34	0.95	1.14	1.16	1.22	1.25	1.33	1.36	1.42	1.54	1.66
Standard Deviation	8.62	6.92	5.94	5.61	5.24	5.11	4.95	4.81	4.74	4.94	5.70
Skewness	0.61	-0.14	-0.35	-0.34	-0.39	-0.43	-0.31	-0.28	-0.01	0.07	0.14
Excess Kurtosis	3.52	1.93	2.32	2.91	4.24	4.09	4.64	4.30	4.88	4.85	4.58
Maximum	46.51	27.69	25.94	27.55	29.68	27.59	29.27	26.85	30.43	30.77	36.27
Minimum	-31.29	-31.59	-29.43	-28.04	-28.65	-28.17	-27.11	-25.66	-22.91	-23.27	-25.56

Note: this table summarizes the return data. Returns are measured monthly. Panel A contains the results of 5 portfolio returns used in implementing the MSVAR model, including market, growth, value, small caps and large caps. The four firm-characteristic portfolio returns are the equal-weighted average returns calculated by the stocks at the top 30% and bottom 30% sorted by the size (or market equity) and book-to-market ratio. The sample period is from Jan. 1928 to Dec. 2007. Panel B reports the results of the portfolios sorted by firm characteristics–size, book-to-market, dividend, and earning–and classified into 10 or 11 deciles. The sample period is from Jan. 1966 to Dec. 2007.

conditions. To this end, we run the regression

$$Z_t = \mathbf{x}_t'\Upsilon + \varepsilon_t,$$

where Z_t denotes Consumer Confidence$_t$ or VXO$_t$, $\mathbf{x}_t = (\text{Short rate}, \text{Term spread}, \text{Default spread})'$. The residuals of regression can be treated as the orthogonal sentiment proxies, labelled by SENTIMENT$_t^{\perp}$ or VXO$_t^{\perp}$.

Figure 2 plots the historical patterns of three various sentiment proxies orthogonal to macroeconomic conditions. It is seen that investor sentiment experienced a big plummet and rebound before 1970's. After then, it was struck by two oil crises in 1970's. Investor (or consumer) sentiment continues to be positive in the 80's until the Gulf War in the early 90's. Before the Dot-Com bubble burst, it experienced two main spikes and two slumps. For the VXO index, investor fear hovered around the bottom until 1997 and then up and down twice before the Dot-Com burst. Then the market becomes jittery until its recovery in 2003. Overall Figure 1 indicates that (1) the Baker and Wurgler's sentiment index SENTIMENT$^{\perp}$ is positive correlated with the orthogonal consumer confidence CONSUMER CONFIDENCE$^{\perp}$; (2) the orthogonal VXO index VXO$^{\perp}$ and the Baker and Wurgler's sentiment index SENTIMENT$^{\perp}$ are negatively correlated.

4.2 The Empirical Results of the Multivariate Markov Switching Model

A practical issue need to discussed out before we proceed to identify regimes driving the joint distribution of returns on the five stock portfolios. How do we decide an appropriate number of regimes and lags on a MSVAR model proposed in previous section? Since economic and financial theories don't provide a practical method to select the number of regimes and lags, in this paper, we use the model selection criterion, i.e. Schwartz information criterion (SIC), to determine the most appropriate setting for the Markov switching model, see for example, Guidolin and Timmermann (2008). One might argue that the information criterion is not the most effective way to assess the model specification in this regard. But how far are we able to reach if we use an alternative sophisticated specification test to determine the number of regime for the Markov switching models, see Otranto and Gallo (2002). There are no simple and powerful specification tests in this regards for the regime switching models so far.

Table 3 reports the model selection results. MSIAH is the Markov switching (MS) specification with regime-dependent intercepts (I), autoregressive terms (A) and covariance matrices (H, heterskedasticity). The first element in the parenthesis is the number of regimes and the second one is the length of lags. It is seen that the preferred specification is the four-regime model without autoregressive terms. This result is consistent with Guidolin and Timmermann (2008). Allowing a lagged term doesn't improve the model fitting given a fixed number of regimes.

Table 2:
Model Selection Results

Model Specification	SIC
MSIAH(2,0)	-26.3653
MSIAH(2,1)	-26.1630
MSIAH(3,0)	-29.1411
MSIAH(3,1)	-28.8367
MSIAH(4,0)	**-30.1519**
MSIAH(4,1)	-29.6586

Note: this table reports the results of model selection based on Schwarz information criterion (SIC). The sample period is from Jan. 1928 to Dec. 2007. MSIAH is the Markov switching (MS) specification with regime-dependent intercepts (I), autoregressive terms (A) and covariance matrices (H, heterskedasticity). The first element in the parenthesis is the number of regimes and the second one is the length of lags.

We now proceed to interpret the economic meanings of regimes. Table 4 reports the parameter estimates of the four-regime Markov switching model, where "Mean Returns" indicates the estimates of intercepts, and "Volatility" and "Correlations" denote the estimates of standard deviations and correlations in covariance matrices. Figure 3 plots the patterns of the smoothed probabilities for four regimes. Figure 4 reports three plots pertaining to the relationships between the smoothed probabilities of regime 1 and 4 and three distinct sentiment indices– $\text{SENTIMENT}^{\perp}, \text{CONSUMER CONFIDENCE}^{\perp}$ and $\text{VXO}^{\perp}$. With the above in mind, the interpretations of regimes are as follows.

- Regime 1 is a bear/crash state materialized by negative mean returns (except the small caps portfolio), high volatility and a short duration. The annual mean return of the market portfolio reaches -10% per annum. This regime captures main bear and crash periods with sharp declines in stock prices since 1960, such as the concerns over Vietnam in the end of 1960s, the two oil shocks in the 1970s, Gulf war in the beginning of 1990s, the Asian financial crisis in the end of 1990s and the internet bubble burst and corporate malfeasance since 2000. During these periods, investor sentiment index tumbled sharply and market emotion became pessimistic dramatically. The size premium is significant in terms of mean returns.

- Regime 2 is a highly persistent, low volatility state, which captures most of the bull markets since 1960. The mean return of the market portfolio is 8% per annum. The size and value premiums appear in this regime. The returns of the four characteristic stock portfolio substantially move with the market portfolio.

- Regime 3 is a persistent and low volatility state with moderate mean returns. The mean return of market portfolio is 4% per annum. This regime describes the market conditions before 1965. There are no size and value anomalies in this regime.

- Regime 4 is an uncertain regime with the highest mean returns, highest volatility and a short duration. The mean return of the market portfolio is 140% per annum. This regime captures stock prices during parts of the Great Depression, the two oil shocks, the 1987's stock market crash, Russia defaults and Long Term Capital Management crashes in 1998, internet bubble crashes and corporate malfeasance of Eron. During these periods, investor sentiment index tumbled sharply and market emotion became pessimistic rapidly. The size premium emerges in this regime.

To infer the state of regime at each time point, our regime decision criterion is to examine which regime has smoothed probability above 0.5[11].

4.3 An Preliminary Test by Sorts

To look for the general association between the return predictability and sentiment, we sort the stock returns by the following ways: (i) one-pass sort: the stock returns are sorted solely based on firm characteristics, like size, profitability or dividend policy, and classified into ten or eleven deciles. Dividend- and earning-oriented stocks have eleven deciles because we involve the additional non-dividend-paying and non-profitable columns (≤ 0); (ii) two-pass sort: we further sort stock returns based on the previous month's level of the sentiment proxy, $\text{SENTIMENT}^{\perp}_{t-1}$, in each decile that is obtained from the previous one-pass sort. Since the sentiment proxy has been centered, the cutting point for the sentiment sorting is 0, i.e. we in turn obtain two classified groups in each decile: positive and negative sentiment groups; (iii) three-pass sort: we sort stock returns based on the inferred regimes in each decile, and then further classify the two-pass sorted (firm characteristics and regime) stock returns based on the previous month's level of the sentiment proxy, $\text{SENTIMENT}^{\perp}_{t-1}$. The equal-weighted average returns are calculated in all sorted groups. We attempt to characterize and investigate the patterns of the changes in cross-sectional effects from the conditional difference of average returns across deciles. Table 4 contains the results.

Several observations are in order. First, the results of the one-pass sort reveal the substantial size and value premiums, 0.5% and 1.2% per month respectively. The conditional effects of firm characteristics for dividends and earnings are weak since the patterns of average returns across eleven deciles are flat. Second, it is seen that a higher level of the sentiment proxy, $\text{SENTIMENT}^{\perp}_{t-1}$, is associated with a lower subsequent average return in

[11] Our criterion is not the most effective way once we face a smoothed probability of a specific regime closed to 0.5, say 0.53. However, there are totally less than 5 points falling into the range of [0.5,0.6) in this study.

Table 3:

Parameter Estimates of the MSVAR Model

	Market	Growth	Value	Small Caps	Large Caps
Panel A: Mean Returns					
Regime 1	-0.0876*	-0.0044	-0.0271*	0.0764*	-0.0789*
Regime 2	0.0072*	0.0063*	0.0106*	0.0096*	0.0068*
Regime 3	0.0039*	0.0041*	0.0036	0.0039	0.0039*
Regime 4	0.0073	0.0919*	0.0909*	0.1381*	0.0886*
Panel B: Volatility					
Regime 1	0.0223*	0.0808*	0.0767*	0.0851*	0.0218*
Regime 2	0.0385*	0.0431*	0.0381*	0.0509*	0.0381*
Regime 3	0.0296*	0.0296*	0.0411*	0.0407*	0.0291*
Regime 4	0.1199*	0.0427*	0.1027*	0.1100*	0.0448*
Panel C: Correlations					
			Regime 1		
Market					
Growth	-0.7531*				
Value	-0.3406*	0.3845*			
Small Caps	0.1086*	-0.3841*	0.1362*		
Large Caps	0.9472*	-0.7742*	-0.2813*	0.3233*	
			Regime 2		
Market					
Growth	0.9678*				
Value	0.8778*	0.7683*			
Small Caps	0.8152*	0.7613*	0.8100*		
Large Caps	0.9898*	0.9670*	0.8520*	0.7359*	
			Regime 3		
Market					
Growth	0.9850*				
Value	0.9252*	0.8633*			
Small Caps	0.8744*	0.8122*	0.9346*		
Large Caps	0.9983*	0.9894*	0.9101*	0.8491*	
			Regime 4		
Market					
Growth	-0.4904*				
Value	0.2974*	0.4167*			
Small Caps	0.1797*	0.1206*	0.6794*		
Large Caps	-0.2826*	0.9492*	0.5750*	0.1203*	
Transition Matrix					
	Regime 1	Regime 2	Regime 3	Regime 4	
Regime 1	0.0697	0.8101*	0.0005	0.1197	
Regime 2	0.0240	0.9345*	0.0182	0.0231	
Regime 3	0.0000	0.0254	0.9696*	0.0050	
Regime 4	0.1476*	0.5056*	0.1631	0.1838*	

Note: this table reports the results of parameter estimates for the Markov Switching model:

$$\mathbf{r}_{t+1} = \mu_{s_{t+1}} + \varepsilon_{t+1},$$

where $\mu_{s_{t+1}}$ is the regime-dependent intercepts and $\varepsilon_{t+1} \sim \mathcal{N}(0, \mathbf{\Omega}_{s_{t+1}})$. The regime is a unobserved state variable driven by a first-order Markov chain. The sample period is from Jan. 1928 to Dec. 2007. *denotes significance at 5% level.

accordance with the results of two-pass sort. The patterns of return spreads between positive and negative sentiment values coincide with the theoretical prediction of the hard-to-value, difficult-to-arbitrage hypothesis or Hypothesis 1, although those of book-to-market equity- and earning-oriented portfolios do not perform a monotonic shape. In particular, the return spreads for small stocks, growth stocks, non-dividend-paying stocks and non-profitable stocks range form 1.5% to 2.3% per month. Third, it is apparent that the conditional effects of firm characteristics depend on sentiment. The size premium appears only in low sentiment periods. Non-dividend payers and non-profitable stocks perform higher average returns than dividend payers and profitable stocks while the sentiment proxy is positive. The patterns are reverse while the sentiment proxy becomes negative. However, the value premium seems to be irrelevant to sentiment. Forth, while regime shifts are considered (based on the results of three-pass sort), the conditional predictability patterns related to sentiment depend on regimes. The predictability patterns of sentiment are stable and robust only conditional on regime 2. It appears that the conditional effects of firm characteristics fairly depend on both sentiment and regimes. The size premium appears in regime 4 and regime 2 conditional on negative sentiment, whereas the value premium occurs in regime 2. These results are consistent the empirical results of the Markov switching model. The patterns of dividend- and earning-oriented portfolios are the same as those in two-pass sort only in regime 2.

In unreported results, we calculate sample medians of stock returns instead of the equal-weighted return averages since those can alleviate the impacts from large firms. The main findings for average returns continue to be valid for the results based on medians. In sum, our results can not reject Hypothesis 1 but Hypothesis 2. It turns out that the predictability patterns related to sentiment is regime-dependent. A bearish or a highly uncertain regime might invalidate the predictive power of sentiment.

4.4 Predictive Regressions for Long-Short Portfolios

We now proceed to the predictive tests based on predictive regressions. Table 5 reports the test results for the predictive power of sentiment. To conserve space, we only report the estimates of the parameter coefficient associated with sentiment $\gamma_{i,1}$. We consider both the restricted and unrestricted conditional characteristics models. The restricted one is the regression with only one regressor, the sentiment proxy $\text{SENTIMENT}^{\perp}_{t-1}$, and the unrestricted one is given by (2). "High", "Low" and "Medium" in Table 5 indicate the 10th (the largest), 1th and 5th deciles. We consider three long-short portfolios for size- and book-to-market-oriented portfolios, that is, High-Low[12], High-Medium and Medium-Low. Moreover, in order to confirm the theoretical prediction of Hypothesis 1, we form the portfolios of High-≤ 0, High-Medium and Medium-≤ 0 for dividend- and earning-oriented portfolios. Note that we exclude SMB and HML from the right side when they are the portfolios being forecast. The column "w/o Regimes" reports to the results without regime sorting. The other columns "Regime i",$i = 1, 2, 3, 4$, show the results based on regime-sorted observations as regime$= i$. The bootstrapped p-values in parentheses.

There are several noticeable features in Table 5. First, the estimates of parameter coefficient associated with sentiment are significant on the portfolio related to small stocks, growth stocks, non-profitable stocks and non-dividend-paying stocks. The signs of those estimates are all positive, coinciding with the theoretical prediction of Hypothesis 1. In comparison to the results reported in the literature, we note that Baker and Wurgler (2006) and Lemmon and Portniaguina (2006)[13] have insignificant estimates $\hat{\gamma}_{i,1}$ on book-to-market-oriented portfolios. The difference can of course be attributed to different testing methodologies or sentiment measures. Second, while the effects of regime shifts are considered, the predictability patterns associated with sentiment depends on the state of regime. The results of regime 2 reveal a identical patterns in $\hat{\gamma}_{i,1}$ significance to those in the case of no regimes. However, a solid predictive ability of sentiment is available only for the portfolios associated with growth stocks conditional on regime 1. We are not able to observe any predictive patterns conditional on the other two regimes. Third, the significant estimates of $\hat{\gamma}_{i,1}$ conditional on regime 1 or 2 have larger magnitude than those in the case of no regimes, suggesting that conditioning on regimes can strengthen the predictive power of sentiment. It is a predictable

[12] The portfolios of High-Low are equivalent to SMB and HML, respectively.

[13] Note that Lemmon and Portniaguina (2006) adopted the level of consumer confidence level, excluding the effects from the macroeconomic variables, as the sentiment proxy. They found that sentiment can forecast the size premium, but not the value and momentum premiums.

result once the effects of regime shifts are isolated in testing return predictability.

In unreported results, we did the out-of-sample test proposed by Clark and West (2007) for the predictive regressions. The predictability patterns associated with sentiment conditional on regime 2 are pretty stable[14]. In sum, the above results confirm the findings of the preliminary tests by sorting. The robust predictability patterns of sentiment appear only on regime 2.

4.5 Systematic Risk

The systematic risk explanation can be materialized by the risk loadings of market betas varying with the sentiment proxies. It predicts that the effects of sentiment on market beta have the same sign as the estimates of $\gamma_{i,1}$. While the level of the sentiment proxy turn to be high, the market betas for the long-short portfolios associated with small stocks, growth stocks, unprofitable and non-dividend payers decrease, driving down the subsequent returns. We use a conditional CAPM model simultaneously capturing the effects from the mispricing and time variation in market beta such that it is helpful to examine the causality of the effects of sentiment on return predictability.

Table 6 reports the results of the estimates of the coefficient parameters associated with sentiment, $\gamma_{i,1}$ and $\beta_{i,1}$. Bootstrapped p-values are in parentheses. Several findings are in order. First, the estimates of $\beta_{i,1}$ are insignificant in all cases. It turns out that the predictability patterns associated with sentiment are not related to the compensation for systematic risk. This finding is still valid once we involve some macroeconomic variables, like term spread, default spread and short rate, in risk loading of market beta[15]. Second, the results of "w/o regimes" show that the estimates of $\gamma_{i,1}$ are significant for the long-short portfolios associated with small stocks, non-profitable stocks and no-dividend payers, except for growth stocks. However, as the effects of regime shifts are involved, our main findings

[14] To effectively implement the out-of-sample test of Clark and West (2007), we need sufficient data sample. Except the observations in regime 2, the others don't have sufficient sample size. As a result, we only implement the case of regime 2.

[15] Since the sentiment measure we use in this paper is orthogonalized to the macroeconomic variables, this result turns out to be understandable in terms of two-stage regression, see Baker and Wurgler (2006).

in Table 5 continue to be valid. For example, the magnitude of the significant estimates of $\gamma_{i,1}$ are larger conditional on regime 2. In short, the predictability patterns associated with sentiment would reflect a mispricing/correction pattern, rather than time variation in risk loading of market beta. This finding is consistent with prediction of Baker and Wurgler (2006, 2007).

5 Robustness Check

In our predictive regressions, we use regime-sorted observations to perform the conditional characteristics model and the conditional CAPM model. Although it is an intuitive and straightforward approach to control the effects of regime shifts, this may give rise to several econometric issues such as the small sample bias, less efficiency and the asymptotic properties of the estimators under a specific regime. To address this concern, we run the following predictive regression model using complete data sample:

$$\begin{aligned} r_{it,high} - r_{it,low} &= \alpha_i + (\delta_{i,1}D_1 + \delta_{i,2}D_2 + \delta_{i,3}D_3 + \delta_{i,4}D_4)\text{SENTIMENT}^{\perp}_{t-1} + \beta_{i,\circ}\text{RMRF}_t \\ &\quad +\gamma_{i,2}\text{SMB}_t + \gamma_{i,3}\text{HML}_t + \gamma_{i,4}\text{UMD}_t + \epsilon_{i,t}, \end{aligned} \tag{5}$$

where D_i is the dummy variable of regime i, which equals to 1 when regime$= i$ and equals 0 otherwise. This specification allows the predictive power of sentiment varies with regimes. Unlike the regime switching models in the econometric literature, our predictive regression model of (5) treat the state variable of regime as an exogenous input. Note that in this paper we look for how the state of regime affects return predictability associated with sentiment, not how to use sentiment to identify regimes. Our approach turns out to be an appropriate one in this regard.

Table 7 reports the results of the predictive regression model (5). Bootstrapped p-values are in the parentheses. To conserve space, we only report the estimates of four coefficient parameters associated with four regime dummies. Broadly speaking, the main findings in Table 5 remain valid. Conditional on regime 2, sentiment displays fairly strong and robust predictive power for the future returns of the long-short portfolios associated with small, growth, unprofitable and non-dividend-paying firms. The significant results in other regimes may not be stable since those are sensitive to methodologies that we use. In sum, Hypothesis 2 substantially is rejected. The validation of Hypothesis 1 conditional on the state of regime.

An alternative robustness check is to see if the results of the association between return predictability and sentiment hold up using different sentiment proxies. To this end, we repeat the preliminary tests by sorting using two alternative sentiment proxies: the consumer confidence level CONSUMER CONFIDENDECE$^{\perp}$ and the VXO index VXO$^{\perp}$. Note that both of them have been orthogonalized to macroeconomic conditions and centered by zero.

Table 8 and 9 contain the results of two- and three-pass sort based on the orthogonal consumer confidence level CONSUMER CONFIDENDECE$^{\perp}$ and the orthogonal VXO index VXO$^{\perp}$. The results of Table 8 are fairly consistent with those of Table 4. Although the sample period of the consumer confidence is shorter than the Baker and Wurgler's sentiment proxy and the correlation between two proxies only reaches 0.19, the conclusions of return predictability associated with sentiment holds up irrespective of sentiment measures. This result is also consistent with Glushkov (2006).

In practice, VXO is interpreted as a fear gauge for investors. A positive value of VXO is equivalent to a negative value of sentiment. Broadly speaking, the results of Table 9 display the predictability patterns associated with the alternative sentiment proxy, except for dividend-oriented portfolio. However, controlling the effects of regime shifts can not affect the predictive power of sentiment. This result may be at add with the findings based on Baker and Wurgler's sentiment proxy and consumer confidence level. A possible explanation for this inconsistent result can be attributed to a short sample period data. Calculation based on regime-sorted observation may give rise to a substantial and severe small sample bias while the data sample period is not long enough[16].

[16]The Baker and Wurgler's sentiment index starts from Jan. 1966 but the VXO index begins from Jan. 1986.

6 Conclusion

In this study, we empirically examine the relationship between return predictability and sentiment while the stock fundamentals perform regime shifts. The study is motivated by the realization that while we examine the predictive power of sentiment, we may not be able to separate identify the price change as a correction pattern for a mispricing or a adjustment dynamic in relation to the regime-switched stock fundamentals. The conventional behaioral finance theory assumes a constant stock fundamentals. Although there are some subsequent studies trying to fix the restrictive and problematic assumption on stock fundamentals, those studies didn't explore the interplay between regime shifts, mispricing and return predictability so far. We empirically address this issue.

We proposed a simple way to explore this issue within the conventional predictive regression framework and a testing procedure to tackle the potential econometric problems in this study. Our main empirical findings are: (1) the effects of sentiment on predicting the cross-section of future stock returns are conditional on the state of regime; (2) dividend- and earning-oriented portfolios perform strong conditional predictability patterns only after conditioning on sentiment and regimes; (3) the appearance of the size and value effects are also conditional on sentiment and the state of regime; (4) the cross-sectional predictability patterns associated with sentiment reflect the mispricing, not the compensation for systematic risk.

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Figure 1:
Mispricing, Correction and Regime Shifts

The top panel plots the systematic pattern of mispricing correction under the single-state stock fundamentals. The bottom panel plots the identification problem that we are not able to separately identify the price changes as a correction pattern for a mispricing or an adjustment dynamic for the regime-shift stock fundamentals.

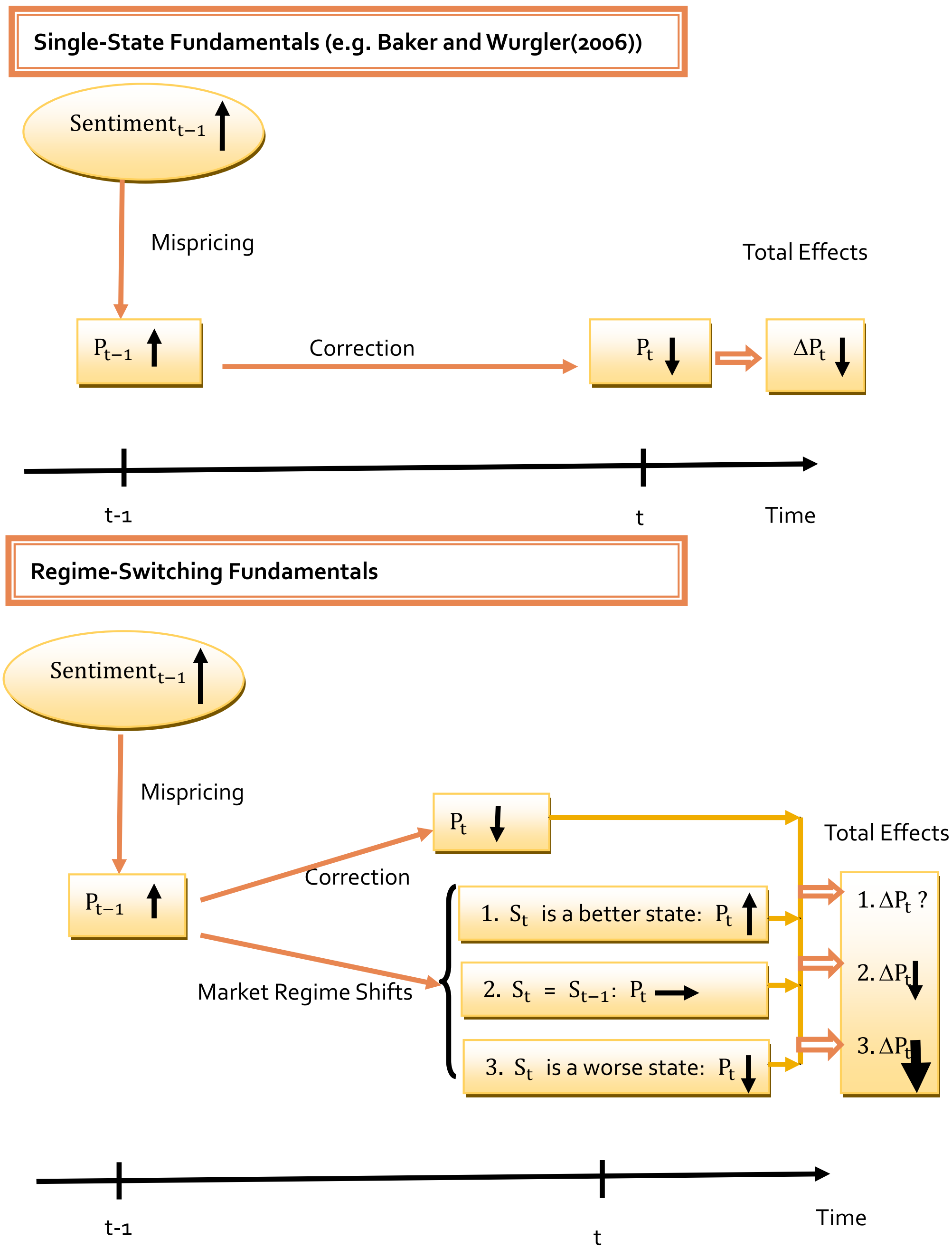

Figure 2:

The Historical Patterns for Three Sentiment Proxies

This picture depicts the curves of three various sentiment proxies, including Baker and Wurgler's orthogonal sentiment proxy for the sample period from Jan. 1966 to Dec. 2005, the orthogonal consumer confidence for the sample period from Jan. 1978 to Dec. 2007, and the investor fear proxy (the orthogonal VXO index) for the sample period from Jan. 1986 to Dec. 2007.

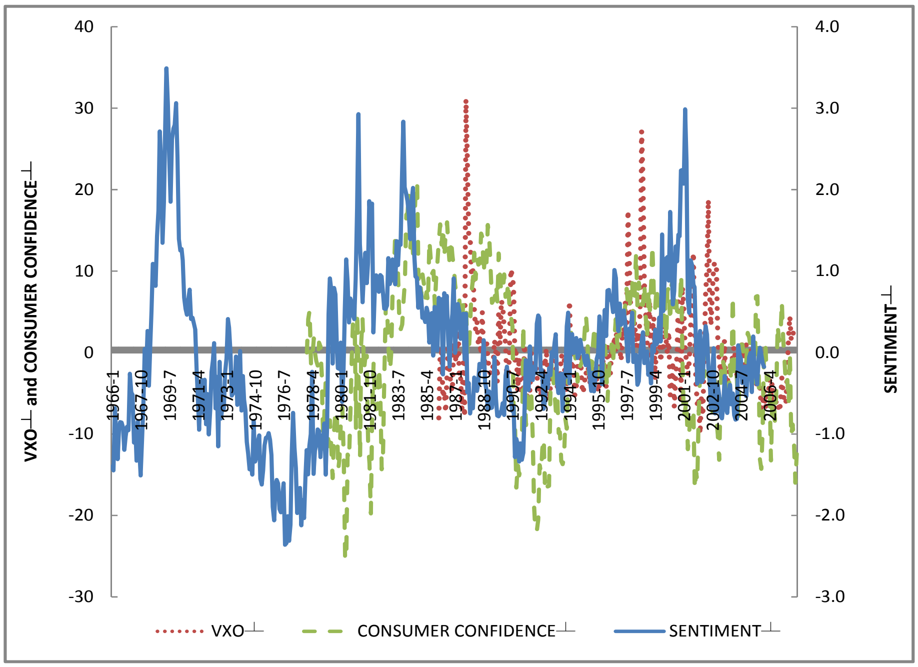

Figure 3:
The Smoothed Probabilities for the Markov-Switching Model

This figure plots smoothed probabilities for the Markov Switching model

$$\mathbf{r}_{t+1} = \mu_{s_{t+1}} + \varepsilon_{t+1},$$

where $\mu_{s_{t+1}}$ is the regime-dependent intercepts and $\varepsilon_{t+1} \sim \mathcal{N}(0, \mathbf{\Omega}_{s_{t+1}})$. The regime is a unobserved state variable driven by a first-order Markov chain. The sample period is from Jan. 1928 to Dec. 2007. Regime 1 is a bear/crash state characterized by negative mean returns, high volatility and a short duration. Regime 2 is a highly persistent, low volatility state, which captures most of the bull markets since 1960. Regime 3 is a persistent and low volatility state with moderate mean returns. Regime 4 is an uncertain regime with the highest mean returns, highest volatility and a

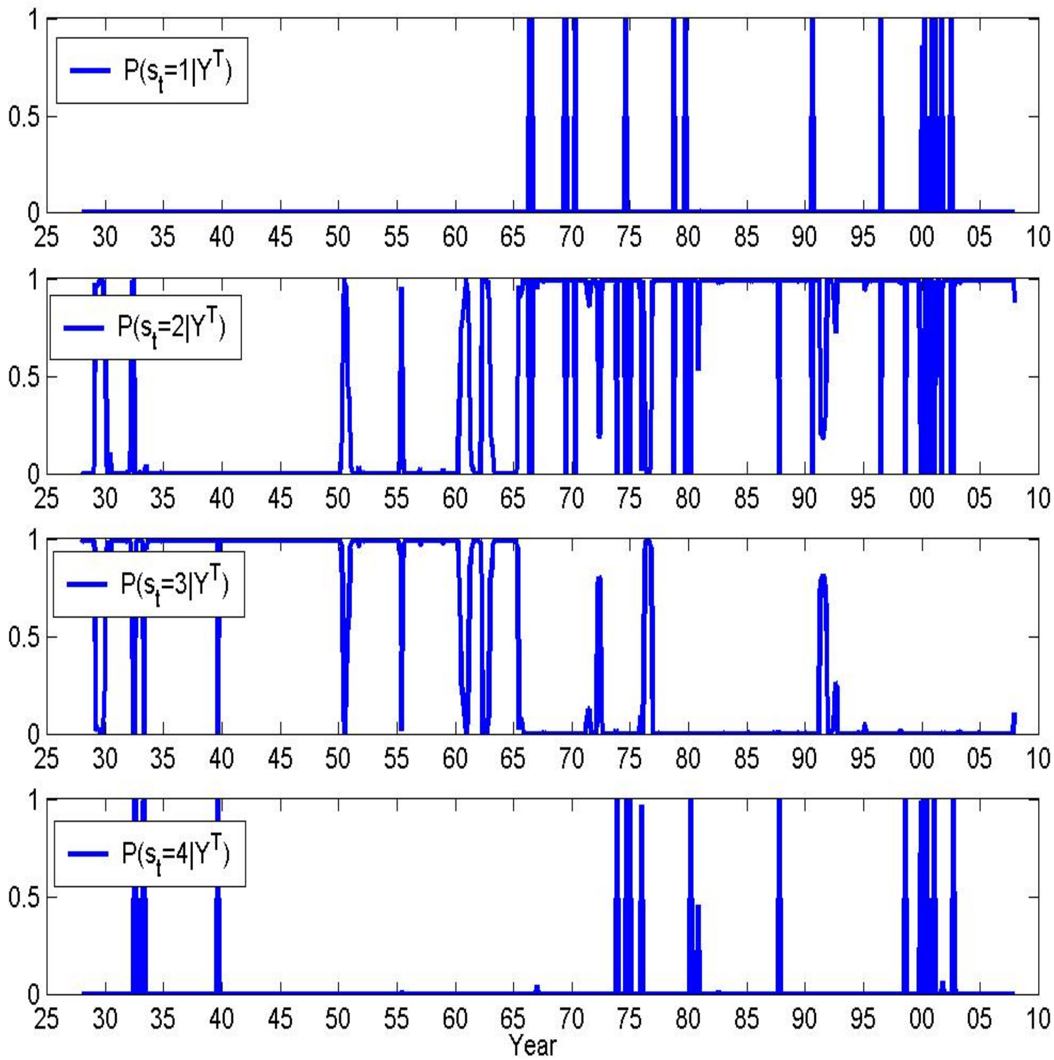

Figure 4:
Smoothed Probabilities and Three Sentiment Proxies

This figure plots smoothed probabilities of regime 1 and 4 and the curves of three sentiment proxies. The sample period is from Jan. 1928 to Dec. 2007.

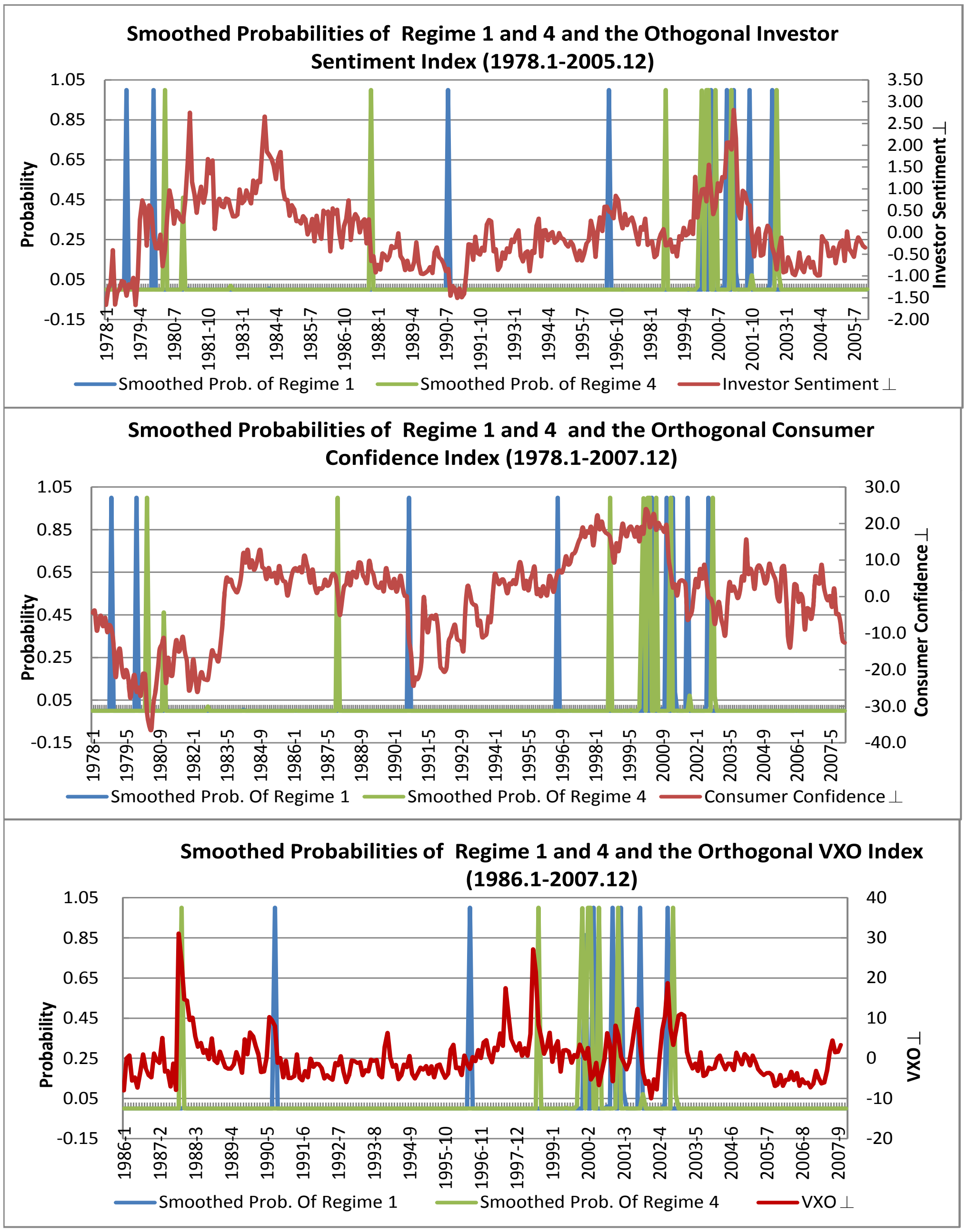

Table 4:
Future Returns by Sentiment Index, Firm Characteristics and Regimes

$\text{SENTIMENT}^{\perp}_{t-1}$	Deciles									
≤ 0	1	2	3	4	5	6	7	8	9	10
					Size-Oriented Portfolios					
Sorted by Size (ME)										
	1.43	1.09	1.13	1.09	1.13	1.06	1.11	1.04	1.01	0.89
Sorted by Size, $\text{SENTIMENT}^{\perp}_{t-1}$										
Positive	0.66	0.45	0.45	0.46	0.60	0.53	0.69	0.68	0.67	0.62
Negative	2.15	1.68	1.74	1.65	1.59	1.52	1.51	1.36	1.30	1.11
Diff	-1.49	-1.23	-1.29	-1.20	-0.99	-1.00	-0.82	-0.69	-0.63	-0.49
Sorted by Size, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime 1										
Positive	-9.04	-10.88	-11.12	-11.08	-10.65	-9.75	-8.85	-8.96	-7.99	-7.42
Negative	-12.18	-12.33	-12.23	-11.63	-11.26	-10.40	-9.94	-9.33	-8.92	-7.73
Diff	3.14	1.45	1.12	0.55	0.61	0.65	1.09	0.37	0.94	0.30
Sorted by Size, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime 2										
Positive	1.14	1.06	1.14	1.13	1.28	1.18	1.28	1.28	1.25	1.21
Negative	2.62	2.10	2.17	2.08	1.96	1.91	1.89	1.72	1.62	1.43
Diff	-1.48	-1.04	-1.03	-0.95	-0.68	-0.73	-0.61	-0.44	-0.36	-0.22
Sorted by Size, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime 3										
Positive	-0.98	-0.33	-1.38	-0.69	-0.94	-0.85	0.05	-0.74	-0.30	0.00
Negative	0.40	0.44	0.39	0.48	0.90	0.64	0.54	0.58	0.73	0.60
Diff	-1.37	-0.78	-1.77	-1.17	-1.84	-1.50	-0.49	-1.32	-1.03	-0.60
Sorted by Size, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime 4										
Positive	2.84	1.32	-0.43	-0.09	-0.49	-1.38	-0.65	-0.89	-1.97	-3.14
Negative	0.00	-0.04	-0.38	-0.84	-0.65	-1.35	-1.32	-1.84	-1.20	-2.86
Diff	2.84	1.36	-0.05	0.75	0.16	-0.03	0.66	0.96	-0.77	-0.28
					Book-to-Market(BE/ME)-Oriented Portfolios					
Sorted by BE/ME										
	0.65	1.00	1.11	1.24	1.28	1.39	1.48	1.50	1.65	1.86
Sorted by BE/ME, $\text{SENTIMENT}^{\perp}_{t-1}$										
Positive	-0.43	0.28	0.52	0.64	0.84	1.03	1.09	1.11	1.25	1.27
Negative	1.56	1.64	1.62	1.78	1.72	1.76	1.89	1.92	2.08	2.46
Diff	-1.99	-1.36	-1.11	-1.13	-0.88	-0.73	-0.80	-0.80	-0.83	-1.19
Sorted by BE/ME, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime 1										
Positive	-13.89	-11.26	-9.87	-9.22	-7.53	-7.63	-6.52	-6.26	-6.48	-7.05
Negative	-12.94	-12.25	-11.96	-11.19	-10.68	-10.57	-10.45	-10.37	-11.14	-11.56
Diff	-0.94	0.99	2.09	1.97	3.15	2.94	3.93	4.11	4.66	4.51
Sorted by BE/ME, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime 2										
Positive	0.13	0.86	1.08	1.25	1.41	1.57	1.60	1.61	1.76	1.78
Negative	2.11	2.14	2.08	2.20	2.08	2.13	2.25	2.27	2.48	2.90
Diff	-1.98	-1.28	-1.00	-0.95	-0.67	-0.56	-0.65	-0.66	-0.72	-1.12
Sorted by BE/ME, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime 3										
Positive	1.54	-0.61	0.88	-0.98	-0.86	-0.84	-0.59	-0.92	-1.06	-1.89
Negative	0.35	0.29	0.36	0.48	0.80	0.59	0.75	0.31	0.39	0.06
Diff	1.19	-0.91	0.52	-1.46	-1.66	-1.43	-1.33	-1.23	-1.45	-1.95
Sorted by BE/ME, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime 4										
Positive	4.40	2.16	0.75	-0.63	-1.80	-0.15	-0.86	-0.75	-0.32	0.86
Negative	-4.86	-3.23	-1.87	-0.87	0.19	0.67	1.01	2.23	1.64	2.85
Diff	9.26	5.39	2.62	0.24	-1.99	-0.82	-1.87	-2.99	-1.96	-1.99

Table 4:-Continued

$\text{SENTIMENT}^{\perp}_{t-1}$	Deciles										
	≤ 0	1	2	3	4	5	6	7	8	9	10
Dividend-Oriented Portfolios											
Sorted by D/ME											
	1.30	1.18	1.28	1.25	1.31	1.28	1.36	1.34	1.38	1.29	1.18
Sorted by D/ME, $\text{SENTIMENT}^{\perp}_{t-1}$											
Positive	0.27	0.67	0.80	0.92	1.03	1.05	1.16	1.28	1.35	1.32	1.24
Negative	2.20	1.68	1.73	1.58	1.61	1.54	1.61	1.47	1.50	1.33	1.16
Diff	-1.93	-1.01	-0.93	-0.66	-0.58	-0.48	-0.45	-0.19	-0.15	-0.01	0.07
Sorted by D/ME, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime 1											
Positive	-11.93	-8.77	-8.06	-6.92	-6.40	-5.68	-5.67	-4.89	-4.78	-3.99	-3.59
Negative	-13.95	-12.77	-11.55	-10.50	-11.07	-10.32	-9.53	-8.93	-8.48	-7.46	-7.86
Diff	2.02	4.00	3.49	3.58	4.67	4.64	3.86	4.04	3.70	3.47	4.27
Sorted by D/ME, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime 2											
Positive	0.85	1.32	1.48	1.55	1.67	1.65	1.77	1.86	1.93	1.80	1.59
Negative	2.75	2.19	2.18	1.97	2.00	1.89	1.97	1.75	1.76	1.55	1.35
Diff	-1.90	-0.87	-0.70	-0.41	-0.34	-0.24	-0.20	0.11	0.17	0.26	0.25
Sorted by D/ME $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime 3											
Positive	-0.79	0.72	-0.07	-0.14	-1.66	-1.02	-1.51	-1.29	-1.29	-0.97	-1.52
Negative	-0.01	0.35	0.34	0.17	0.52	0.62	0.66	0.98	1.01	0.94	0.56
Diff	-0.78	0.37	-0.40	-0.30	-2.18	-1.64	-2.17	-2.26	-2.30	-1.91	-2.08
Sorted by D/ME, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime 4											
Positive	3.30	-3.08	-4.17	-4.28	-4.56	-4.63	-4.59	-4.63	-4.56	-3.42	-0.53
Negative	-0.54	-2.96	-1.60	-0.08	-0.57	-0.14	-0.78	0.30	0.94	1.13	2.96
Diff	3.84	-0.13	-2.57	-4.20	-3.99	-4.49	-3.81	-4.92	-5.50	-4.55	-3.49
Earning-Oriented Portfolios											
Sorted by E/ME											
	1.34	0.95	1.14	1.16	1.22	1.25	1.33	1.36	1.42	1.54	1.66
Sorted by E/ME, $\text{SENTIMENT}^{\perp}_{t-1}$											
Positive	0.13	2.40	0.48	0.63	0.80	0.88	1.04	1.08	1.17	1.25	1.28
Negative	2.43	2.47	1.72	1.63	1.61	1.57	1.63	1.66	1.72	1.86	2.10
Diff	-2.30	-0.07	-1.24	-1.00	-0.81	-0.70	-0.59	-0.58	-0.55	-0.61	-0.81
Sorted by E/ME, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime1											
Positive	-13.05	13.04	-9.08	-8.50	-6.99	-6.89	-6.36	-5.99	-5.39	-5.94	-6.84
Negative	-14.33	5.20	-11.22	-11.11	-11.00	-10.81	-10.44	-10.48	-10.53	-10.75	-12.34
Diff	1.28	7.84	2.14	2.61	4.00	3.92	4.08	4.50	5.14	4.80	5.50
Sorted by E/ME, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime2											
Positive	0.64	1.31	1.08	1.22	1.38	1.48	1.61	1.66	1.69	1.79	1.86
Negative	2.98	2.27	2.18	2.07	1.99	1.96	1.98	2.01	2.07	2.19	2.52
Diff	-2.34	-0.96	-1.10	-0.85	-0.61	-0.48	-0.37	-0.35	-0.38	-0.40	-0.66
Sorted by E/ME, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime3											
Positive	-1.37	0.32	0.01	-1.63	-0.02	-0.54	-0.66	-0.95	-1.01	-1.14	-1.55
Negative	-0.17	-0.12	0.24	0.28	0.89	0.23	0.59	0.63	0.48	0.74	0.30
Diff	-1.20	0.43	-0.23	-1.90	-0.91	-0.76	-1.24	-1.58	-1.49	-1.88	-1.85
Sorted by E/ME, $\text{SENTIMENT}^{\perp}_{t-1}$ and Regime4											
Positive	6.79	17.07	-1.24	-1.12	-2.99	-3.69	-3.09	-3.55	-2.60	-1.97	-1.36
Negative	1.44	14.53	-1.89	-1.43	-0.86	0.12	0.56	0.54	1.41	2.03	2.18
Diff	5.35	2.55	0.65	0.31	-2.13	-3.82	-3.65	-4.09	-4.01	-4.00	-3.53

Note: This table contains the results of one-, two- and three-pass sort. (i) one-pass sort: stock returns are sorted based on firm characteristics and divided into 10 or 11 deciles; (ii) two-pass sort: stock returns are sorted based on the previous month's sentiment proxy in each decile. Two classified groups in each decile are available: positive and negative sentiment groups; (iii) three-pass sort: we sort stock returns based on the inferred regimes in each decile, and then classify the two-pass sorted stock returns based on the previous month's sentiment proxy. The equal-weighted average returns are calculated in all sorted groups.

Table 5: Conditional Characteristics Regressions of Portfolio Returns

	w/o Regimes		Regime 1		Regime 2		Regime 3		Regime 4	
Size-Oriented Portfolios										
Only Sentiment$^{\perp}$										
High-Low	0.752*	(0.004)	-0.272	(0.720)	1.013*	(0.000)	-0.142	(0.668)	-2.665	(0.812)
High-Medium	0.390*	(0.008)	-0.215	(0.734)	0.439*	(0.000)	0.186	(0.140)	-1.180	(0.724)
Medium-Low	0.362*	(0.002)	-0.056	(0.566)	0.573*	(0.004)	-0.328	(0.946)	-1.485	(0.880)
Controlling for RMRF, SMB, HML and UMD										
High-Low	0.794*	(0.004)	1.188	(0.064)	1.065*	(0.000)	-1.325	(0.904)	-2.614	(0.756)
High-Medium	0.341*	(0.028)	0.454	(0.196)	0.407*	(0.004)	0.054	(0.444)	-0.931	(0.680)
Medium-Low	0.453*	(0.012)	0.734	(0.084)	0.658*	(0.000)	-1.380	(0.936)	-1.683	(0.852)
Book-to-Market-Oriented Portfolios										
Only Sentiment$^{\perp}$										
High-Low	0.241*	(0.024)	1.584*	(0.030)	0.282*	(0.008)	-0.453	(0.944)	-6.887	(1.000)
High-Medium	-0.221	(1.000)	0.263	(0.066)	-0.351	(1.000)	0.533	(0.076)	-0.087	(0.508)
Medium-Low	0.462*	(0.038)	1.321*	(0.030)	0.634*	(0.000)	-0.986	(0.788)	-6.799	(0.994)
Controlling for RMRF, SMB, HML and UMD										
High-Low	0.152	(0.116)	2.069*	(0.046)	0.190*	(0.034)	-0.247	(0.808)	-7.971	(0.976)
High-Medium	-0.132	(0.996)	0.158	(0.264)	-0.268	(1.000)	-0.109	(0.568)	-0.288	(0.716)
Medium-Low	0.285	(0.006)	1.910*	(0.032)	0.459*	(0.004)	-0.138	(0.682)	-7.682	(0.996)
Dividend-Oriented Portfolios										
Only Sentiment$^{\perp}$										
High-<0	1.019*	(0.003)	1.164	(0.012)	1.211*	(0.000)	-1.631	(0.914)	-4.861	(0.937)
High-Medium	0.193	(0.073)	0.178	(0.440)	0.179*	(0.003)	-1.210	(0.904)	0.250	(0.220)
Medium-<0	0.826*	(0.003)	0.986	(0.022)	1.031*	(0.000)	-0.420	(0.944)	-5.112	(0.957)
Controlling for RMRF, SMB, HML and UMD										
High-<0	0.385*	(0.020)	0.886*	(0.046)	0.562*	(0.000)	-3.462	(0.994)	-5.758	(0.977)
High-Medium	-0.011	(0.444)	0.743	(0.053)	-0.006	(0.554)	-2.897	(0.957)	1.905	(0.180)
Medium-<0	0.397*	(0.036)	0.143	(0.353)	0.568*	(0.000)	-0.565	(0.857)	-7.663	(0.977)
Earning-Oriented Portfolios										
Only Sentiment$^{\perp}$										
High-<0	0.775*	(0.006)	1.633	(0.006)	0.952*	(0.000)	-1.014*	(0.990)	-5.349*	(0.987)
High-Medium	-0.071	(0.927)	0.710*	(0.023)	-0.156	(1.000)	-0.117	(0.943)	0.425	(0.226)
Medium-<0	0.846*	(0.013)	0.922	(0.043)	1.108*	(0.000)	-0.897*	(0.910)	-5.774	(0.964)
Controlling for RMRF, SMB, HML and UMD										
High-<0	0.449*	(0.003)	0.469	(0.160)	0.607*	(0.000)	-1.332	(0.924)	-7.930	(0.970)
High-Medium	-0.015	(0.593)	0.894	(0.066)	-0.112	(1.000)	0.394*	(0.028)	1.912*	(0.044)
Medium-<0	0.465*	(0.005)	-0.425	(0.373)	0.720*	(0.000)	-1.727	(0.987)	-9.842	(0.973)

Note: This table contains the results about regressions of long-short portfolio returns on lagged SENTIMENT$^{\perp}$, the market risk premium (RMRF), the Fama-French factors (HML and SMB), and a momentum factor (UMD), see (2). The sample period is from Jan. 1966 to Dec. 2005. The long-short portfolios are based on firm characteristics: size, book-to-market ratio, dividend policy and earning. "High", "Low" and "Medium" indicate the 10th (the largest), 1th and 5th deciles. ≤ 0 is the non-dividend-paying or non-earning decile. SENTIMENT$^{\perp}$ is Baker and Wurgler's orthogonal sentiment proxy. We exclude SMB and HML from the right side when they are the portfolios being forecast. The column "w/o Regimes" reports the results without regime sorting. The other columns "Regime i", $i = 1, 2, 3, 4$, show the results based on regime-sorted observations as regime$= i$. The bootstrapped p-values are in parentheses.

Table 6:
Conditional Market Betas

		w/o Regime		Regime 1		Regime 2		Regime 3		Regime 4	
						Size-Oriented Portfolios					
High-Low	$\gamma_{i,1}$	0.800*	(0.012)	-4.731	(0.922)	1.061*	(0.000)	-1.493	(0.984)	-2.540	(0.726)
	$\beta_{i,1}$	0.018	(0.400)	-0.762	(0.944)	0.024	(0.428)	-0.249	(0.952)	-0.026	(0.564)
High-Medium	$\gamma_{i,1}$	0.338*	(0.024)	-0.504	(0.668)	0.410*	(0.000)	0.000	(0.470)	-0.820	(0.624)
	$\beta_{i,1}$	-0.010	(0.732)	-0.123	(0.796)	-0.012	(0.726)	-0.081	(0.924)	-0.038	(0.632)
Medium-Low	$\gamma_{i,1}$	0.462*	(0.012)	-4.226	(0.908)	0.650*	(0.000)	-1.493	(0.980)	-1.719	(0.842)
	$\beta_{i,1}$	0.029	(0.188)	-0.638	(0.912)	0.036	(0.086)	-0.167	(0.956)	0.012	(0.488)
						Book-to-Market-Oriented Portfolios					
High-Low	$\gamma_{i,1}$	0.058	(0.344)	-4.238	(0.940)	0.205*	(0.022)	-0.191	(0.704)	-6.717	(0.876)
	$\beta_{i,1}$	-0.211	(1.000)	-0.781	(0.960)	-0.102	(1.000)	0.081	(0.384)	-0.309	(0.928)
High-Medium	$\gamma_{i,1}$	-0.162	(1.000)	2.466	(0.074)	-0.262	(1.000)	-0.006	(0.442)	0.629	(0.194)
	$\beta_{i,1}$	-0.067	(1.000)	0.285	(0.126)	-0.043	(1.000)	0.148	(0.148)	-0.227	(0.970)
Medium-Low	$\gamma_{i,1}$	0.221	(0.056)	-6.705	(0.974)	0.468*	(0.004)	-0.184	(0.602)	-7.347	(0.952)
	$\beta_{i,1}$	-0.143	(1.000)	-1.067	(0.988)	-0.059	(0.970)	-0.066	(0.694)	-0.082	(0.724)
						Dividend-Oriented Portfolios					
High-<0	$\gamma_{i,1}$	0.349*	(0.006)	-3.611	(0.960)	0.570*	(0.000)	-3.315	(0.914)	-5.805	(0.863)
	$\beta_{i,1}$	-0.095	(1.000)	-0.584	(0.947)	-0.046	(0.980)	0.223	(0.176)	-0.253	(0.737)
High-Medium	$\gamma_{i,1}$	-0.017	(0.647)	2.519	(0.236)	-0.004	(0.507)	-2.742	(0.963)	1.880	(0.246)
	$\beta_{i,1}$	-0.015	(0.960)	0.230	(0.113)	-0.014	(0.853)	0.234	(0.116)	-0.133	(0.724)
Medium-<0	$\gamma_{i,1}$	0.366*	(0.006)	-6.131	(0.947)	0.574*	(0.000)	-0.572	(0.797)	-7.685	(0.880)
	$\beta_{i,1}$	-0.079	(1.000)	-0.815	(0.937)	-0.032	(0.937)	-0.011	(0.477)	-0.119	(0.794)
						Earning-Oriented Portfolios					
High-<0	$\gamma_{i,1}$	0.411*	(0.006)	-8.128	(0.973)	0.614*	(0.000)	-1.476	(0.957)	-7.971	(0.884)
	$\beta_{i,1}$	-0.099	(0.994)	-1.117	(0.957)	-0.035	(0.873)	-0.218	(0.912)	-0.221	(0.827)
High-Medium	$\gamma_{i,1}$	-0.026	(0.710)	1.677	(0.333)	-0.106	(0.980)	0.481	(0.053)	1.897	(0.150)
	$\beta_{i,1}$	-0.029	(0.974)	0.101	(0.370)	-0.030	(0.994)	0.131	(0.166)	-0.080	(0.834)
Medium-<0	$\gamma_{i,1}$	0.438*	(0.003)	-9.806	(0.910)	0.721*	(0.000)	-1.957	(0.990)	-9.868	(0.820)
	$\beta_{i,1}$	-0.070	(0.977)	-1.219	(0.957)	-0.005	(0.514)	-0.349	(0.960)	-0.140	(0.734)

Note: This table contains the results about regressions of long-short portfolio returns on lagged SENTIMENT$^{\perp}$, the market risk premium (RMRF), the Fama-French factors (HML and SMB), a momentum factor (UMD), and interaction of RMRF and SENTIMENT$^{\perp}$, see (3). The sample period is from Jan. 1966 to Dec. 2005. The long-short portfolios are based on firm characteristics: size, book-to-market ratio, dividend policy and earning. "High", "Low" and "Medium" indicate the 10th (the largest), 1th and 5th deciles. ≤ 0 is the non-dividend-paying or non-earning decile. SENTIMENT$^{\perp}$ is Baker and Wurgler's orthogonal sentiment proxy. We exclude SMB and HML from the right side when they are the portfolios being forecast. The column "w/o Regimes" reports the results without regime sorting. The other columns "Regime i",$i = 1, 2, 3, 4$, show the results based on regime-sorted observations as regime= i. The bootstrapped p-values are in parentheses.

Table 7:
Conditional Characteristics Regressions of Portfolios Returns

	$\delta_{i,1}$		$\delta_{i,2}$		$\delta_{i,3}$		$\delta_{i,4}$	
Size-Oriented Portfolios								
High-Low	0.824	(0.106)	1.073*	(0.000)	-0.538	(0.982)	-3.052	(0.926)
High-Medium	0.509	(0.138)	0.419*	(0.000)	0.030	(0.376)	-1.168	(0.840)
Medium-Low	0.315	(0.248)	0.653*	(0.000)	-0.568	(1.000)	-1.883	(0.974)
Book-to-Market-Oriented Portfolios								
High-Low	1.475	(0.080)	0.215*	(0.026)	1.003*	(0.006)	-6.598	(0.998)
High-Medium	0.065	(0.358)	-0.270	(1.000)	0.989*	(0.006)	0.622	(0.290)
Medium-Low	1.410*	(0.052)	0.486*	(0.002)	0.014	(0.492)	-7.220	(0.992)
Dividend-Oriented Portfolios								
High-<0	0.993*	(0.002)	0.696*	(0.000)	-0.756	(1.000)	-6.479	(1.000)
High-Medium	-0.058	(0.632)	0.017	(0.380)	-0.445	(1.000)	0.240	(0.330)
Medium-<0	1.052*	(0.016)	0.679*	(0.000)	-0.310	(0.996)	-6.719	(0.998)
Earning-Oriented Portfolios								
High-<0	1.500*	(0.008)	0.6860*	(0.000)	-0.412	(0.976)	-6.185	(0.998)
High-Medium	0.222	(0.176)	-0.1138	(0.998)	0.107	(0.054)	1.592*	(0.038)
Medium-<0	1.278*	(0.036)	0.7998*	(0.000)	-0.519	(0.978)	-7.777	(0.996)

Note: This table contains the results about regressions of long-short portfolio returns on the interactions of regime dummy variables and lagged SENTIMENT$^{\perp}$, the market risk premium (RMRF), the Fama-French factors (HML and SMB), and a momentum factor (UMD), see (5). The sample period is from Jan. 1966 to Dec. 2005. The long-short portfolios are based on firm characteristics: size, book-to-market ratio, dividend policy and earning. "High", "Low" and "Medium" indicate the 10th (the largest), 1th and 5th deciles. ≤ 0 is the non-dividend-paying or non-earning decile. SENTIMENT$^{\perp}$ is Baker and Wurgler's orthogonal sentiment proxy. We exclude SMB and HML from the right side when they are the portfolios being forecast. The bootstrapped p-values are in parentheses.

Table 8:
Future Returns by Consumer Confidence, Regimes and Firm Characteristics

Consumer	Deciles									
Confidence$^{\perp}_{t-1}$	1	2	3	4	5	6	7	8	9	10
Size (ME)-Oriented Portfolios										
Sorted by Size, CONSUMER CONFIDENDECE$^{\perp}_{t-1}$										
Positive	0.89	0.81	0.89	0.89	1.02	0.97	1.20	1.16	1.22	1.28
Negative	2.09	1.57	1.62	1.57	1.57	1.55	1.47	1.30	1.27	0.98
Diff	-1.20	-0.75	-0.73	-0.68	-0.56	-0.58	-0.27	-0.15	-0.05	0.30
Sorted by Size, CONSUMER CONFIDENDECE$^{\perp}_{t-1}$ and Regime 1										
Positive	-8.11	-10.71	-10.72	-10.68	-10.65	-9.52	-8.77	-8.55	-8.02	-6.96
Negative	-8.95	-11.87	-12.61	-12.49	-11.98	-10.82	-9.60	-10.59	-9.12	-8.52
Diff	0.84	1.16	1.89	1.81	1.34	1.30	0.83	2.04	1.11	1.56
Sorted by Size, CONSUMER CONFIDENDECE$^{\perp}_{t-1}$ and Regime 2										
Positive	1.23	1.30	1.43	1.40	1.55	1.47	1.65	1.58	1.67	1.75
Negative	2.44	1.97	2.09	2.04	2.01	1.98	1.90	1.76	1.66	1.36
Diff	-1.21	-0.68	-0.67	-0.64	-0.46	-0.51	-0.25	-0.18	0.01	0.39
Sorted by Size, CONSUMER CONFIDENDECE$^{\perp}_{t-1}$ and Regime 3										
Positive	5.59	0.47	0.21	0.14	1.11	0.39	0.28	1.50	1.89	-0.21
Negative	1.59	2.00	1.62	1.42	1.93	1.75	1.39	1.44	1.31	1.07
Diff	4.00	-1.53	-1.41	-1.28	-0.82	-1.36	-1.11	0.06	0.58	-1.28
Sorted by Size, CONSUMER CONFIDENDECE$^{\perp}_{t-1}$ and Regime 4										
Positive	-2.17	-3.18	-4.47	-3.80	-4.35	-4.40	-2.91	-2.74	-3.97	-4.76
Negative	2.17	0.73	-0.44	-0.57	-0.45	-2.04	-3.32	-4.20	-2.59	-3.82
Diff	-4.33	-3.91	-4.04	-3.22	-3.90	-2.36	0.41	1.46	-1.38	-0.94
Book-to-Market(BE/ME)-Oriented Portfolios										
Sorted by BE/ME, CONSUMER CONFIDENDECE$^{\perp}_{t-1}$										
Positive	0.31	0.78	0.96	1.08	1.20	1.31	1.29	1.29	1.29	1.45
Negative	1.12	1.59	1.65	1.79	1.76	1.79	1.91	1.86	2.23	2.49
Diff	-0.81	-0.81	-0.70	-0.71	-0.56	-0.47	-0.62	-0.57	-0.94	-1.04
Sorted by BE/ME, CONSUMER CONFIDENDECE$^{\perp}_{t-1}$ and Regime 1										
Positive	-14.28	-10.99	-9.62	-8.90	-7.15	-7.42	-6.40	-5.99	-6.54	-7.10
Negative	-14.69	-12.42	-11.36	-9.79	-8.55	-8.27	-7.23	-7.32	-7.48	-8.32
Diff	0.41	1.43	1.75	0.89	1.41	0.84	0.84	1.32	0.94	1.23
Sorted by BE/ME, CONSUMER CONFIDENDECE$^{\perp}_{t-1}$ and Regime 2										
Positive	0.79	1.22	1.41	1.55	1.64	1.71	1.68	1.66	1.70	1.84
Negative	1.52	2.06	2.09	2.22	2.14	2.17	2.27	2.23	2.61	2.93
Diff	-0.72	-0.84	-0.68	-0.66	-0.50	-0.46	-0.58	-0.57	-0.91	-1.10
Sorted by BE/ME, CONSUMER CONFIDENDECE$^{\perp}_{t-1}$ and Regime 3										
Positive	4.77	0.69	2.29	2.76	4.68	3.51	2.67	1.63	0.56	4.85
Negative	2.03	1.47	1.68	1.66	2.00	1.46	1.71	1.19	2.05	1.09
Diff	2.74	-0.78	0.61	1.10	2.68	2.05	0.96	0.44	-1.49	3.76
Sorted by BE/ME, CONSUMER CONFIDENDECE$^{\perp}_{t-1}$ and Regime 4										
Positive	-1.77	-1.76	-3.10	-4.16	-4.85	-2.94	-3.63	-3.21	-3.43	-2.88
Negative	4.16	-0.69	-0.38	-1.74	-2.35	-2.02	-1.88	-1.73	-1.53	-0.94
Diff	-5.92	-1.07	-2.71	-2.42	-2.50	-0.92	-1.74	-1.47	-1.90	-1.94

Table 8-Continued

CONSUMER CONFIDENCE$_{t-1}^{\perp}$	Deciles $\leq$	1	2	3	4	5	6	7	8	9	10
Dividend-Oriented Portfolios											
Sorted by D/ME, CONSUMER CONFIDENDECE$_{t-1}^{\perp}$											
Positive	0.80	1.14	1.26	1.18	1.23	1.17	1.28	1.23	1.22	1.14	1.13
Negative	1.90	1.58	1.71	1.69	1.70	1.69	1.71	1.75	1.80	1.59	1.33
Diff	-1.10	-0.44	-0.46	-0.51	-0.47	-0.52	-0.43	-0.52	-0.58	-0.44	-0.20
Sorted by D/ME,CONSUMER CONFIDENDECE$_{t-1}^{\perp}$ and Regime 1											
Positive	-10.82	-9.07	-7.62	-6.50	-6.40	-5.89	-6.28	-5.78	-5.10	-3.82	-2.80
Negative	-12.32	-8.97	-8.23	-6.74	-6.68	-5.72	-5.17	-4.33	-4.44	-4.12	-4.70
Diff	1.49	-0.10	0.61	0.24	0.27	-0.16	-1.12	-1.45	-0.66	0.30	1.89
Sorted by D/ME, CONSUMER CONFIDENDECE$_{t-1}^{\perp}$ and Regime 2											
Positive	1.21	1.66	1.77	1.66	1.73	1.63	1.79	1.72	1.68	1.50	1.35
Negative	2.36	2.04	2.16	2.08	2.10	2.05	2.05	2.03	2.07	1.87	1.63
Diff	-1.15	-0.38	-0.39	-0.42	-0.37	-0.41	-0.26	-0.31	-0.39	-0.37	-0.29
Sorted by D/ME, CONSUMER CONFIDENDECE$_{t-1}^{\perp}$ and Regime 3											
Positive	4.39	0.86	1.07	1.26	-0.07	2.94	1.60	2.18	2.11	2.35	1.15
Negative	1.72	1.30	1.43	1.12	1.27	1.33	0.99	1.65	1.53	1.30	-0.39
Diff	2.67	-0.44	-0.36	0.14	-1.34	1.62	0.61	0.53	0.58	1.05	1.54
Sorted by D/ME, CONSUMER CONFIDENDECE$_{t-1}^{\perp}$ and Regime 4											
Positive	-1.66	-4.92	-5.83	-6.00	-6.31	-6.29	-6.74	-6.66	-6.70	-4.99	-1.82
Negative	0.76	-5.30	-5.77	-4.67	-5.19	-4.68	-3.85	-3.15	-2.44	-3.74	-1.98
Diff	-2.42	0.39	-0.05	-1.32	-1.12	-1.61	-2.90	-3.51	-4.26	-1.24	0.16
Earning-Oriented Portfolios											
Sorted by E/ME, CONSUMER CONFIDENDECE$_{t-1}^{\perp}$											
Positive	0.76	1.96	0.98	1.00	1.10	1.20	1.27	1.23	1.33	1.34	1.36
Negative	1.72	2.87	1.69	1.79	1.70	1.65	1.73	1.76	1.72	1.94	2.14
Diff	-0.96	-0.90	-0.71	-0.79	-0.60	-0.45	-0.46	-0.53	-0.38	-0.60	-0.78
Sorted by E/ME, CONSUMER CONFIDENDECE$_{t-1}^{\perp}$ and Regime 1											
Positive	-11.73	13.05	-8.83	-8.77	-7.11	-7.24	-6.42	-6.80	-6.42	-6.79	-7.42
Negative	-14.09	13.03	-9.62	-8.71	-7.12	-6.81	-6.80	-6.07	-5.99	-6.48	-8.47
Diff	2.35	0.02	0.79	-0.05	0.02	-0.42	0.38	-0.73	-0.43	-0.31	1.06
Sorted by E/ME, CONSUMER CONFIDENDECE$_{t-1}^{\perp}$ and Regime 2											
Positive	1.10	1.16	1.45	1.47	1.56	1.70	1.72	1.72	1.78	1.78	1.82
Negative	2.16	2.42	2.12	2.19	2.06	2.04	2.10	2.10	2.04	2.28	2.57
Diff	-1.06	-1.26	-0.67	-0.72	-0.50	-0.34	-0.37	-0.38	-0.26	-0.50	-0.76
Sorted by E/ME, CONSUMER CONFIDENDECE$_{t-1}^{\perp}$ and Regime 3											
Positive	6.85	1.58	1.10	0.19	1.66	0.88	1.42	1.91	2.11	3.76	3.05
Negative	1.88	1.47	1.57	1.37	1.88	0.87	1.39	1.48	1.31	1.66	1.20
Diff	4.97	0.11	-0.47	-1.18	-0.22	0.01	0.03	0.43	0.79	2.10	1.85
Sorted by E/ME, CONSUMER CONFIDENDECE$_{t-1}^{\perp}$ and Regime 4											
Positive	0.43	15.31	-4.09	-4.21	-5.28	-5.72	-5.14	-5.94	-4.86	-4.67	-4.44
Negative	3.31	12.96	-2.75	-1.94	-3.64	-3.89	-3.22	-2.81	-2.23	-1.92	-1.94
Diff	-2.87	2.35	-1.34	-2.27	-1.64	-1.84	-1.92	-3.13	-2.62	-2.75	-2.50

Note: This table contains the results of two- and three-pass sort. We first sort stock returns based on firm characteristics and divided into 10 or 11 deciles. Then (i) two-pass sort: stock returns are sorted based on the previous month's consumer confidence in each decile. Two classified groups in each decile are available: positive and negative sentiment groups; (ii) three-pass sort: we sort stock returns based on the inferred regimes in each decile, and then classify the two-pass sorted stock returns based on the previous month's consumer confidence. The equal-weighted average returns are calculated in all sorted groups.

Table 9:
Future Returns by Investor Fear Proxy, Regimes and Firm Characteristics

	Deciles									
$\text{VXO}^{\dagger}_{t-1}$	1	2	3	4	5	6	7	8	9	10
Size (ME)-Oriented Portfolios										
Sorted by Size, $\text{VXO}^{\dagger}_{t-1}$										
Positive	1.54	1.54	1.63	1.71	1.80	1.64	1.86	1.72	1.78	1.63
Negative	1.14	0.54	0.64	0.47	0.61	0.73	0.78	0.68	0.71	0.63
Diff	0.40	0.99	0.98	1.24	1.19	0.91	1.08	1.05	1.07	1.00
Sorted by Size, $\text{VXO}^{\dagger}_{t-1}$ and Regime 1										
Positive	-2.84	-8.62	-9.74	-11.03	-11.30	-10.14	-9.22	-10.04	-8.98	-7.75
Negative	-9.61	-11.07	-11.22	-10.78	-10.38	-9.24	-8.16	-8.85	-7.79	-7.76
Diff	6.76	2.45	1.48	-0.25	-0.92	-0.90	-1.06	-1.19	-1.19	0.01
Sorted by Size, $\text{VXO}^{\dagger}_{t-1}$ and Regime 2										
Positive	1.44	1.74	1.95	2.05	2.17	2.04	2.20	2.13	2.21	2.10
Negative	1.62	1.03	1.19	1.00	1.13	1.22	1.26	1.15	1.16	1.09
Diff	-0.18	0.71	0.76	1.05	1.05	0.82	0.94	0.98	1.04	1.01
Sorted by Size, $\text{VXO}^{\dagger}_{t-1}$ and Regime 3										
Positive	2.86	4.18	3.77	4.03	4.98	5.52	4.86	4.51	4.81	4.77
Negative	2.04	1.38	1.03	0.77	1.29	0.89	0.63	0.94	0.82	0.24
Diff	0.82	2.80	2.74	3.26	3.70	4.63	4.23	3.57	3.98	4.53
Sorted by Size, $\text{VXO}^{\dagger}_{t-1}$ and Regime 4										
Positive	5.04	2.99	1.81	2.35	2.03	0.54	1.52	0.71	0.02	-1.69
Negative	-9.63	-8.70	-10.91	-11.44	-11.73	-10.93	-11.83	-10.97	-11.32	-11.17
Diff	14.67	11.69	12.72	13.79	13.77	11.46	13.35	11.68	11.35	9.48
Book-to-Market(BE/ME)-Oriented Portfolios										
Sorted by BE/ME, $\text{VXO}^{\dagger}_{t-1}$										
Positive	1.64	1.70	1.77	1.60	1.66	1.67	1.67	1.55	1.71	1.79
Negative	-0.26	0.37	0.65	0.94	1.05	1.12	1.23	1.32	1.48	1.80
Diff	1.90	1.33	1.12	0.66	0.60	0.54	0.44	0.24	0.23	-0.01
Sorted by BE/ME, $\text{VXO}^{\dagger}_{t-1}$ and Regime 1										
Positive	-8.46	-8.88	-8.20	-8.26	-6.71	-6.60	-5.31	-5.15	-5.03	-3.77
Negative	-17.44	-12.17	-10.31	-8.26	-6.32	-6.20	-5.32	-5.12	-5.43	-7.15
Diff	8.98	3.28	2.10	0.00	-0.40	-0.39	0.01	-0.03	0.40	3.39
Sorted by BE/ME, $\text{VXO}^{\dagger}_{t-1}$ and Regime 2										
Positive	1.61	1.86	1.98	1.89	2.00	1.91	1.92	1.77	1.91	1.87
Negative	0.36	0.92	1.15	1.41	1.42	1.51	1.60	1.70	1.87	2.30
Diff	1.25	0.94	0.83	0.47	0.58	0.39	0.32	0.06	0.03	-0.43
Sorted by BE/ME, $\text{VXO}^{\dagger}_{t-1}$ and Regime 3										
Positive	3.16	4.72	3.55	4.75	3.60	1.79	2.48	3.93	2.61	4.72
Negative	2.29	0.79	1.47	1.33	2.18	1.75	1.75	0.80	1.71	1.11
Diff	0.87	3.92	2.09	3.42	1.42	0.04	0.73	3.13	0.90	3.61
Sorted by BE/ME, $\text{VXO}^{\dagger}_{t-1}$ and Regime 4										
Positive	7.00	3.97	3.11	1.45	0.09	2.06	1.19	1.20	1.87	2.83
Negative	-10.44	-9.68	-11.11	-11.79	-10.81	-10.63	-10.45	-9.16	-10.75	-10.39
Diff	17.44	13.64	14.22	13.23	10.90	12.69	11.64	10.36	12.62	13.21

Table 9-Continued

$VXO^{\dagger}_{t-1}$	Deciles ≤ 0	1	2	3	4	5	6	7	8	9	10
Dividend-Oriented Portfolios											
Sorted by D/ME, $VXO^{\dagger}_{t-1}$											
Positive	1.81	1.47	1.47	1.12	1.23	1.14	1.24	1.15	1.20	0.95	0.84
Negative	0.73	0.82	1.15	1.18	1.23	1.23	1.30	1.32	1.30	1.29	1.16
Diff	1.08	0.64	0.33	-0.06	0.00	-0.09	-0.06	-0.17	-0.10	-0.33	-0.32
Sorted by D/ME, $VXO^{\dagger}_{t-1}$ and Regime 1											
Positive	-6.03	-10.07	-8.46	-7.21	-7.99	-6.75	-7.61	-6.94	-6.22	-4.73	-4.82
Negative	-12.93	-5.71	-5.04	-3.30	-2.67	-2.34	-2.39	-1.42	-1.18	-1.19	-1.73
Diff	6.90	-4.35	-3.42	-3.91	-5.31	-4.41	-5.22	-5.51	-5.05	-3.54	-3.09
Sorted by D/ME, $VXO^{\dagger}_{t-1}$ and Regime 2											
Positive	1.82	1.91	1.97	1.53	1.71	1.59	1.73	1.59	1.61	1.27	1.04
Negative	1.29	1.25	1.56	1.54	1.58	1.53	1.64	1.59	1.56	1.53	1.42
Diff	0.52	0.66	0.41	-0.01	0.13	0.05	0.09	-0.01	0.04	-0.25	-0.38
Sorted by D/ME, $VXO^{\dagger}_{t-1}$ and Regime 3											
Positive	3.35	3.65	3.82	2.87	3.34	3.22	1.92	4.07	4.80	4.83	3.23
Negative	1.90	0.83	0.97	0.85	0.70	1.28	0.94	1.34	1.08	0.89	-0.74
Diff	1.45	2.82	2.85	2.02	2.64	1.94	0.98	2.74	3.72	3.94	3.97
Sorted by D/ME, $VXO^{\dagger}_{t-1}$ and Regime 4											
Positive	5.41	-0.04	-1.75	-1.47	-2.08	-2.31	-2.07	-2.10	-2.06	-1.92	0.10
Negative	-9.91	-13.58	-12.96	-12.98	-12.82	-12.29	-13.10	-12.07	-11.33	-9.14	-5.06
Diff	15.32	13.53	11.21	11.52	10.74	9.98	11.03	9.97	9.27	7.22	5.17
Earning-Oriented Portfolios											
Sorted by E/ME, $VXO^{\dagger}_{t-1}$											
Positive	2.00	2.79	1.56	1.59	1.37	1.42	1.49	1.28	1.29	1.38	1.54
Negative	0.54	1.71	0.80	0.91	1.03	1.05	1.11	1.22	1.26	1.35	1.42
Diff	1.46	1.07	0.77	0.68	0.34	0.37	0.38	0.06	0.04	0.04	0.12
Sorted by E/ME, $VXO^{\dagger}_{t-1}$ and Regime 1											
Positive	-4.12	10.02	-7.02	-8.05	-7.43	-7.16	-7.19	-7.01	-6.42	-6.43	-7.82
Negative	-16.67	13.51	-8.46	-7.04	-4.76	-4.45	-3.79	-3.61	-3.14	-3.98	-5.14
Diff	12.55	-3.50	1.43	-1.02	-2.67	-2.70	-3.39	-3.40	-3.28	-2.45	-2.69
Sorted by E/ME, $VXO^{\dagger}_{t-1}$ and Regime 2											
Positive	1.76	1.98	1.83	1.89	1.75	1.83	1.87	1.67	1.63	1.67	1.84
Negative	1.17	1.07	1.28	1.36	1.38	1.44	1.46	1.56	1.57	1.68	1.84
Diff	0.60	0.92	0.55	0.53	0.37	0.39	0.41	0.11	0.06	-0.01	0.01
Sorted by E/ME, $VXO^{\dagger}_{t-1}$ and Regime 3											
Positive	2.68	2.67	3.69	4.00	3.32	2.27	2.23	3.43	4.20	4.57	3.24
Negative	2.57	1.29	1.14	0.73	1.61	0.64	1.25	1.23	0.97	1.53	1.17
Diff	0.11	1.38	2.55	3.27	1.71	1.63	0.98	2.21	3.23	3.04	2.07
Sorted by E/ME, $VXO^{\dagger}_{t-1}$ and Regime 4											
Positive	8.65	11.76	1.28	1.34	-0.56	-0.98	-0.34	-1.12	-0.56	0.32	1.20
Negative	-8.59	20.56	-12.31	-11.82	-12.31	-12.90	-12.45	-11.78	-9.81	-10.18	-11.64
Diff	17.23	-8.80	13.59	13.16	11.75	11.92	12.11	10.66	9.26	10.50	12.83

Note: This table contains the results of two- and three-pass sort. We first sort stock returns based on firm characteristics and divided into 10 or 11 deciles. Then (i) two-pass sort: stock returns are sorted based on the previous month's $VXO^{\dagger}$ in each decile. Two classified groups in each decile are available: positive and negative sentiment groups; (ii) three-pass sort: we sort stock returns based on the inferred regimes in each decile, and then classify the two-pass sorted stock returns based on the previous month's $VXO^{\dagger}$. The equal-weighted average returns are calculated in all sorted groups.