Investor Sentiment and Paradigm Shifts in Equity Premium Forecasting

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Abstract

Applying Baker and Wurgler's investor sentiment index as a switch, we find that fundamental economic variables forecast the equity premium well only when sentiment is low. They lose their predictive power when sentiment is high, since their fundamental links with the equity premium become weakened. In contrast, non-fundamental variables predict the equity premium well only when sentiment is high but not when it is low, since their performance relies on behavioral biases that become reduced during low-sentiment periods. This sheds some light on the recent debate about the limited power of both fundamental and non-fundamental variables to forecast the equity premium.

JEL classifications: C53, G02, G12, G14, G17

Keywords: Return predictability, Investors sentiment, Economic predictors, Non-fundamental predictors

I. Introduction

The predictability of the equity risk premium has been actively debated in recent years (e.g., Cooper and Gulen, 2006; Welch and Goyal, 2008; Campbell and Thompson, 2008; Rapach, Strauss and Zhou, 2010). Stambaugh, Yu and Yuan (2012), among others, have shown that Baker and Wurgler's (2006) sentiment index operates as a switch.[1] Abnormal patterns and anomalies tend to be significant only when sentiment is high. In this paper, we apply the idea of using sentiment as a switch to forecast the equity risk premium. We find that fundamental variables are strong predictors when sentiment is low while tend to lose their predictive power when sentiment is high. In contrast, non-fundamental variables are strong predictors when sentiment is high but do not predict the equity premium well when sentiment is low. We interpret periods of high sentiment as periods when the market is dominated by unsophisticated investors.[2] This sheds some light on the recent debate about the limited predictability of the equity premium by both fundamental and non-fundamental variables.

Recently, Welch and Goyal (2008) show that the fundamental predictors documented in the literature turn out to be questionable. Specifically, the predictive power of economic variables seems limited to the oil crisis of 1973–1975 and that most forecasting variables have performed poorly since 1975. In contrast, we find that fundamental variables remain strong predictors in low-sentiment periods, even after 1975. Therefore, their forecasting power is robust across subsamples as long as the link between fundamental variables and the equity premium or expected market return (e.g., Campbell and Shiller,1988 and Cochrane, 2008) is not distorted by sentiment. The non-robust or limited forecasting power seems due to the sentiment impact.[3]

[1]Yu and Yuan (2011) and Stambaugh, Yu and Yuan (2015) also use Baker and Wurglers sentiment index as a switch.

[2]This is consistent with the literature showing that investor sentiment can cause prices to deviate from their fundamentals. For instance, De Long, Shleifer, Summers and Waldmann (1990) illustrate that, in the presence of limits to arbitrage, noise traders with irrational sentiment can cause prices to deviate from their fundamentals, even when informed traders recognize the mispricing. More recently, Shen, Yu and Zhao (2017) document that pervasive macro-related factors are priced in the cross-section of stock returns following low sentiment, but not following high sentiment. Refer to work by Richard Thaler, the winner of the 2017 Nobel Prize in Economics, for more details on the impact of behavioral biases on financial markets.

[3]Nelson and Schwert (1982), among others, provide earlier studies on testing predictive regressions. Recently, Carlson, Chapman, Kaniel and Yan (2015) provide a novel general equilibrium model that endogenizes return pre-

In addition, many studies, such as Rapach, Strauss, and Zhou (2010) and Henkel, Martin, and Nardari (2011), find that the predictive ability of economic variables (e.g., the price-dividend ratio) is significant only during economic recessions, accounting for 20%–30% of the time, and insignificant during economic expansions, again suggesting that the predictive ability of fundamental economic variables is limited. However, we find that fundamental variables perform well during all low-sentiment periods, which represent about 80% of our sample period; this includes 83% of all expansionary periods.[4] Our result suggests that the reason for the economic variables to have limited forecasting power during expansionary periods is also due to the sentiment impact.

Moreover, prior studies also suggest that the in-sample predictive power of economic variables does not remain robust out-of-sample (e.g., Welch and Goyal, 2008). We show that economic variables maintain some out-of-sample forecasting power as long as investor sentiment is low. Therefore, the limited out-of-sample forecasting power of the fundamental variables seems also driven by the sentiment impact. Additionally, some methods, such as the fixed coefficients approach in Campbell and Thompson (2008), have been documented to effectively restore economic variables' out-of-sample forecasting power. We show that those remedies do not seem to work during high-sentiment periods. Essentially, such methods are based on theoretically-motivated restrictions from rational economic models.[5] During high-sentiment periods, those economic models no longer hold; hence the methods no longer work.[6]

Furthermore, in addition to the fundamental predictors of the equity premium, some recent studies report that various behavioral-bias-motivated non-fundamental variables have strong pre-

dictability. They show that fundamental variables, such as dividend yield, can significantly forecast future excess returns based on their general-equilibrium-model-generated excess returns and dividend yields.

[4]In addition, our sentiment regimes do not co-move with business cycles, with a low correlation of 0.23 between the NBER recession dummy and our high sentiment dummy.

[5]Carlson, Chapman, Kaniel and Yan (2015) seem providing an additional and independent evidence to support Campbell and Thompson (2008)'s fixed coefficients restriction, which sets the coefficient of a given single predictor to one – the value implied by a simple steady-state model, such as the Gordon (1962) growth model. In Carlson, Chapman, Kaniel and Yan (2015), the density of the slope coefficient is centered around 1.0, based on the simulated returns versus dividend yield regressions from their general equilibrium model that endogenizes return predictability.

[6]Other methods are mainly based on econometric reasons, such as reducing estimation errors (e.g., Rapach, Strauss and Zhou, 2010) or capturing time-varying predicting coefficient (Dangl and Halling, 2012). Although sentiment can affect or distort economic links, it is not clear how sentiment affects econometric issues. Therefore, we do not discuss these econometrics-based approaches.

dictive ability. For instance, Li and Yu (2012) propose some anchoring variables.[7] They show that, although one anchoring variable (the Dow Jones Industrial Average index's nearness to its 52-week high) has significant predictive power, another anchoring variable (the NYSE/AMEX total market value index's nearness to its 52-week high) has none. Li and Yu (2012) hypothesize that the Dow index is more visible than the NYSE/AMEX index and that investors have limited attention. However, given that many index funds track the performance of both the Dow index and the NYSE/AMEX index or their close proxies, it is puzzling to find such substantial differences in predictive power. By splitting the sample into high- and low-sentiment periods, we solve this puzzle: both anchoring variables turn out to have strong predictive power during high-sentiment periods, but not during low-sentiment periods. We also examine other non-fundamental predictors, including time series momentum (Moskowitz, Ooi and Pedersen, 2012), and technical indicators (Brock, Lakonishok and LeBaron, 1992; Neely, Rapach, Tu and Zhou, 2014). Those non-fundamental predictors also have strong predictive power during high-sentiment periods but not low-sentiment periods.[8] Therefore, the predictive strength of non-fundamental variables seems to depend on behavioral activities that are significant only during high-sentiment periods.[9]

Overall, a high level of sentiment may significantly weaken the predictive ability of fundamental variables while a low level of sentiment may be associated with a substantial deterioration in the predictive ability of non-fundamental variables. Since the market is likely to be dominated by unsophisticated investors during high-sentiment periods, this study may provide a unified answer to why we observe weak or non-existent predictive power in recent studies, such as Welch and Goyal (2008) and Li and Yu (2012). Once we control for the impact of investor sentiment, a key underlying reason for this weakness in forecasting power, both fundamental variables and non-fundamental variables turn out to have robust predictive ability.

In addition, to the best of our knowledge, this paper is the first to use a regime-switching

[7]These anchoring variables are based on potential under-reactions to sporadic past news due to psychological anchoring biases.

[8]In the appendix, we propose a simple model to theoretically illustrate the mechanism of sentiment's asymmetric impact on the performance of non-fundamental predictors.

[9]For more details on behavioral asset pricing theories, please see, among others, Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) , and Hong and Stein (1999).

model to formally classify time periods into high- and low-sentiment regimes. In contrast, the existing studies usually adopt ad hoc approaches to classifying sentiment regimes. For example, one popular approach is to split the sentiment index at the median: periods above the median are classified as the high-sentiment regime, while periods below the median are classified as the low-sentiment regime. Although the ad hoc median cut approach appears to be qualitatively similar in capturing the idea that sentiment varies over time, it assumes that sentiment is high for 50% of the time and low for the remaining 50% of the time. This may yield misleading implications.[10] For instance, the median cut approach may suggest that both fundamental and non-fundamental predictors have forecasting power 50% of the time.[11] In contrast, our proposed regime-switching model indicates that the low-sentiment regime represents about 80% of the whole sample, and that fundamental variables have significant predictive power during these periods. In contrast, non-fundamental variables are significant predictors only during high-sentiment periods, which is about 20% of the whole sample. Therefore, our approach indicates that fundamental variables more frequently function as effective predictors of the equity premium than non-fundamental variables do.

This paper fits into the growing literature about the asymmetric sentiment effect on many asset price behaviors and anomalies, including the mean-variance relation (Yu and Yuan, 2011), financial anomalies (Stambaugh, Yu and Yuan, 2012), the momentum phenomenon (Antoniou, Doukas and Subrahmanyam, 2013), the idiosyncratic volatility puzzle (Stambaugh, Yu and Yuan, 2015), the slope of the security market line (Antoniou, Doukas and Subrahmanyam, 2015), and hedge fund investment (Smith, Wang, Wang and Zychowicz, 2016).[12] In addition, this paper is also broadly

[10] One indication that the median cut approach may be problematic is that the shifts between high- and low-sentiment regimes become quite frequent in the latter part of the Baker and Wurglers sentiment index. Very often, high-sentiment regimes last for just two or three months, followed by low-sentiment regimes of similar duration. However, there seem to be no corresponding major events that would trigger such frequent sentiment shifts.

[11] In fact, there is a lack of studies comparing the effectiveness of fundamental versus non-fundamental predictors over time.

[12] This strand of literature relies on behavioral and psychological explanations by combining two prominent concepts, investor sentiment and short-selling constraints. Particularly, Antoniou, Doukas and Subrahmanyam (2013) argue that the cognitive dissonance caused by news that contradicts investor sentiment gives rise to under-reaction, which is strengthened mainly during high-sentiment periods due to short-selling constraints, raising the profits from cross-sectional momentum.

related to the regime-switching predictive regression models in Perez-Quiros and Timmermann (2000) and Henkel, Martin and Nardari (2011), which allow regime-dependent performance of predictors and find that the risk premium based on predictive variables is very sensitive to market states.

The rest of the paper is organized as follows. We present an econometric methodology in Section II. Sentiment regimes and predictors are summarized in Section III. Section IV reports the main empirical findings, Section V provides further analysis and Section VI concludes. In the Appendix, we present a simple model to illustrate the intuition of sentiment impact on forecasting.

II. Econometric Methodology

In this section, we first introduce the conventional predictive regression model under a single regime framework. Then, we develop a regime-dependent predictive regression model in order to examine predictive performance conditional on different sentiment regimes. We also detail the method for identifying sentiment regimes and the procedures for constructing both fundamental and non-fundamental predictors.

A. Single-regime predictive regression

To evaluate the overall return predictive performance of individual macroeconomic fundamental variables, we follow the conventional regression model in the literature,

$$r_{t+1} = \alpha + \beta_i x_{i,t} + \varepsilon_{i,t+1}, \tag{1}$$

where r_{t+1} is the return on a stock market index in excess of the risk-free rate, $x_{i,t}$ is a macroeconomic predictor, and $\varepsilon_{i,t+1}$ is zero-mean unforecastable noise. The expected excess return based on the macroeconomic variables can be estimated by

$$E_t[r_{t+1}] = \hat{\alpha} + \hat{\beta}_i x_{i,t}. \tag{2}$$

Given that macroeconomic variables are usually highly persistent, the Stambaugh (1999) bias potentially inflates the t-statistic for $\hat{\beta}_i$ in (2) and distorts the prediction size. We address this issue by computing the p-values using a wild bootstrap procedure to account for the persistence in predictors, correlations between the equity premium and predictor innovations, and heteroskedasticity.

Similarly, we conduct the following regressions to examine the overall forecasting performance for individual non-fundamental variables:

$$r_{t+1} = a + b_j m_{j,t} + \varepsilon_{j,t+1}, \tag{3}$$

where $m_{j,t}$ is a non-fundamental predictor, and $\varepsilon_{j,t+1}$ is zero-mean unforecastable noise.

The forecasting power of individual fundamental predictors can be unstable across time, since each of them may be just one specific proxy (with noise) of some common fundamental condition (for instance, the economy doing well or doing badly). For the same reason, non-fundamental variables may act as one specific proxy of a common trend condition (like the market trending up or trending down). In light of this, we conduct predictive regressions using a combined fundamental predictor μ_t and a combined non-fundamental predictor m_t, as follows:

$$r_{t+1} = \alpha_\mu + \beta_\mu \mu_t + \varepsilon_{\mu,t+1}, \tag{4}$$

and

$$r_{t+1} = \alpha_m + \beta_m m_t + \varepsilon_{m,t+1}, \tag{5}$$

where $\varepsilon_{\mu,t+1}$ and $\varepsilon_{m,t+1}$ are unforecastable and unrelated to μ_t and m_t, respectively. Here μ_t is extracted from individual fundamental predictors and m_t is extracted from individual non-fundamental predictors by applying the partial least squares procedure described in Subsection E.

To incorporate information from the entire set of fundamental and non-fundamental variables, we parsimoniously estimate a predictive regression based on the combined fundamental variable

μ_t in (4) and non-fundamental variable m_t in (5),

$$r_{t+1} = a + b_\mu \mu_t + b_m m_t + \varepsilon_{t+1}, \tag{6}$$

where ε_{t+1} is unforecastable and unrelated to μ_t and m_t.

B. Regime-dependent predictive regression

It is well documented that a high level of investor sentiment may potentially distort the fundamental link between macroeconomic variables and the stock market. Empirically, investor sentiment is not always high or low, but rather shifts between high- and low-sentiment regimes. The forecasting performances of the two main categories of predictors, namely, fundamental economic variables and non-fundamental variables, can significantly depend on the level of investor sentiment. Motivated by this, we extend the above single-regime predictive regression to a regime-dependent regression by allowing the predictive relation to switch across sentiment regimes.

More specifically, to investigate the asymmetric impact of sentiment on fundamental and non-fundamental forecasting variables, we run the following regime shifting predictive regressions,

$$r^i_{t+1} = a^i_\mu + b^i_\mu \mu^i_t + \varepsilon^i_{t+1}, \qquad i = H, L \tag{7}$$

$$r^i_{t+1} = a^i_m + b^i_m m^i_t + \varepsilon^i_{t+1}, \qquad i = H, L \tag{8}$$

$$r^i_{t+1} = a^i + b^i_1 \mu^i_t + b^i_2 m^i_t + \varepsilon^i_{t+1}, \qquad i = H, L, \tag{9}$$

where i represents either the high-sentiment regime ($i = H$) or the low-sentiment regime ($i = L$) at time t.

We rely on the Markov regime switching model to identify sentiment regimes. The sentiment index S_t is assumed to have a regime dependent mean value ψ_{ρ_t}

$$S_t|_{\rho_t} \sim N(\psi_{\rho_t}, \sigma^2_S), \qquad \rho_t = H, L, \tag{10}$$

where ρ_t follows a Markov chain with the transition probabilities between one regime at time t and the other regime at time $t+1$ fixed and contained in a transition matrix.[13] To back out the unobservable regime from the data, we assume that the market is at regime H at time t if the probability of staying in this regime $\pi_t := Prob(\rho_t = H|S_t) \geq 0.5$, otherwise; we assume a low-sentiment period.

C. Fundamental variables

Although price-scaled variables such as the dividend-price ratio are normally considered as fundamental variables in return forecasting, these variables also depend on price, which can be potentially affected by investor sentiment. Cassella and Gulen (2016) treat dividend-price ratio as a behavioral variable and find evidence of stronger predictive ability when the degree of behavioral bias is higher. Moreover, our analyses (presented in Table 9 and discussed in Section IV) indicate that the price-scaled predictors perform like behavioral non-fundamental predictors. Therefore, to conduct an accurate analysis on the impact of investor sentiment on the return forecasting powers of fundamental versus non-fundamental variables, we do not use the variables from Campbell and Thompson (2008) and Rapach, Strauss and Zhou (2010) as fundamental predictors in our analysis.

Instead, we consider a wide range of fundamental macroeconomic variables used in Jurado, Ludvigson and Ng (2015), where more than one hundred macroeconomic variables are selected to represent broad categories of macroeconomic time series. In order to effectively incorporate information from a large number of macroeconomic variables into a smaller set of forecasting variables, we extract some common factors from the 132 macroeconomic series in the paper (Jurado et al., 2015). More specifically, the 132 series are organized into eight categories according to a priori information. After excluding 21 time series of bond and stock market data,[14] we have seven categories of macroeconomic variables, including (i) output and income; (ii) labour market;

[13]These transition probabilities could be made more realistic by allowing them to vary dependent on the state variables. Nevertheless, given the results with fixed probabilities, it appears that this refinement would not add much economic insight, considering the increased complexity and computational costs.

[14]We exclude these financial market variables as they may contain investor sentiment related content.

(iii) housing; (iv) consumption, orders, and inventories; (v) money and credit; (vi) exchange rates; and (vii) prices. We implement principal component analysis (PCA) to derive seven individual macroeconomic predictors from these seven categories of macroeconomic variables (denoted as F_{jt}, $j = 1, 2, \cdots, 7$).[15] The seven extracted series may be treated as a set of representative macroeconomic predictors.[16]

D. Non-fundamental variables

We collect a variety of behavioral/sentiment-related variables, including time series momentum (Moskowitz, Ooi and Pedersen, 2012), anchoring variables (Li and Yu, 2012), and technical indicators (Neely, Rapach, Tu and Zhou, 2014). These variables have been shown to deliver significant predictive ability that is difficult to explain using rational finance theory.

For a large set of futures and forward contracts, Moskowitz, Ooi and Pedersen (2012) provide strong evidence for the existence of time series momentum that characterizes significantly positive predictive ability of the moving average of a security's own past returns. Following the literature, we define momentum the moving averages of historical excess returns. We consider different momentum variables with diversified time horizons varying from 6 to 12 months. That is,

$$M_t^{\tau} := \frac{1}{\tau} \sum_{j=1}^{\tau} r_{t+1-j}, \qquad \tau = 6, 9, 12. \tag{11}$$

Li and Yu (2012) find that nearness to the 52-week high (historical high) positively (negatively) predicts future aggregate market returns. They use nearness to the Dow 52-week high and nearness to the Dow historical high as proxies for the degree to which traders under- and over-react to news, respectively, and show that the two proxies have strong forecasting power for aggregate stock market returns, albeit in opposite directions. More specifically, nearness to the Dow 52-week high

[15] We take the first principal component of each category of macroeconomic variables to capture a higher proportion of total variations in the individual proxies than the other principal components, given that incorporating more principal components will increase estimating noise and worsen out-of-sample performance.

[16] We also obtain similar results by employing alternative non-price-related economic variables frequently used in the finance literature, such as equity risk premium volatility, treasury-bill rate, default return spread and inflation, examined in Welch and Goyal (2008).

$x_{52,t}$ and nearness to the Dow historical high $x_{max,t}$ are defined as

$$x_{52,t} = \frac{p_t}{p_{52,t}}, \qquad x_{max,t} = \frac{p_t}{p_{max,t}}, \tag{12}$$

where p_t denotes the level of the Dow Jones Industrial Average index at the end of day t, and $x_{52,t}$ and $x_{max,t}$ represent its 52-week high and historical high at the end of day t, respectively. The value at month t is defined as the value on the last trading day of month t. Given that there might be some salient information in recent past news such that the stock price is very close to its 52-week high, nearness to the 52-week high may also partially proxy for overreaction. Therefore, we also construct the anchoring predictor $\hat{x}_{52,t}$, which is nearness to the 52-week high orthogonal to nearness to the historical high. We use $\hat{x}_{52,t}$ as one of our non-fundamental variables, and expect it to be a more accurate proxy for under-reaction, since we remove any potential overreaction captured by the variable by controlling for nearness to the historical high. Other anchoring variables based on alternative stock indices will be also constructed in the same way later in Section C for comparison.

In addition, Li and Yu (2012) indicate that the negative predictive power of nearness to the historical high, in addition to reflecting overreaction, may be based on a rational model with a mean-reverting state variable. Given that nearness to the historical high $x_{max,t}$ could act partially as a non-fundamental predictor and partially as a fundamental predictor, the impact of market sentiment on the predictability of nearness to the historical high $x_{max,t}$ is unclear. Therefore, we do not use the nearness to historical high as a non-fundamental variable.

Neely, Rapach, Tu and Zhou (2014) show that technical indicators display statistically and economically significant predictive power and offer complementary information to macroeconomic variables. We also use the moving-average (MA) indicators studied in Neely et al. (2014). The MA rule generates a buy or sell signal ($S_t = 1$ or 0, respectively) at the end of t by comparing two moving averages:

$$S_t = \begin{cases} 1 & \text{if} \quad MA_{s,t} \geq MA_{l,t}, \\ 0 & \text{if} \quad MA_{s,t} < MA_{l,t}, \end{cases} \tag{13}$$

where

$$MA_{j,t} = \frac{1}{j}\sum_{i=0}^{j-1} p_{t-i} \quad \text{for} \quad j = s, l, \tag{14}$$

p_t is the level of a stock price index, and s (l) is the length of the short (long) MA ($s < l$). We denote the moving-average indicator with lengths s and l as MA(s, l). Intuitively, the MA rule detects changes in stock price trends because the short MA is more sensitive to recent price movement than the long MA. We analyze monthly MA rules with $s = 1$ and $l = 9, 12$.[17]

E. Extracting combined predictors

In order to reduce the noise in individual predictors and to synthesize their common components, we summarize information from various fundamental forecasting variables and, separately, various non-fundamental variables into two consensus combined variables. In general, at period t ($t = 1, \cdots, T$), we derive combined fundamental and non-fundamental predictors using N_1 fundamental economic proxies

$$X_t = \{X_{1,t}, X_{2,t}, \cdots, X_{N_1,t}\}$$

and N_2 non-fundamental proxies

$$M_t = \{M_{1,t}, M_{2,t}, \cdots, M_{N_2,t}\}$$

respectively. Following Wold (1966, 1975), and especially Kelly and Pruitt (2013, 2015), we apply the partial least squares (PLS) approach to effectively extract a combined fundamental variable μ_t and a combined non-fundamental variable m_t from X_t and M_t respectively.

To extract μ_t, which is used in equation (4), from the N_1 fundamental economic proxies $X_t =$

[17]We find a similar pattern when using other technical indicators considered in Neely et al. (2014). In order to be consistent with the time series momentum and anchoring variables, we also replace the "0/1" technical indicators from Neely et al. (2014) with the variable $MA_{s,t} - MA_{l,t}$. The patterns are similar to but less significant than the "0/1" technical indicators (results not reported here).

$\{X_{1,t}, X_{2,t}, \cdots, X_{N_1,t}\}$, we assume that $X_{i,t} (i = 1, 2, \cdots, N_1)$ has a factor structure

$$X_{i,t} = \gamma_{i,0} + \gamma_{i,1}\,\mu_t + \gamma_{i,2}\,\delta_t + u_{i,t}, \qquad i = 1, 2, \cdots, N_1, \tag{15}$$

where $\gamma_{i,1}$ and $\gamma_{i,2}$ are the factor loadings measuring the sensitivity of the fundamental economic proxy $X_{i,t}$ to μ_t and the common approximation error component δ_t of all the N_1 proxies that is irrelevant to returns, respectively. $u_{i,t}$ is the idiosyncratic noise associated with proxy $X_{i,t}$ only. By imposing the above factor structure on the proxies, we can efficiently estimate the collective contribution of X_t to μ_t, and, at the same time, eliminate the common approximation error δ_t and the idiosyncratic noise $u_{i,t}$. In general, μ_t can also be estimated as the first principal component analysis (PCA) of the cross-section of X_t. However, as discussed in Huang, Jiang, Tu and Zhou (2015), the PCA estimation is unable to separate δ_t from $u_{i,t}$ and may fail to generate significant forecasts for returns which are indeed strongly predictable by μ_t. The PLS approach extracts μ_t efficiently and filters out the irrelevant component δ_t in two steps. In the first step, we run N_1 time-series regressions. That is, for each $X_{i,t}$, we run a time-series regression of $X_{i,t-1}$ on a constant and realized return:

$$X_{i,t-1} = \eta_{i,0} + \eta_{i,1}\,r_t + v_{i,t-1}, \qquad t = 1, 2, \cdots, T, \tag{16}$$

where the loading $\eta_{i,1}$ captures the sensitivity of fundamental economic proxy $X_{i,t-1}$ to μ_{t-1} instrumented by future return r_t. In the second step, we run T cross-sectional regressions. That is, for each time t, we run a cross-sectional regression of $X_{i,t}$ on the corresponding loading $\hat{\eta}_{i,1}$ estimated in (16),

$$X_{i,t} = c_t + \mu_t\,\hat{\eta}_{i,1} + w_{i,t}, \qquad i = 1, 2, \cdots, N_1, \tag{17}$$

where the regression slope μ_t in (17) is the extracted μ_t.

Similarly, the non-fundamental variable m_t is extracted by applying the PLS procedure to M_t. For more details on this aligned approach, we refer to Huang et al. (2015).[18]

[18]By comparing PLS to the first principal component analysis, Huang et al. (2015) show that PLS can filter out the common approximation error components of all the proxies that are irrelevant to returns. They conclude that the variables constructed using PLS should outperform those constructed using PCA.

III. Data Summary

A. Sentiment regimes

We estimate the regime switching model (10) for sentiment by applying the maximum likelihood estimation method (MLE) and report the results in Figure 1. The sentiment data spans from 1965:07 to 2010:12.[19] The solid blue line in Figure 1 (a) depicts the estimated probability π_t of a high-sentiment regime H over time. Generally, long periods of relatively low investor sentiment are interrupted by short periods of extremely high sentiment, which occur at the end of the 1960s, the first half of the 1980s and the beginning of the 2000s. We assume that regime L represents periods of relatively normal sentiment, while regime H captures more irrational phases, which lead to steep increases in the level of market sentiment. Alternatively, we also follow Stambaugh, Yu and Yuan (2012) to define a high-sentiment month as one in which the value of the Baker and Wurgler's (2006; 2007) sentiment index in the previous month is above the median value for the sample period, and a low-sentiment month as one in which the index remains below the median value. The high- and low-sentiment regimes are labelled as H and L and plotted as red dots in Figure 1 (a). Using the Markov switching approach, we find 116 (430) high (low) sentiment months in our sample (21.25% and 78.75% of the total, respectively). In contrast, defining high- and low-sentiment regimes based on the median level yields 273 high-sentiment months and 273 low-sentiment months. The correlation between the estimates from the regime switching approach and the median cut approach is 0.54.

Figures 1 (b) and (c) depict the investor sentiment index from July 1965 to December 2010. The shaded areas are the high-sentiment months estimated by the regime-switching approach in 1 (b) and the median cut approach in 1 (c), respectively. The high-sentiment periods identified by the regime switching approach coincide well with anecdotal evidence, such as the "Nifty Fifty" episode between the late 1960s and early 1970s, the speculative episodes associated with Reagan era optimism from the late 1970s through the mid-1980s (involving natural resource startups in

[19] We obtain investor sentiment data from Jeffrey Wurgler's homepage *http://people.stern.nyu.edu/jwurgler/*

early 1980s after the second oil crisis and the high-tech and biotech booms in the first half of 1983), and the Internet bubble of the late 1990s/early 2000s.

B. Data and Summary statistics

Following the literature, we measure the equity risk premium as the difference between the log return on the S&P 500 (including dividends) and the log return on a risk-free bill.[20] Panel A of Table 1 reports summary statistics for the monthly equity premium. The moments of the excess market returns differ between high- and low-sentiment regimes. The mean of the excess market returns during the high sentiment regime is -0.07%, much lower than its counterpart during the low-sentiment regime (0.41%). This pattern is consistent with the general consensus in the existing literature, which suggests that high sentiment drives up prices and depresses returns. In contrast, the standard deviations of the excess market returns are similar across the two regimes, yielding a higher realized Sharpe ratio during the low sentiment regime. The overall stock market displays weak time-series momentum with a positive first-order autocorrelation of 0.06; during the high-sentiment regime, the market returns become more persistent with a first-order autocorrelation of around 0.10.

To examine the forecasting performance of combined fundamental and non-fundamental predictors, we consider seven individual fundamental variables and six individual non-fundamental variables. Applying the PLS procedure to the seven fundamental variables F_{jt} ($j = 1, 2, \cdots, 7$), we obtain a combined fundamental variable μ_t,

$$\mu_t = -0.11F_{1t} - 0.25F_{2t} + 0.25F_{3t} - 0.34F_{4t} - 0.18F_{5t} - 0.12F_{6t} - 0.32F_{7t}, \tag{18}$$

where each underlying individual proxy is standardized. The summary statistics of the combined fundamental predictor and individual fundamental predictors are reported in Panels B and C of Table 1. The combined fundamental predictor is more stable than the individual predictors overall.

[20]The monthly data is from the Center for Research in Security Prices (CRSP).

It has a higher average and is slightly more volatile and less persistent during the high-sentiment regime than during the low-sentiment regime. In contrast, the seven individual macroeconomic predictors F_i $(i = 1,2,3,4,5,6,7)$ hardly exhibit consistent patterns across the sentiment regimes, possibly due to the noise in the individual variables. Hence, we summarize information by extracting common components from various individual forecasting variables to alleviate the potential noise in each individual proxy.

Panel A of Figure 3 depicts the time series of the combined fundamental predictor μ_t, where the shaded areas are the high sentiment regimes. Interestingly, for all three continuous high sentiment periods, μ_t reaches local minima near the investor sentiment peaks. Equation (18) above displays the estimated loadings for the seven individual macroeconomic predictors F_{it}, $(i = 1,2,3,4,5,6,7)$ on the combined fundamental predictor μ_t. It reveals that the macroeconomic factors extracted from the labor market, housing, consumption and prices load relatively heavily on μ_t, indicating that the combined fundamental predictor primarily captures common fluctuations in various fundamental information, which may help μ_t to forecast the equity risk premium better than the individual macroeconomic predictors. As shown in Panel A of Table 3, the signs of the regression coefficients on the seven economic variables are consistent with the fact that each variable is a specific proxy for some common fundamental economic condition.

Similarly, by applying the PLS procedure to the six non-fundamental variables, we generate a combined non-fundamental variable m_t,

$$m_t = 0.15M_t^6 + 0.07M_t^9 + 0.13M_t^{12} + 0.27\hat{x}_{52,t} + 0.23MA(1,9) + 0.34MA(1,12), \qquad (19)$$

where each underlying individual variable is standardized. The loadings on the six proxies are all positive, implying an overall positive predictive pattern of the momentum, psychological anchor and moving average proxies. Panel B of Figure 3 plots the time series of the combined non-fundamental predictor m_t. It is evident that the time series of m_t displays a less smooth pattern than that of μ_t. In contrast to μ_t, m_t reaches local maxima near the market sentiment peaks and drops abruptly as it enters the high-sentiment periods. Equation (19) shows that a number of individual non-fundamental variables load relatively strongly on m_t, including time series momentum proxy M_t^6, anchoring variable $\hat{x}_{52,t}$, and moving average indicators $MA(1,9)$ and $MA(1,12)$. Consequently, m_t reflects a wide variety of individual non-fundamental variables and potentially captures more useful predictive information than any single non-fundamental variable. As shown in Table 3, the extracted non-fundamental variables forecast the equity risk premium with a positive sign, which is consistent with the phenomenon based on individual proxies.

IV. Main Empirical Results

In this section, we examine the forecasting performance of the fundamental economic variables and non-fundamental variables for both the full sample and the high-/low-sentiment regimes determined using the Markov regime-switching approach. Our data spans from July 1965 to December 2010, a period determined by the availability of the sentiment series. In subsection A, we show that mispricing is much more significant during the high-sentiment regime than the low-sentiment regime. In subsection B, we analyze the in-sample predictive performances across sentiment regimes. In subsection C, we address several important issues, including the lack of predictive ability of the anchoring variables based on alternative indices, the lack of predictive ability after the oil shock of 1973–1975, sentiment regimes determined by median cut approach and predictability during expansions. Finally, in subsection D, we conduct out-of-sample analysis. Particularly, we show that the fundamental predictors tend to lose their forecasting power out-of-sample and that recent remedies, such as the no-negativity constraint, cannot help when investor sentiment is high.

A. Mispricing across sentiment regimes

We explore the distinct patterns of mispricing across the high- and low-sentiment regimes using the regime switching approach specified in Section III.B. We consider 17 long-short anomaly returns from Novy-Marx and Velikov (2016) as well as a combination strategy which takes a simple average of all 17 long-short anomaly returns,[21] and report pricing errors (returns adjusted by benchmark factor models) during the high- and low-sentiment regimes, respectively, in Table 2. The baseline regression is as follows:

$$r_{t+1} = \alpha_H I_{H,t} + \alpha_L I_{L,t} + \beta_1 MKT_{t+1} + \beta_2 SMB_{t+1} + \beta_3 HML_{t+1} + \beta_4 WML_{t+1} + \varepsilon_{t+1}, \qquad (20)$$

where r_{t+1} is one of the long-short anomaly returns, I_H is the high-sentiment regime dummy, I_L is the low-sentiment regime dummy, and MKT, SMB, HML and WML are market, size, value and momentum factors.

The results in Table 2 reveal that the pricing errors indicated by the long-short anomaly returns are generally higher following periods of high-sentiment. Specifically, the combined long-short benchmark-adjustment anomaly return is 99 bps higher per month following high-sentiment periods, using the Carhart four-factor model as a benchmark. Furthermore, the mispricing mainly stems from the high-sentiment regime, with average mispricing (measured as the combined long-short benchmark-adjustment anomaly return) in the high-sentiment months accounting for 81% of overall average mispricing benchmarked on the Carhart four-factor model. The tendencies are consistent with the findings in Stambaugh et al. (2012), which uses the median level of Baker and Wurgler sentiment index to differentiate high- and low-sentiment periods and show that combining market wide sentiment with short-sale constraints leads to greater mispricing following high-sentiment periods. The difference in the degree of mispricing across the high- and low-sentiment regimes echoes the literature suggesting that investor sentiment could drive prices away from their fundamentals. Therefore, in forecasting the cross-time equity premium, investor sentiment may break the link between economic predictors and the equity premium.

[21] There are 32 long-short strategy returns in Novy-Marx and Velikov's (2016) data library. The 17 anomalies considered in our study constitute a majority of these, after excluding anomalies related to risk factors.

B. In-sample predictive performance across sentiment regimes

We focus our empirical analysis on a one-month horizon for three reasons. First, short-horizon return predictability is usually magnified at longer horizons (Campbell, Lo and MacKinlay, 1997; Cochrane, 2011). Second, long-horizon predictability may result from highly correlated sampling errors (Boudoukh, Richardson and Whitelaw, 2008) while our choice of monthly frequency abstracts away from the econometric issues associated with long-horizon regressions and overlapping observations (Hodrick, 1992). Finally, as market sentiment evolves through time, longer-horizon predictive regressions would include random combinations of the high- and low-sentiment periods that would undoubtedly obscure predictors' forecasting performance.

We start by examining the overall forecasting performances of the fundamental and non-fundamental variables over the full sample period. We then compare the predictive strength of these two sets of variables during the high- and low-sentiment regimes. When fundamental or non-fundamental variables are highly persistent, the well-known Stambaugh (1999) bias potentially inflates the t-statistic for b_i in (6) and (9) and distorts the test size. To address this concern, we compute p-values using a wild bootstrap procedure that accounts for complications in statistical inferences. Table 3 summarizes the differences in in-sample predictive ability between the high and low sentiment regimes for the fundamental and non-fundamental variables. Panels A and B in Table 3 report the regression coefficients, the corresponding t-statistics, and R^2s for the seven fundamental and six non-fundamental variables, respectively. Panel C reports the regression results for the combined fundamental and non-fundamental variables. All the standard errors are adjusted for heteroscedasticity and serial correlation according to Newey and West (1987). We report the wild bootstrapped p-value and the Newey-West t-statistic (which is computed using a lag of 12 throughout). The results show complementary patterns for the fundamental and non-fundamental variables.

First, both the individual and the combined economic variables, perform well during the whole sample and the low-sentiment periods, but their predictive strength is attenuated during the high-sentiment regime. Panel A indicates that the overall predictability of the individual economic variables is mainly concentrated in the low-sentiment regime. Among the seven fundamental predictors, the fourth predictor F_{4t} has a sizeable in-sample R^2 statistic of 2.54% during the low-sentiment regime, larger than that of the remaining six predictors. When sentiment is high, economic variables typically do not behave well, with five of the seven individual economic variables unable to predict future stock returns at conventional levels of significance. This pattern holds in Panel C for the combined fundamental variable, which is insignificant in the high-sentiment periods, but significant over the whole sample (with a t-statistic of 3.47 and an R^2 of 2.51%), and the low-sentiment periods (with a t-statistic of 3.85 and an R^2 of 3.52%). This supports our findings that, at the individual predictor level, the predictive ability of the fundamental variable is driven primarily by the low sentiment periods. Furthermore, the coefficient estimated for the combined fundamental variable is economically large. More explicitly, a one-standard-deviation increase in the combined fundamental variable μ_t predicts increases of 0.71% and 0.84% in the expected market return over the whole sample and the low-sentiment periods, respectively.

Second, the predictive performances of the individual non-fundamental variables and the combined non-fundamental variable are much stronger during the high-sentiment regime than during the low-sentiment regime. Panel B shows that the predictive coefficients of the non-fundamental variables at an individual predictor level differ across the sentiment regimes, with larger predictive power occurring during high-sentiment regime. Moreover, each of the six individual non-fundamental variables significantly forecasts the equity risk premium in periods of the high sentiment. Particularly, within the six individual non-fundamental variables, the time series momentum with 6-month horizon M_t^6, anchoring variable $x_{52,t}$, and the two moving averaging indicators $MA(1,9)$ and $MA(1,12)$ convey relatively stronger predictive strength than the remaining non-fundamental predictors, with in-sample R^2 statistics ranging from 2.71% to 4.41% in periods of high sentiment. In contrast, we fail to find significant predictability from the non-fundamental variables in the low sentiment periods. In Panel C, this pattern extends to the combined non-fundamental variable, whose coefficient is significant during the high-sentiment regime (a t-statistics of 3.27 and an R^2 of 4.07%) but insignificant during the low-sentiment regime (an t-statistics of 0.65 and an R^2 of approximately 0.1%). This indicates that the combined non-fundamental variable is predominantly able to forecast the equity premium in the high-sentiment periods. In fact, when sentiment is high, a one-standard-deviation increase in the combined non-fundamental variable m_t corresponds to an increase of 0.89% in the future excess market return, more than two times larger than that documented over the entire sample period.[22]

Third, as monthly stock returns inherently contain a substantial unpredictable component, a monthly R^2 near 0.5% can signal an economically significant degree of equity risk premium predictability (e.g., Campbell and Thompson, 2008). Based on our empirical findings, all R^2s over the sample period for regressions with both fundamental variable μ_t and non-fundamental variable m_t exceed this 0.5% benchmark.[23]

In Figure 4, we summarize the cross-regime differences in correlations between the excess market return and the two combined predictors, as well as the associated regression coefficients, t-statistics and R^2s in percentage points. The first row of Figure 4 shows that μ_t is more highly correlated with the excess market return during the low-sentiment regime while m_t has a higher correlation with excess market return during the high-sentiment regime. The following three rows in Figure 4 consistently reveal the complementary cross-regime predictive patterns for the two combined predictors μ_t and m_t, with higher beta, higher t-statistic and higher R^2 for the fundamental predictor μ_t during the low-sentiment regime and higher beta, higher t-statistic and higher R^2 for the non-fundamental predictor m_t during the high-sentiment regime.

Figure 5 further illustrates the complementary roles of fundamental predictor μ_t and non-fundamental predictor m_t. Panels A and B in Figure 5 show in-sample forecasts of the monthly equity premium for μ_t and m_t, respectively. The expected equity premium predicted by μ_t (Panel A of Figure 5) displays a relatively smooth pattern, in line with Panel A of Figure 3. The movements in the expected equity premium predicted by m_t (Panel B of Figure 5) are relatively more abrupt, in line with the trend in Panel B of Figure 3. When the information from μ_t and m_t is combined

[22]We find the same pattern when we simply use principal components to extract the combined predictors from the individual proxies.

[23]We also consider a case in which m_t is orthogonal to μ_t (or μ_t is orthogonal to m_t) to eliminate the overlapping forecasting power and find the same patterns as in Table 3 (results not reported here).

(Panel C of Figure 5), the expected equity premium rises to lower levels before extremely high-sentiment dates relative to that in Panel B, while it falls less after entering extremely high sentiment periods, indicating that the complementary information in μ_t and m_t reduces the fluctuations in the expected equity premium predicted by μ_t or m_t alone.

In summary, when the investor sentiment is shifting between high- and low-sentiment regimes, our findings yield several implications. First, economic variables have strong forecasting ability when sentiment is low, but lose predictive power when it is high. In contrast, the predictability of non-fundamental variables becomes strong when sentiment is high. Secondly, the predictability of the non-fundamental variables tends to peak when sentiment is high and vanish when sentiment is low. Using both the fundamental and non-fundamental variables as predictors confirms these patterns. Moreover, because about 80% time is at the low-sentiment regime, the results suggest that economic variables could have stronger predictability than non-fundamental variables.

C. Discussion

In this subsection, we conduct four robustness analyses by constructing anchoring variables using alternative indices, addressing the effect of the 1973–1975 oil shock, considering the ad hoc method of classifying sentiment regimes, and examining predictive ability during economic expansion and recession periods.

C.1 The predictive ability of anchoring variables

Li and Yu (2012) document that two psychological anchors—nearness to the 52-week high $x_{52,t} = \frac{p_t}{p_{52,t}}$ and nearness to the historical high $x_{max,t} = \frac{p_t}{p_{max,t}}$—have strong predictive ability when calculated using daily stock prices of the Dow Jones Industrial Average index. They contend that, when prices are far below the 52-week high (i.e. nearness to the 52-week high has a low value), it is likely that the firm has recently experienced sporadic bad news. A conservatism bias with psychological evidence suggests that investors may under-react to such bad news. This under-reaction hypothesis is also consistent with the experimental research on adjustment and anchoring bias. In particular, when bad news pushes a stock's price far below the 52-week high, investors may become reluctant to bid the price further down, even if the news justifies a large drop; this leads to under-reaction. Later, when the bad news is absorbed and the under-reaction is corrected, the price falls to the correct level. This leads to a lower return in the subsequent period. Consequently, a lower $x_{52,t}$ predicts a lower return, or, said differently, nearness to the 52-week high is expected to be positively associated with future returns.

Conversely, if $x_{max,t}$ is large (i.e. the current price level is very close to the historical high), it is likely that the firm has enjoyed a prolonged series of good news. The psychology research indicates that, in this situation, investors may overreact to a series of good news, leading to subsequent lower returns in the future. As a consequence, a larger $x_{max,t}$ predicts a lower return or, said differently, nearness to the historical high is expected to be negatively associated with future returns.

Given that there might be some salient information in recent past news, such as when the stock is very close to its 52-week high, nearness to the 52-week high may also partially proxy for overreaction. Therefore, we control for nearness to the historical high $x_{max,t}$ along with the nearness to the 52-week high $x_{52,t}$.

At the same time, Li and Yu (2012) indicate that the negative predictive power of nearness to the historical high, $x_{max,t}$ could also be explained by a rational model with a mean-reverting state variable. Thus, given that nearness to the historical high $x_{max,t}$ may behave both as a non-fundamental predictor and a fundamental predictor, the impact of market sentiment on its predictive ability is unclear. Hence, we focus on nearness to the 52-week high in our study.

We calculate the two psychological anchoring variables, nearness to the 52-week high $x_{52,t}$ and nearness to the historical high $x_{max,t}$, using the daily prices of the Dow Jones Industrial Average index, the NYSE/AMEX total market value index, and the S&P 500 index, respectively. The three panels in Table 4 present in-sample regression results for $x_{52,t}$, calculated using these three indices as a predictor of future monthly NYSE/AMEX value-weighted excess returns.[24]

[24]Following Li and Yu (2012), we control for past return, nearness to the historical high, a historical high indicator, and a "52-week high equal-historical high" indicator in these regressions. In addition, predict monthly NYSE/AMEX value-weighted excess returns in Table 4 to facilitate an easy comparison with Li and Yu (2012). In all other analyses, we follow Welch and Goyal (2008) and predict future monthly S&P 500 excess returns.

Panel A of Table 4 echoes the results we report in Panel B of Table 3. More specifically, although the anchoring variable $x_{52,t}$ based on the Dow Jones Industrial Average index exhibits significant predictive power during the whole sample period, the power is driven by the high-sentiment regime, disappearing in the low-sentiment regime.

Panel B of Table 4 indicates that the predictive power of $x_{52,t}$ based on the NYSE/AMEX total market value index is weak and insignificant over the whole sample, which is consistent with Li and Yu (2012). This finding is puzzling, as Li and Yu (2012) provide a strong argument and detailed explanations on why nearness to the 52-week high should have predictive power, as summarized above. Investors should tend to underreact to sporadic past news due to the behavioral biases. But, why does this behavioral bias only kick in when using the Dow Jones Industrial Average index and not the NYSE/AMEX total market value index? Li and Yu (2012) do not provide a thorough discussion of this loss of predictive power.[25]

Given that many index funds track both the Dow Jones Industrial Average index and the NYSE/AMEX total market value index or their close proxies, the "limited attention" hypothesis seems to be an insufficient explanation for the fact that we only document under-reaction when using the Dow to calculate nearness to the 52-week high. Considering investor sentiment sheds light on this puzzle. During the high-sentiment regime, nearness to the 52-week high based on the NYSE/AMEX total market value index strong and statistically significant, with a t-statistic of 3.76. This is almost three times higher than the t-statistic of 1.30 for the whole sample and the t-statistic of 1.37 for the low-sentiment regime. This is also true of nearness to the 52-week high calculated based on the S&P 500 index (see Panel C of Table 4), which supports the argument that the predictive power of nearness to the 52-week high is strong regardless of index used as long as market sentiment is high. Overall, these results indicate that the ability of psychological anchors to predict aggregate excess market returns is not exclusive to the Dow index. Anchoring variables constructed based on other indices, whether they capture market-wide or firm-specific information,

[25]Li and Yu (2012) use "limited attention" to explain why nearness to the historical high has weaker predictive power when the Dow Jones Industrial Average index is replaced by the NYSE/AMEX total market value index. Li and Yu (2012) claim that the Dow index represents more visible market-wide information, which investors favor over firm-specific information (NYSE/AMEX).

all present substantial predictive power in forecasting the aggregate excess market return once we understand and control for the impact of market sentiment.

C.2 The effect of the oil shock period

This subsection addresses the effect of the oil shock period. Welch and Goyal (2008) comprehensively examine the forecasting power of a large set of economic variables. They find that the predictive power of these variables seems to peak in the period of the 1973-1975 oil shock; after 1975 most forecasting models perform poorly. To address this issue, we first examine the predictive performance of the combined fundamental predictor μ_t and the combined non-fundamental predictor m_t from January 1976 to December 2005 following Welch and Goyal (2008). The results in Table 5 exhibit similar patterns to those in Panel C of Table 3 (though less significant).

Next, we re-run the regressions over the entire sample period (July 1965 to December 2010), excluding only the years 1973–1975. Panel A of Table 6 shows that exclusion of this period does not substantially alter our results. The fundamental variable still performs well in the whole sample and the low sentiment regime, while the non-fundamental variable still has significant forecasting power in the high-sentiment regime. After removing the 1973-1975 oil shock period, both the t-statistics and R^2 become slightly weaker for the fundamental variable in the whole-sample and the low-sentiment regime, compared to Panel C of Table 3. Since the oil shock occurs within our low-sentiment periods, the results for the high-sentiment regime are less affected.

C.3 Ad hoc approach to classifying sentiment regimes

In this robustness test, we re-estimate the regimes based on the median cut approach. More specifically, we follow Stambaugh et al. (2012) to define a high-sentiment month as any month for which the value of the previous month's Baker and Wurger's sentiment index is above its median for the sample period, and a low-sentiment month as one for which the previous month's sentiment index value is below the median. Panel B of Table 6 reports the results when the regimes are determined by the median cut approach. Compared to the main results in Panel C of Table 3, the coefficients and t-statistics become larger for fundamental variable μ_t but smaller for non-fundamental variable m_t in regime H. The reason seems straightforward: our new definition classifies 50% of the sample as high-regime periods, a substantial increase from the regime switching approach, under which they only comprise 20% of the sample. Thus, for 30% of months in the sample, sentiment is above the median but below the high-sentiment threshold set by the regime switching approach. These months decrease the mean value of sentiment in the high-sentiment regime defined using the 50%–50% cutoff. This, in turn, strengthens the forecasting power of the fundamental variable while weakening the predictive strength of the non-fundamental variable.

C.4 Predictability during expansions

A large number of studies present evidence that the predictive ability of economic variables is concentrated in recession periods, with little forecasting power during expansions. It is therefore interesting to see whether the forecasting patterns of both the fundamental and non-fundamental variables are affected by the business cycle expansions and recessions documented by the National Bureau of Economic Research (NBER). We label expansion periods as EXP and recessions as REC. During the whole sample period, from July 1965 to December 2010, 456 months are classified as EXP while 90 months are identified as REC (see Figure 2). For comparison, we also plot the high-sentiment months estimated by the regime switching approach as the shaded areas in Figure 2. Our sentiment regimes do not co-move substantially with the business cycles: the correlation between the NBER recession dummy and the high-sentiment dummy is only 0.23.

We re-run the regressions in Table 3 for expansion periods only and detail the results in Table 7. The "whole sample period" in Table 7 refers to the aggregate of the expansion periods; the "high/low periods" are the months within these expansion periods during which investor sentiment is high or low. We find similar predictive patterns over the expansion periods. The combined fundamental predictor μ_t is significant both for expansions as a whole and low-sentiment months and insignificant in the high-sentiment months; the combined non-fundamental variable m_t is significant in the high-sentiment months but insignificant over all expansion periods and low-sentiment months.

D. Out-of-sample analysis

D.1 Out-of-sample forecasting performance

Although the in-sample analysis provides more efficient parameter estimates and thus more precise return forecasts by utilizing all available data, Welch and Goyal (2008), among others, argue that out-of-sample tests seem more relevant for assessing genuine return predictability in real time and avoiding the in-sample over-fitting issue.[26] More importantly, some recent studies argue that the out-of-sample forecasting performance of fundamental variables can be substantially improved by imposing some additional restrictions on forecasting regressions. This raises the question of whether fundamental variables still display poor out-of-sample performance during high sentiment periods after adding these restrictions. It is also interesting to determine whether fundamental variables show positive out-of-sample predictability during low-sentiment periods with no such additional remedies imposed. We expect that the regime-dependent predictive performances of both fundamental and non-fundamental variables are driven by the underlying behavioral force of investor sentiment rather than any additional remedies. Particularly, a high level of market sentiment distorts the link between fundamental variables and the equity premium while boosting the underlying behavioral activities behind non-fundamental predictors, such as under-reaction and overreaction. Hence, it is of interest to investigate the robustness of out-of-sample predictive performance conditional on investor sentiment.

The key requirement for out-of-sample forecasts at time t is that we can only use information available up to t in order to forecast stock returns at $t+1$. Following Welch and Goyal (2008), Kelly and Pruitt (2013), and many others, we run the out-of-sample analysis by estimating the

[26] In addition, out-of-sample tests are much less affected by the small-sample size distortions such as the Stambaugh bias (Busetti and Marcucci, 2012) and the look-ahead bias concern of the PLS approach (Kelly and Pruitt, 2013, 2015).

predictive regression model recursively,

$$\hat{r}_{t+1} = \hat{a}_t + \hat{b}_{1,t}\mu_{1:t;t} + \hat{b}_{2,t}m_{1:t;t}, \tag{21}$$

where $\hat{a}_t$ and $\hat{b}_{i,t}$ are the OLS estimates from regressing $\{r_{s+1}\}_{s=1}^{t-1}$ on a constant and the fundamental and non-fundamental variables $\{\mu_{1:t;s}\}_{s=1}^{t-1}$, $\{m_{1:t;s}\}_{s=1}^{t-1}$. Due to concerns of look-ahead bias, we use a real-time sentiment index to estimate the regimes. Following Baker and Wurgler (2006), we form the sentiment index at time t by taking the first principal component of the six measures of investor sentiment up to time t. The six measures are the closed-end fund discount, the number and the first-day returns of IPOs, NYSE turnover, the equity share in total new issues, and the dividend premium. At each time t, we use the recursively estimated sentiment index $\{X_s\}_{s=1}^{t}$ to estimate the regimes during time periods $1:t$. If the market is in regime H (L) at time t, then we regress $\{R_s\}_{s=2}^{t}$ on $\{\mu_s\}_{s=1}^{t-1}$ and $\{m_s\}_{s=1}^{t-1}$ in regime H (L), and the out-of-sample forecast in regime H (L) at time $t+1$ is given by (21).

Let u be a fixed number chosen for the initial sample training, so that future expected return can be estimated at time $t = u+1, u+2, \cdots, T$. Hence, there are $v(= T-u)$ out-of-sample evaluation periods. That is, we have v out-of-sample forecasts: $\{\hat{r}_{t+1}\}_{t=u}^{T-1}$.

We evaluate the out-of-sample forecasting performance based on the widely used Campbell and Thompson (2008) R^2_{OS} statistic. The R^2_{OS} statistic measures the proportional reduction in the mean squared forecast error (MSFE) for the predictive regression forecast relative to the historical average benchmark,

$$R^2_{OS} = 1 - \frac{\sum_{t=u}^{T-1}(r_{t+1} - \hat{r}_{t+1})^2}{\sum_{t=u}^{T-1}(r_{t+1} - \bar{r}_{t+1})^2}, \tag{22}$$

where $\bar{r}_{t+1}$ denotes the historical average benchmark corresponding to the constant expected return model ($r_{t+1} = a + \varepsilon_{t+1}$),

$$\bar{r}_{t+1} = \frac{1}{t}\sum_{s=1}^{t} r_s. \tag{23}$$

Welch and Goyal (2008) show that the historical average is a very stringent out-of-sample benchmark, which individual economic variables typically fail to outperform. The R^2_{OS} statistic lies in the range $(-\infty, 1]$. If $R^2_{OS} > 0$, it means that the forecast $\hat{r}_{t+1}$ outperforms the historical average $\bar{r}_{t+1}$ in terms of MSFE. The R^2_{OS} statistic in regime H (L) is calculated using the out-of-sample forecasts in regime H (L) and realized returns r_{t+1} for the same time periods.

We select the first half of the sample as the training sample. Table 8 reports the differences in out-of sample predictive performances of the fundamental and non-fundamental predictors across sentiment regimes.[27] The results have several implications. First, when we use the fundamental variable as the only predictor, Column 2 shows that the R^2_{OS} is 0.81% in the low-sentiment regime, exceeding the 0.5% benchmark (Campbell and Thompson, 2008), but becomes negative in the high-sentiment regime (−2.10%) and in the whole sample period (−2.28%). This indicates that the fundamental variable has predictive power in the low-sentiment regime even without imposing any of the remedies proposed in recent literature, as we expected. However, this variable underperforms the historical average benchmark in the full sample period as documented in the previous literature, and also in the high sentiment regime, which is also intuitively expected. This is consistent with our in-sample results.

Second, when we use the combined non-fundamental variable as the single predictor, Column 3 in Panel A shows that it fails to outperform the historical average benchmark in the low-sentiment regime, with a negative R^2_{OS} of -0.90%. Column 3 also verifies that the non-fundamental variable performs considerably better in the high-sentiment regime, as expected, with a positive R^2_{OS} of 3.30% – nearly fourfold increase from the low-sentiment regime. This stark difference again, highlights the importance of considering shifts in market sentiment in predicting stock returns.[28]

Additionally, we find that compared with using fundamental or non-fundamental information alone, or incorporating both of them unconditionally as reported in Column 4, the out-of-sample predictability can be substantially improved when we consider a predictor that switches between the fundamental and non-fundamental variables conditional on the sentiment regime. Specifically,

[27]To reduce estimation errors, at each period t we estimate the weights of individual predictors using partial least squares analysis, and set the weight at time t equal to zero if the product of the weight at time t and the average weight estimated from period 1 to $t-1$ is less than 0.05.

[28]The complementary roles of the two major categories of predictors, fundamental and non-fundamental, suggest that the two groups indeed capture different information relevant for predicting the equity risk premium, supporting the findings in Neely et al. (2014).

we use $I_{H,t}m_t + (1 - I_{H,t})\mu_t$ as a predictor in (21), where $I_{H,t}$ is an indicator of regime H. That is, we use non-fundamental predictor m_t conditional on being in the high-sentiment regime and switch to fundamental predictor μ_t in the low-sentiment regime. Column 5 shows that the corresponding R^2_{OS} reaches 1.38%, the largest across Panel A for the whole sample period. Therefore, shifting between fundamental and non-fundamental predictors conditional on sentiment regimes outperforms both using the fundamental or non-fundamental predictor alone and using both of them unconditionally. This is because the former approach incorporates the impact of sentiment on equity premium forecasting while all of the latter methods ignore it.

D.2 Price-scaled predictors: fundamental or behavioral?

In this paper, we use the macroeconomic variables studied in Jurado et al. (2015) rather than the economic variables used in Campbell and Thompson (2008) and Rapach et al. (2010) as our fundamental predictors. The reason is as follows. Although the dividend-price ratio is normally considered as a fundamental variable in return forecasting, it may also be partially sentiment-driven since it depends on price, which is potentially affected by sentiment. For instance, Cassella and Gulen (2017) propose a behavioral explanation for the forecasting power of the dividend-price ratio and show that this power depends on the degree of extrapolation bias: it is strong when the degree of extrapolation bias is high, but disappears as the degree of extrapolation bias decreases.

In this section, we further explore the fundamental and behavioral elements of price-scaled variables by examining their out-of-sample predictive strength during high- and low-sentiment regimes when different types of forecasting restrictions are imposed. We expect unadjusted price-scaled predictors to deliver better out-of-sample forecasting performance during the high-sentiment regime, reflecting their behavioral element. However, we expect growth-adjusted price-scaled predictors to have better out-of-sample performance during the low-sentiment regime, capturing their fundamental element.[29]

Table 9 reports out-of-sample forecasting results of the eleven variables in Table 2 of Campbell

[29]The adjustment is motivated by the Gordon (1962) growth model as in Campbell and Thompson (2008).

and Thompson (2008). We use the "fixed coefficients" restriction developed in Campbell and Thompson (2008) by setting the coefficient of a given single predictor to one—the value implied by a simple steady-state model, such as the Gordon (1962) growth model. During the high-sentiment regime, the three R^2_{OS}s of the three price-scaled predictors, namely dividend-price ratio, earnings-price ratio and smoothed earnings-price ratio, are all larger than 1%. During the low-sentiment regime, all three R^2_{OS}s are lower than 0.5%; in fact, the R^2_{OS} of dividend-price ratio is negative. Therefore, the three price-scaled predictors, particularly the dividend-price ratio, act like non-fundamental predictors, given that they perform better in the high-sentiment regime than the low-sentiment regime.

We next examine the growth-adjusted price-scaled ratios, calculated as the sum of each price-scaled ratio plus its corresponding growth rate. For instance, the growth-adjusted dividend-price ratio is equal to the dividend-price ratio plus the dividend growth rate. Campbell and Thompson (2008) document that the out-of-sample predictive ability of valuation ratios can be substantially improved by the "fixed coefficient" restriction. For instance, for the dividend-price ratio, this restriction essentially assumes that the expected return is equal to dividend-price ratio plus dividend growth, which is hence the best predictor of the expected return in the next period.

Rows 6 to 9 of Table 9 show that the R^2_{OS}s of the growth-adjusted price-scaled predictors are generally much higher in the low-sentiment regime than in the high-sentiment regime after when the "fixed coefficient" restriction is imposed. The R^2_{OS}s of all four growth-adjusted price-scaled predictors during the low-sentiment regime are all positive and exceed 0.5%, while during the high-sentiment regime, none of the four R^2_{OS}s are positive. The same pattern can be found in Rows 10 to 13 of Table 9, where the risk-free rate of return is deducted from the growth-adjusted price-scaled ratios.

The results in Table 9 indicate that price-scaled predictors, such as the well-documented dividend-price ratio, perform like behavioral non-fundamental predictors. Although growth-adjusted price-scaled predictors are more similar to fundamental variables, the overall picture indicates that price-scaled predictors are a kind of hybrid, consisting of both "fundamental" and "behavioral" elements.

Therefore, to conduct a precise analysis of the impact of investor sentiment on the equity premium forecasting powers of fundamental versus non-fundamental variables, we choose not to use the price-scaled variables in Campbell and Thompson (2008) and Rapach et al. (2010) as fundamental variables in our analysis.

V. Forecasting channel

In this section, we explore the possible economic channels driving the predictive ability of the fundamental and non-fundamental variables. Valuation models suggest that stock prices are determined by both future expected cash flows and discount rates. From this perspective, the ability of fundamental and non-fundamental variables to forecast the aggregate stock market may stem from the cash flow channel, the discount rate channel, or both. We use dividend price ratio as our discount rate proxy, since its time variation is primarily driven by discount rates (Cochrane 2008, 2011). We use dividend growth as our cash flow proxy; this variable has been widely examined and used in similar studies in the literature (Campbell and Shiller, 1988; Lettau and Ludvigson, 2005; Huang et al., 2015).

The Campbell and Shiller (1988) log-linearization of stock returns generates an approximate identity, as argued in Cochrane (2008, 2011) and Campbell, Polk and Vuolteenaho (2010):

$$r_{t+1} \approx k + g_{t+1}^{12} - \rho dy_{t+1}^{12} + dy_t^{12}, \tag{24}$$

where r_{t+1} is the continuously compounded stock market return from t to $t+1$, k is a constant term, g_{t+1}^{12} is the log dividend growth rate, ρ is a positive log-linearization constant, and dy_{t+1}^{12} is the log dividend price ratio. Since g_{t+1}^{12} and dy_{t+1}^{12} represent cash flows and discount rates, respectively, the power of m_t and μ_t to forecast g_{t+1}^{12} and dy_{t+1}^{12} can distinguish between the cash flow channel and the discount rate channel. Accordingly, our study focuses on the following predictive regressions:

$$y_{t+1} = \alpha + \beta_1 \mu_t + \beta_2 m_t + \beta_3 dy_t^{12} + \varepsilon_{t+1}, \qquad y = dy^{12}, g^{12}. \tag{25}$$

We construct dividend price ratio and dividend growth based on the total market returns and market returns with dividends. To avoid spurious predictability arising from seasonal components, dividends are calculated as twelve-month moving sums of dividends paid on the S&P 500 index (Ang and Bekaert, 2007).

Table 10 reports the results. Both m_t and μ_t display distinct patterns for cash flow and discount rate predictability. μ_t significantly forecasts discount rates in the whole sample period and the low-sentiment regime, while its predictive power becomes less significant in the high-sentiment regime. Neither μ_t nor m_t can predict time variation in cash flow. The evidences suggests that aggregate stock market predictability is derived from the time variation in discount rates (Fama and French, 1989; Cochrane 2008, 2011). Furthermore, we find that discount rates can be predicted by m_t in the high sentiment regime, supporting the implications in Campbell et al. (2010). The results suggest that the cross-regime predictive ability of both fundamental and non-fundamental variables appears to stem from the discount rate channel.

VI. Conclusion

Overall, we show that fundamental variables' predictive ability is significantly weakened when investor sentiment is high, while non-fundamental variables' predictive ability deteriorates when sentiment is low. Nevertheless, once we control for the impact of sentiment, both fundamental variables and non-fundamental variables can have robust predictive ability. Therefore, investor sentiment could be one key to settling the recent debate over the predictive ability of both fundamental and non-fundamental variables. In addition, we find that the low- (high-)sentiment regime represents about 80% (20%) of our sample. Consequently, fundamental variables may be deemed as superior predictors based on the fact that they are able to predict the equity premium much more frequently than their non-fundamental counterparts.

Appendix. A Simple Model

In this section, we present a simple model to show that the combination of short-sale constraints and sentiment (noise) trading can give rise to time series momentum during the high-sentiment regime, but not during the low-sentiment regime, when asset prices immediately adjust to reflect fundamentals.

We consider a financial market with a positive net supply of a risky asset. The final payoff D of the risky asset is normally distributed

$$D \sim N(\mu_D, \sigma_D). \tag{26}$$

There are two investors: a rational trader and a noise trader indexed by $i = R, N$ respectively. We assume both investors are risk neutral and subject to short-sale constraints.[30] Before observing any signals, the investors have prior beliefs about the final payoff D of the risky asset,

$$D \sim N(\mu_{i,D}, \sigma_D), \quad i = R, N. \tag{27}$$

For simplicity, we postulate that investors have homogeneous and correct beliefs about volatility. Suppose the rational investor has a correct prior belief about the mean value of D, i.e., $\mu_{R,D} = \mu_D$, while the noise investor believes that $\mu_{N,D} = \mu_D(1 + e_N)$, where $e_N \sim N(\mu_e, \sigma_e)$ can be interpreted as sentiment. If $\mu_e = 0$, then the noise investor has a rational belief and the asset price is determined by the expected payoff. In the following analysis, we assume $\mu_e \neq 0$, with $\mu_e > 0$ (< 0) corresponding to high- (low-) sentiment periods.[31]

[30] Risk neutral investors are also considered by Harrison and Kreps (1978), Hong and Stein (2003) and Scheinkman and Xiong (2003). Bai, Chang and Wang (2006) consider risk averse agents in a one-period model; however, in multi-period environments, the optimal demands cannot be explicitly solved from the first order conditions due to the nonlinear expectations caused by the short-sale constraints.

[31] We consider exogenous sentiment in our model because we are concerned with the impact of sentiment rather than its formation. This is also consistent with this paper's empirical analysis, in which the sentiment is exogenously given. The interaction between price and sentiment has been studied in the theoretical literature; see, for example, Barberis, Greenwood, Jin and Shleifer (2015).

At each date $0 < t < T$, investors observe a public signal s_t and believe

$$s_t = D + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_{\varepsilon,t}). \tag{28}$$

Investors observe the same signals and the priors of both investors, so there is no asymmetry of information. We normalize the time discount rate to zero. Investor i is willing to pay $E_{i,t}[D]$ at time t for a unit of the asset, and price at time t is given by

$$P_t = \max_{i=R,N} \left\{ E_{i,t}[D] \right\}. \tag{29}$$

In order to show the momentum effect, we consider a multi-period model with $T = 2$ for simplicity.[32] Due to the difference in priors, investors hold different posterior beliefs about the distribution of D at time 1:

$$E_{R,1}[D|s_1] = \beta s_1 + (1-\beta)\mu_D, \quad E_{N,1}[D|s_1] = \beta s_1 + (1-\beta)\mu_D(1+\mu_e)$$

where $\beta = \frac{1/\sigma_{\varepsilon,1}}{1/\sigma_D + 1/\sigma_{\varepsilon,1}}$.

We further explore the differences in patterns during high- and low-sentiment periods respectively.

Case (I) Low-sentiment period ($\mu_e < 0$):

$$\begin{aligned} P_0 &= \mu_{R,D} = \mu_D, \\ P_1 &= E_{R,1}[D] = \beta s_1 + (1-\beta)\mu_D, \end{aligned} \tag{30}$$

because $E_{N,0}[D] < E_{R,0}[D]$ and $E_{N,1}[D] < E_{R,1}[D]$. The prices are determined by the rational trader's belief. In addition, under rational (or objective) belief,

$$cov_{R,0}[P_2 - P_1, P_1 - P_0] = \beta[(1-\beta)\sigma_D - \beta\sigma_{\varepsilon,1}] = 0. \tag{31}$$

[32] Our model can be easily extended to more than two periods.

Therefore, in the low-sentiment period, there are no autocorreltions in price changes, since, at any given time, the price reflects the asset's fundamentals.

Case (II) High-sentiment period ($\mu_e > 0$):

$$
\begin{aligned}
P_0 &= \mu_{N,D} = \mu_D(1+e_N), \\
P_1 &= E_{N,1}[D] = \beta s_1 + (1-\beta)\mu_{N,D},
\end{aligned}
\tag{32}
$$

because $E_{N,0}[D] > E_{R,0}[D]$ and $E_{N,1}[D] > E_{R,1}[D]$. The prices are determined by the noise trader's belief. In this case,

$$
cov_{N,0}[P_2 - P_1, P_1 - P_0] = \beta(1-\beta)\mu_D^2\sigma_e > 0. \tag{33}
$$

Therefore, we observe a price momentum caused by the gradual incorporation of information that adjusts the price towards the fundamental level. In other words, momentum stems from the noise trader's learning process.[33] The price gradually converges to the asset's fundamental value as the new information comes to dominate priors.[34]

In summary, during high-sentiment periods, the noise investor tends to take long positions and the rational investor cannot arbitrage away the mispricing due to short-sale constraints. Hence, the asset price initially includes both fundamental and mispricing components. However, as the noise investor learns gradually, he corrects his beliefs and information comes to dominate priors, giving rise to momentum. In contrast, during low-sentiment periods, the rational investor faces no constraints, so the asset price always reflects its fundamentals. Hence there is no momentum effect in the low-sentiment regime. Our model implies that short-sale constraints, when combined with sentiment (noise) trading, can create momentum in the high-sentiment regime even in the absence of any behavioral preference hypothesis (e.g. the cognitive dissonance described in Antoniou et al.,

[33]This is, in spirit, similar to the findings in Diamond and Verrecchia (1987), who show that short-sale constraints reduce the speed at which prices adjust to private information.

[34]In one extreme case when $\sigma_e = 0$, we have $cov_{N,0}[P_2 - P_1, P_1 - P_0] = 0$. In this case, there will be no price momentum. However, the reason for the lack of price momentum differs from the low-sentiment periods: noise traders hold a dogmatic prior belief and do not update it to adjust the price toward the fundamental level after observing new information.

2013).[35]

[35] There is no trading in our simple model. Trading can be generated by introducing time-varying beliefs, which is beyond our scope.

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Figure 1. Time series of investor sentiment and high/low sentiment regime.

The top figure plots the estimated probability of high-sentiment regime (solid blue line), as well as regime estimates using the median cut approach, as in Stambaugh, Yu and Yuan (2012) (red dots). The middle figure depicts the investor sentiment index from 1965:07 to 2010:12; high-sentiment months estimated using the regime switching approach are shaded in yellow. The bottom figure also depicts the investor sentiment index; high-sentiment months estimated using the median cut approach are shaded in yellow.

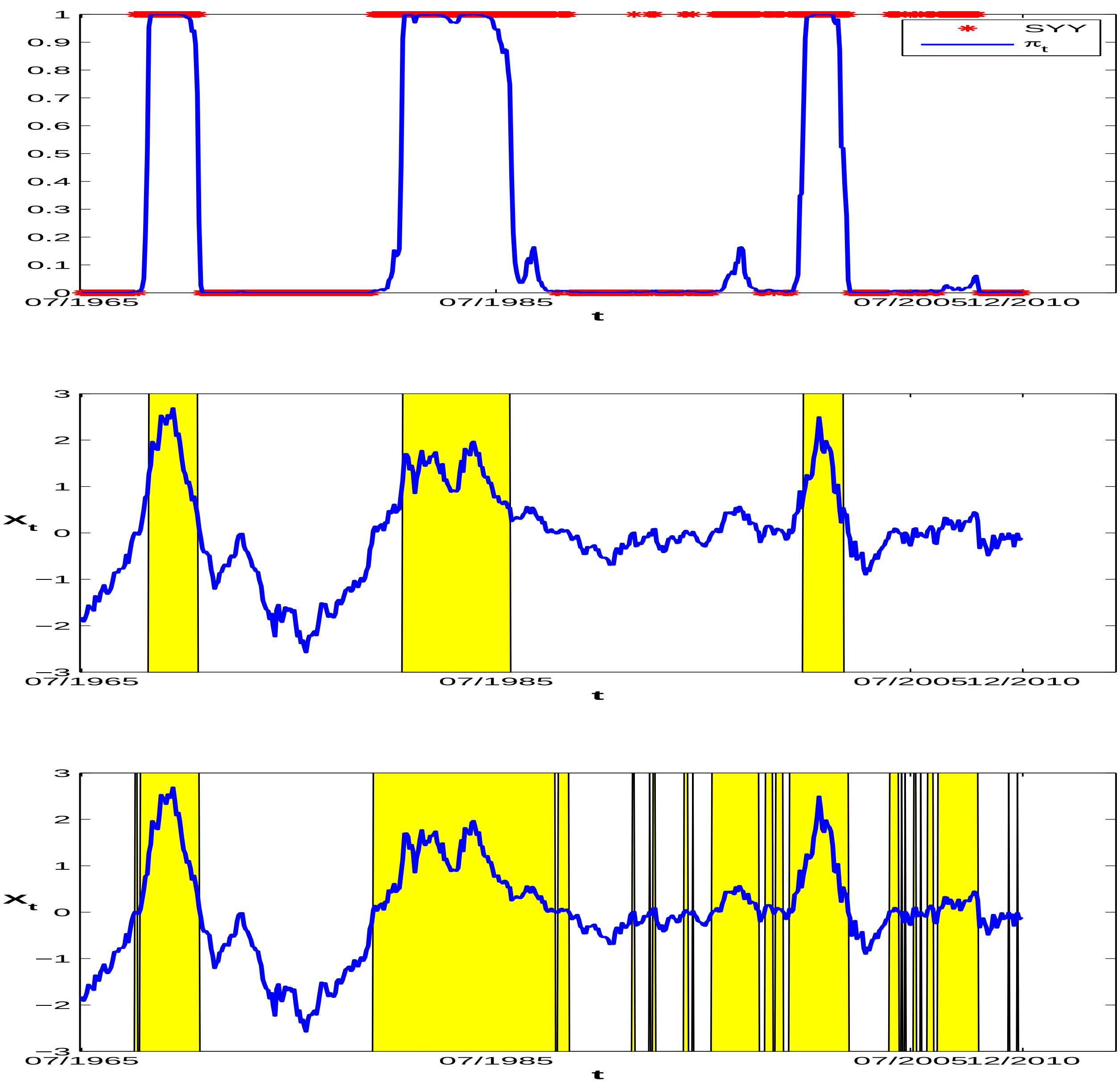

Figure 2. Times series of business cycle and investor sentiment regimes.

This figure plots the NBER recession dummy and high/low investor sentiment regimes. The shaded areas represent the high-sentiment months estimated using the regime switching approach. The red dots represent NBER recession dates. The sample period spans from July 1965 to December 2010.

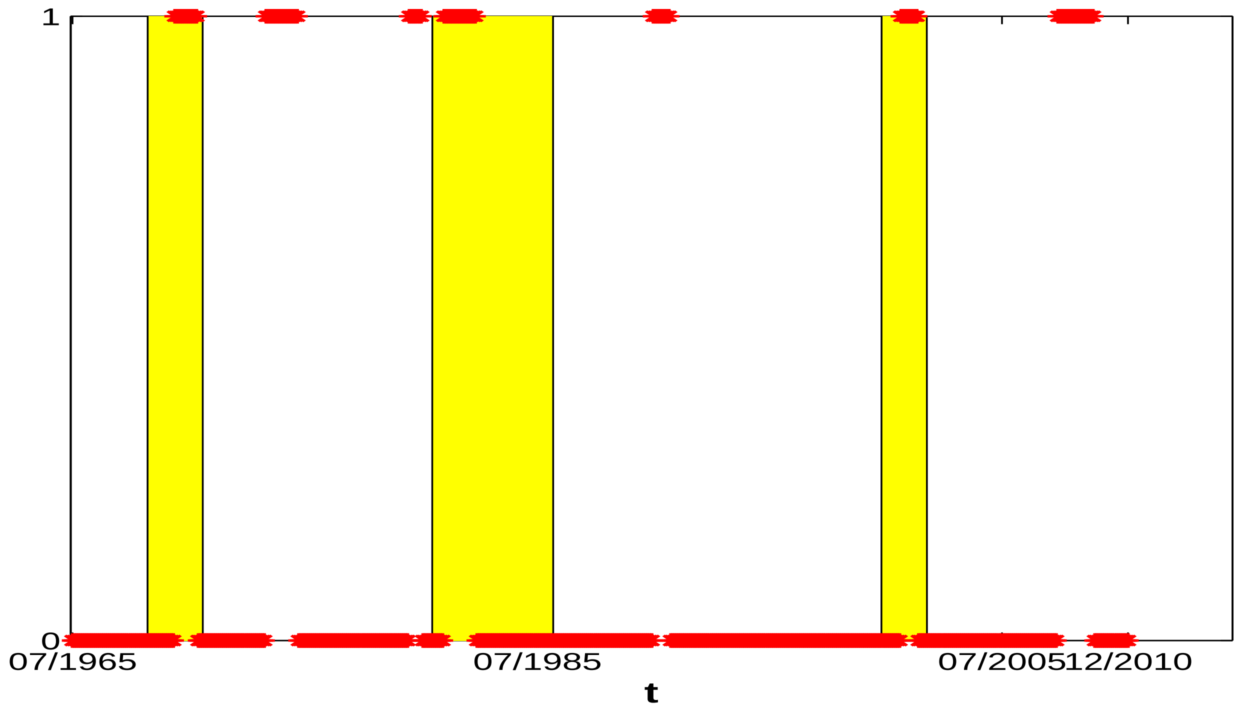

Figure 3. Times series of combined fundamental predictor μ_t and combined non-fundamental predictor m_t.

Panel A plots the combined fundamental predictor μ_t, constructed from 7 categories of macroeconomic variables described in Jurado, Ludvigson and Ng (2015). Panel B plots the combined non-fundamental predictor m_t extracted from 6 individual non-fundamental variables, including three time series momentum proxies, one anchoring variable and two moving average indicators. The shaded area in each panel represents the high-sentiment months estimated by the regime switching approach. The sample period spans from July 1965 to December 2010.

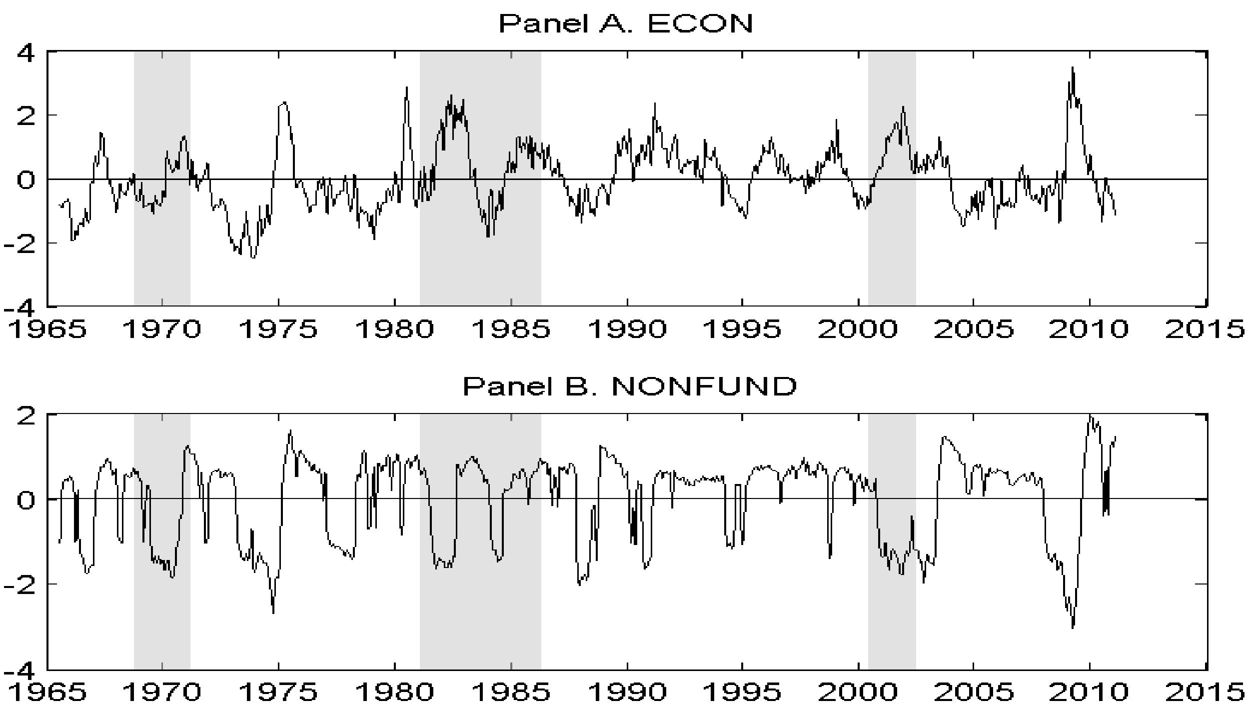

Figure 4. Correlations between predictors and equity premium and in sample predictive regression patterns.

The first three bars in Panel A (B) display correlations between the combined fundamental predictor μ_t (the combined non-fundamental predictor m_t) during the whole sample period, the high-sentiment regime, and low-sentiment regime, respectively. The fourth bar in both panels depicts the difference in correlations between the high-sentiment and low-sentiment regimes. The first three bars in Panels C, E, and G (Panels D, F, and H) display coefficients, t-statistics and R^2s in percentage points of in-sample predictive regressions based on μ_t (m_t) during the whole sample period, the high-sentiment regime, and the low-sentiment regime, respectively. The fourth bar in Panels C, E, and G (Panel D, F, and H) depicts the differences in coefficients, t-statistics and R^2s in percentage points between the high-sentiment and low-sentiment regimes. μ_t is constructed from the 7 macroeconomic categories described in Jurado, Ludvigson and Ng (2015). m_t is extracted from 6 non-fundamental variables, including three time series momentum proxies, one anchoring variable, and two moving average indicators. The sample period spans from July 1965 to December 2010.

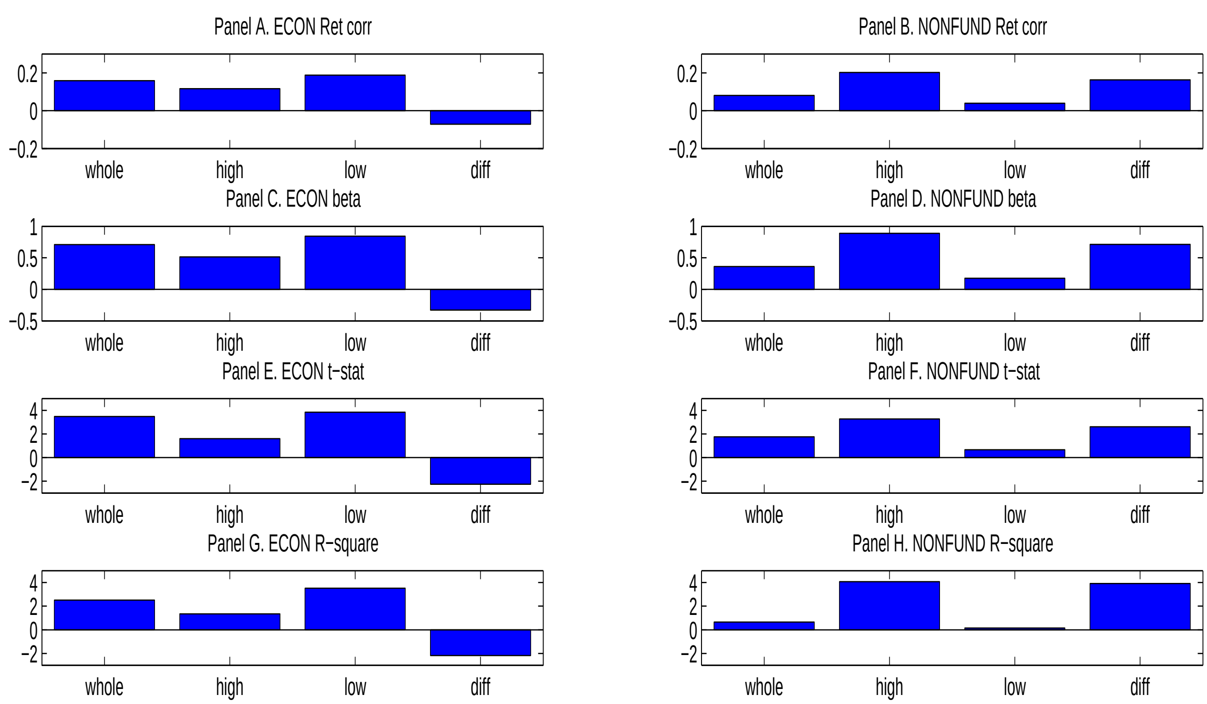

Figure 5. Time series of in-sample equity premium forecasts based on combined fundamental predictor μ_t and combined non-fundamental predictor m_t.

This figure plots monthly equity premium forecasts (in percent). The shaded area in each panel represents the high-sentiment months estimated using the regime switching approach. The sample period spans from July 1965 to December 2010. Panel A (B) depicts the forecasts for a predictive regression model with a constant and the combined fundamental predictor μ_t (non-fundamental predictor m_t) serving as the regressor. Panel C depicts the forecasts for a predictive regression model with a constant and both the combined fundamental predictor μ_t and the combined non-fundamental predictor m_t serving as regressors. μ_t is constructed from the 7 macroeconomic categories described in Jurado, Ludvigson and Ng (2015). m_t is extracted from 6 non-fundamental variables, including three time series momentum proxies, one anchoring variable and two moving average indicators.

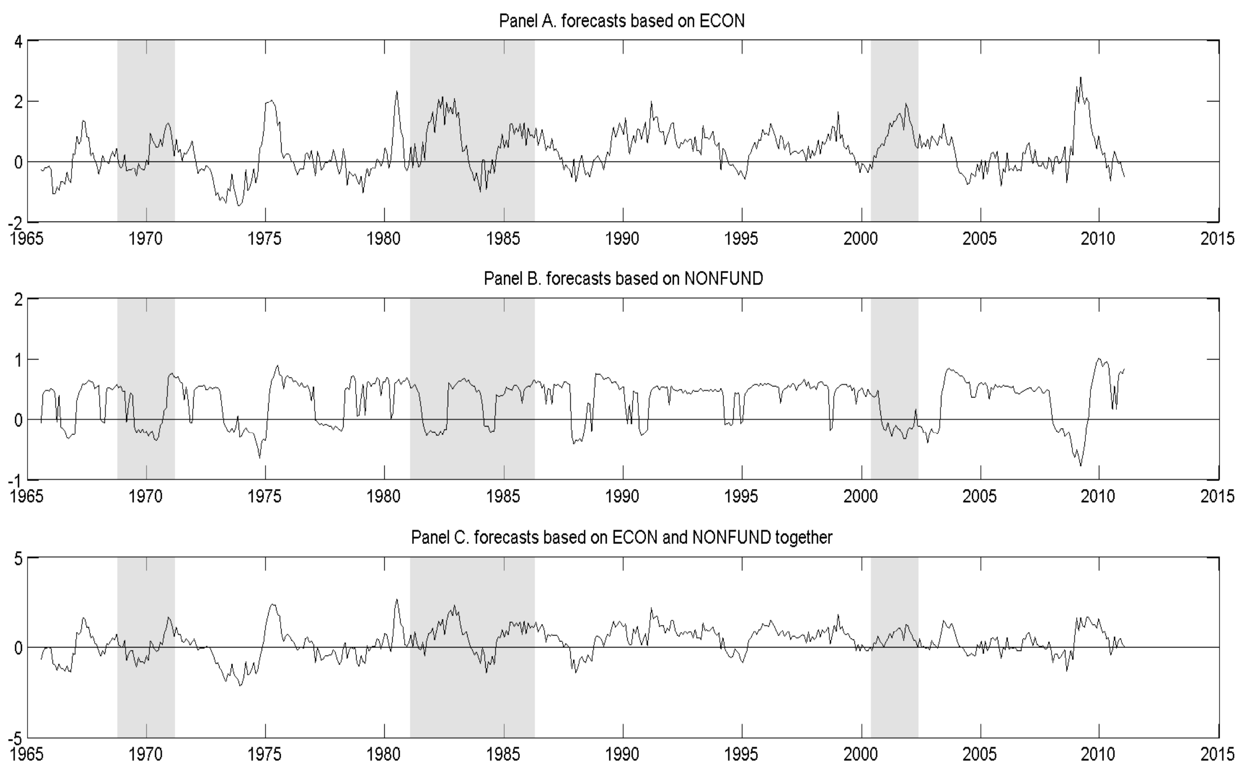

Table 1 Summary statistics

This table reports the summary statistics of the excess market return (the log return on the S&P 500 index in excess of the log one-month T-bill rate) and fundamental predictors during the whole sample period, the high-sentiment regime, and the low-sentiment regime, respectively. Panel A presents the mean (Mean), standard deviation (Std), the first-order autocorrelation ($\rho(1)$), minimum (Min), maximum (Max), and the monthly Sharpe ratio (SR) of the excess market return. Panel B presents the mean (Mean), standard deviation (Std), the first-order autocorrelation ($\rho(1)$), minimum (Min), and maximum (Max) of the combined fundamental predictor μ_t constructed from the 7 macroeconomic categories described in Jurado, Ludvigson and Ng (2015). Panel C presents the mean (Mean), standard deviation (Std), the first-order autocorrelation ($\rho(1)$), minimum (Min), and maximum (Max) of each of the 7 individual macroeconomic predictors F_i, $i = 1,2,3,4,5,6,7$ respectively: (1) output and income; (2) labour market; (3) housing; (4) consumption, orders, and inventories; (5) money and credit; (6) exchange rates; and (7) prices. The Sharpe ratio is defined as the mean of excess market return divided by its standard deviation. High- and low-sentiment regimes are estimated using the regime switching approach over the sample period 1965.07 to 2010.12.

			Panel A: Excess market return			
	Mean	Std	$\rho(1)$	Min	Max	SR
Whole	0.31	4.47	0.06	-24.84	14.87	0.07
High	-0.07	4.41	0.10	-9.98	11.05	-0.02
Low	0.41	4.48	0.05	-24.84	14.87	0.09
			Panel B: μ_t			
	Mean	Std	$\rho(1)$	Min	Max	
Whole	0.00	1.00	0.86	-2.49	3.47	
High	0.41	1.02	0.83	-1.86	2.59	
Low	-0.11	0.97	0.86	-2.49	3.47	
			Panel C: Individual macroeconomic predictors			
	Mean	Std	$\rho(1)$	Min	Max	
F_1						
Whole	0.00	1.00	0.89	-3.81	3.38	
High	-0.41	1.10	0.88	-2.51	3.38	
Low	0.11	0.94	0.88	-3.81	2.34	
F_2						
Whole	0.00	1.00	0.92	-3.38	2.78	
High	-0.54	1.10	0.92	-3.00	1.74	
Low	0.15	0.92	0.91	-3.38	2.78	
F_3						
Whole	0.00	1.00	-0.18	-3.93	3.27	
High	0.06	1.13	-0.32	-3.93	2.57	
Low	-0.02	0.96	-0.12	-3.07	3.27	
F_4						
Whole	0.00	1.00	0.95	-3.40	3.32	
High	-0.35	0.90	0.94	-2.19	1.92	
Low	0.09	1.00	0.95	-3.40	3.32	
F_5						
Whole	0.00	1.00	0.73	-5.57	7.78	
High	-0.07	0.58	0.65	-2.25	1.94	
Low	0.02	1.09	0.73	-5.57	7.78	
F_6						
Whole	0.00	1.00	0.31	-3.51	3.52	
High	0.17	1.03	0.25	-3.51	2.65	
Low	-0.04	0.99	0.32	-3.14	3.52	
F7						
Whole	0.00	1.00	0.95	-3.00	2.22	
High	-0.32	0.93	0.95	-2.08	1.41	
Low	0.09	1.00	0.94	-3.00	2.22	

Table 2 Mispricing during high and low sentiment regimes

Panel A reports mispricing (alpha) during high and low sentiment regimes with the Carhart four-factor model:

$$r_{t+1} = \alpha_H I_{H,t} + \alpha_L I_{L,t} + \beta_1 MKT_{t+1} + \beta_2 SMB_{t+1} + \beta_3 HML_{t+1} + \beta_4 WML_{t+1} + \varepsilon_{t+1}$$

Panel B reports pricing error (alpha) in high- and low-sentiment periods based on the Fama French three-factor model:

$$r_{t+1} = \alpha_H I_{H,t} + \alpha_L I_{L,t} + \beta_1 MKT_{t+1} + \beta_2 SMB_{t+1} + \beta_3 HML_{t+1} + \varepsilon_{t+1}$$

r_{t+1} represents an anomaly long-short strategy return, as described in Novy-Marx and Velikov (2016). I_H is the high-sentiment regime indicator and I_L is the low-sentiment regime dummy. The sample period is from 1965.08 to 2011.01 for all variables except Ohlson's O-score, return-on-book equity, failure probability, and return-on-assets, for which data is available from 1973.07. Combination is the simple average of all the individual anomalies. All t-statistics are computed using White heteroscedasticity robust standard errors.

	Panel A: Carhart four-factor model				Panel B: Fama French three-factor model			
Anomaly	α_H	t-stat	α_L	t-stat	α_H	t-stat	α_L	t-stat
Gross Profitability	1.31	3.94	0.33	2.09	1.40	4.09	0.40	2.61
ValProf	1.62	5.00	0.19	1.33	1.55	4.88	0.13	0.98
Net Issuance (rebal.:A)	1.50	5.19	0.50	4.14	1.61	5.43	0.59	4.95
Asset Growth	0.25	0.90	0.07	0.48	0.30	1.09	0.11	0.79
Investment	0.55	2.32	0.29	1.90	0.63	2.64	0.35	2.38
Piotroski's F-score	1.06	2.68	0.18	0.86	1.23	3.04	0.32	1.52
Asset Turnover	1.18	2.88	0.14	0.76	1.22	2.92	0.18	1.02
Gross Margins	1.04	4.32	0.30	2.29	0.98	4.19	0.25	1.97
Net Issuance (rebal.:M)	1.08	4.08	0.48	3.03	1.12	4.16	0.51	3.58
ValMomProf	1.70	6.44	0.44	2.85	2.57	5.89	1.12	5.21
Idiosyncratic Volatility	2.35	6.54	0.45	2.22	2.69	6.52	0.72	3.87
Beta Arbitrage	1.04	3.07	-0.18	-0.80	1.07	3.28	-0.15	-0.77
Short-run Reversals	1.18	2.30	0.35	1.44	0.75	1.38	0.01	0.05
Ohlson's O-score	1.88	5.84	0.35	2.50	2.26	6.39	0.55	3.77
Return-on-book equity	1.85	3.71	0.65	2.95	2.40	4.27	0.94	4.06
Failure Probability	2.68	5.59	0.55	2.61	4.01	5.17	1.23	4.63
Return-on-assets	1.79	4.06	0.58	3.17	2.29	4.61	0.84	4.39
Combination	1.31	8.10	0.31	4.04	1.49	7.77	0.46	6.02

Table 3 In-sample predictive regressions

Panel A (B) displays in-sample regression results based on individual macroeconomic (non-fundamental) predictors during the whole sample, the high-sentiment and the low-sentiment regimes, respectively. Panel A shows 7 individual fundamental predictors from the 7 categories of macroeconomic variables described in Jurado, Ludvigson and Ng (2015). Panel B shows 6 individual non-fundamental predictors, including three time series momentum proxies, one anchoring variable and two moving average indicators. Panel C presents in-sample regression results based on the combined fundamental predictor μ_t extracted from the 7 individual macroeconomic predictors, the combined non-fundamental predictor m_t extracted from the 6 non-fundamental variables, and both μ_t and m_t taken together as predictors. Regression coefficients, Newey-West t-statistics (with a lag of 12), and R^2s in percentage points are reported. $*, **$ and $***$ indicate significance based on bootstrapped p-values at the $10\%, 5\%$ and 1% levels, respectively. High- and low-sentiment regimes are estimated based on the regime switching approach. The sample period spans from 1965.07 to 2010.12.

Panel		Whole	High	Low	Whole	High	Low	Whole	High	Low	Whole	High	Low
A	F_{1t}	-0.20	0.08	-0.35									
		[-0.79]	[0.25]	[-1.09]									
	F_{2t}				-0.44**	-0.57*	-0.51**						
					[-1.99]	[-1.84]	[-1.90]						
	F_{3t}							0.45**	0.05	0.59**			
								[2.01]	[0.10]	[2.39]			
	F_{4t}										-0.59***	-0.34	-0.71***
											[-2.83]	[-1.00]	[-3.22]
	R^2 (%)	0.20	0.04	0.62	0.99	1.66	1.29	1.01	0.01	1.72	1.76	0.60	2.54
	F_{5t}	-0.32	-0.06	-0.37									
		[-1.47]	[-0.19]	[-1.60]									
	F_{6t}				-0.20	-0.28	-0.16						
					[-1.13]	[-0.72]	[-0.79]						
	F_{7t}							-0.56***	-0.74*	-0.58***			
								[-2.84]	[-2.15]	[-2.52]			
	R^2 (%)	0.51	0.02	0.69	0.21	0.40	0.13	1.60	2.78	1.65			

Table 3 In-sample predictive regressions—Contiued

Panel		Whole	High	Low	Whole	High	Low	Whole	High	Low	Whole	High	Low
B	M_t^6	0.18	0.73***	0.01									
		[1.00]	[3.17]	[0.03]									
	M_t^9				0.08	0.38**	-0.04						
					[0.37]	[1.76]	[-0.14]						
	M_t^{12}							0.16	0.21*	0.11			
								[0.73]	[0.88]	[0.37]			
	$\hat{x}_{52,t}$										0.34**	0.87**	0.22
											[1.91]	[2.31]	[1.12]
	R^2 (%)	0.17	2.71	0.00	0.03	0.73	0.01	0.13	0.23	0.06	0.58	3.90	0.25
	$MA(1,9)$	0.29*	0.88**	0.08									
		[1.38]	[2.83]	[0.28]									
	$MA(1,12)$				0.43**	0.93***	0.25						
					[1.99]	[3.08]	[0.87]						
	R^2 (%)	0.41	4.00	0.03	0.95	4.41	0.30						
C	μ_t	0.71***	0.51	0.84***				0.72***	0.64*	0.83***			
		[3.47]	[1.59]	[3.85]				[3.95]	[2.03]	[3.88]			
	m_t				0.36**	0.89***	0.18	0.38**	0.97***	0.13			
					[1.77]	[3.27]	[0.65]	[1.68]	[3.36]	[0.43]			
	R^2 (%)	2.51	1.36	3.52	0.65	4.07	0.15	3.23	6.13	3.61			

Table 4 Anchoring variables constructed based on alternative indices

This table presents in-sample regression results using $x_{52,t}$ (nearness to the 52-week high) as a predictor for future monthly NYSE/AMEX value-weighted excess returns with control variables including past returns, nearness to the historical high, a historical high indicator, and a "52-week high equal-historical high" indicator. $x_{52,t}$ is based on the Dow Jones Industrial Average index, the NYSE/AMEX total market value and the S&P 500 index in Panels A, B and C, respectively. We report in each panel the regression coefficients, Newey-West t-statistics with a lag of 12, and R^2s in percentage points. The sample period spans from 1965.07 to 2010.12.

Panel		Whole	High	Low
A	$x_{52,t}$	0.91	2.89	0.49
		[2.28]	[4.53]	[1.25]
	R^2 (%)	3.12	11.97	2.31
B	$x_{52,t}$	0.60	3.87	0.82
		[1.30]	[3.76]	[1.37]
	R^2 (%)	2.61	8.58	3.21
C	$x_{52,t}$	0.47	2.92	0.32
		[1.61]	[2.74]	[0.86]
	R^2 (%)	2.23	6.55	2.03

Table 5 In-sample predictive regressions for 1976:01-2005:12

This table reports results for an in-sample predictive regression for the period 1976:01-2005:12, following Welch and Goyal (2008). The combined fundamental predictor μ_t is constructed from the 7 macroeconomic categories described in Jurado, Ludvigson and Ng (2015) and the combined non-fundamental predictor m_t is extracted from 6 individual non-fundamental predictors, including three time series momentum proxies, one anchoring variable and two moving average indicators. Regression coefficients, Newey-West t-statistics (with a lag of 12), and R^2s in percentage points are reported. $*, **$ and $***$ indicate significance based on bootstrapped p-values at the $10\%, 5\%$, and 1% levels, respectively.

	Whole	High	Low	Whole	High	Low	Whole	High	Low
μ_t	0.43*	0.42	0.61**				0.45**	0.68	0.63**
	[1.87]	[1.18]	[2.42]				[2.13]	[1.53]	[2.29]
m_t				0.11	0.86***	-0.28	0.16	1.04***	-0.31
				[0.42]	[2.79]	[-0.91]	[0.57]	[2.58]	[-0.97]
R^2 (%)	0.81	0.98	1.37	0.05	3.73	0.29	0.92	6.12	1.73

Table 6 Robustness checks

Panel A presents in-sample regression results excluding the oil shock recession of 1973–1975 based on the combined fundamental predictor μ_t and combined non-fundamental predictor m_t during the whole sample, the high-sentiment and the low-sentiment regimes, respectively. μ_t is constructed from the 7 macroeconomic categories described in Jurado, Ludvigson and Ng (2015) while m_t is extracted from 6 individual non-fundamental predictors, including three time series momentum proxies, one anchoring variable and two moving average indicators. High- and low-sentiment regimes are estimated based on the regime switching approach. Panel B reports in-sample regression results based on μ_t and m_t during the whole sample, the high-sentiment and low-sentiment regimes, respectively, where high- and low-sentiment periods are determined by the median value of the Baker and Wurgler sentiment index. We report in each panel the regression coefficients, Newey-West t-statistics (with a lag of 12), and R^2s in percentage points. $*, **$, and $***$ indicate significance based on bootstrapped p-values at the $10\%, 5\%$, and 1% levels, respectively. The sample period spans from 1965.07 to 2010.12.

	Panel A			Panel B		
	Whole	High	Low	Whole	High	Low
μ_t	0.54***	0.62*	0.58***	0.72***	0.70***	0.81***
	[3.30]	[1.92]	[3.29]	[3.95]	[2.68]	[3.06]
m_t	0.34*	0.97***	0.05	0.38**	0.82**	-0.03
	[1.45]	[3.40]	[0.17]	[1.68]	[2.39]	[-0.13]
R^2 (%)	1.97	6.29	1.80	3.23	4.13	4.38

Table 7 Predictive regressions during expansions

Panel A (B) displays in-sample regression results during expansion periods based on individual macroeconomic (non-fundamental) predictors. In Panel A, we consider 7 individual fundamental predictors from the 7 categories of macroeconomic variables described in Jurado, Ludvigson and Ng (2015). In Panel B, we consider 6 individual non-fundamental predictors, including three time series momentum proxies, one anchoring variable and two moving average indicators. Panel C presents in-sample regression results during expansions based on combined fundamental predictor μ_t extracted from the 7 individual macroeconomic predictors, combined non-fundamental predictor m_t extracted from the 6 non-fundamental variables, as well as μ_t and m_t taken together as predictors. In each panel, we present results during all expansion periods, the high-sentiment portions of the expansion periods, and the low-sentiment portions of the expansion periods, respectively. Regression coefficients, Newey-West t-statistics (with a lag of 12), and R^2s in percentage points are reported. $*, **$, and $***$ indicate significance based on bootstrapped p-values at the $10\%, 5\%$, and 1% levels, respectively. High- and low-sentiment regimes are estimated based on the regime switching approach.

Panel		Whole	High	Low	Whole	High	Low	Whole	High	Low	Whole	High	Low
A	F_{1t}	-0.35*	0.36	-0.59***									
		[-1.57]	[0.60]	[-3.40]									
	F_{2t}				-0.43**	-0.40	-0.49***						
					[-2.11]	[-0.80]	[-2.67]						
	F_{3t}							0.08	-0.57*	0.25			
								[0.45]	[-1.90]	[1.25]			
	F_{4t}										-0.56***	-0.41	-0.61***
											[-3.72]	[-0.82]	[-4.59]
	R^2 (%)	0.76	0.89	2.07	1.13	1.06	1.44	0.04	2.19	0.38	1.91	1.11	2.24
	F_{5t}	0.02	-0.02	0.02									
		[0.09]	[-0.05]	[0.09]									
	F_{6t}				-0.09	-0.41	-0.00						
					[-0.62]	[-1.05]	[-0.01]						
	F_{7t}							-0.52***	-0.83**	-0.49***			
								[-3.35]	[-2.82]	[-3.04]			
	R^2 (%)	0.00	0.00	0.00	0.05	1.12	0.00	1.64	4.67	1.45			

Table 7 Predictive regressions during expansions—Continued

Panel		Whole	High	Low	Whole	High	Low	Whole	High	Low	Whole	High	Low
B	M_t^6	-0.05	0.96***	-0.30									
		[-0.26]	[3.63]	[-1.53]									
	M_t^9				-0.13	0.69**	-0.34*						
					[-0.63]	[2.16]	[-1.58]						
	M_t^{12}							-0.04	0.39*	-0.16			
								[-0.19]	[1.23]	[-0.69]			
	$\hat{x}_{52,t}$										0.11	0.24	0.06
											[0.84]	[0.68]	[0.39]
	R^2 (%)	0.02	6.22	0.54	0.11	3.24	0.70	0.01	1.01	0.15	0.08	0.38	0.02
	$MA(1,9)$	-0.07	0.67*	-0.26									
		[-0.33]	[1.76]	[-1.22]									
	$MA(1,12)$				0.17	0.86*	-0.01						
					[0.72]	[1.84]	[-0.05]						
	R^2 (%)	0.03	2.99	0.42	0.19	5.00	0.00						
C	μ_t	0.53***	0.28	0.62***				0.54**	0.11	0.68***			
		[2.94]	[0.63]	[3.77]				[2.49]	[0.27]	[3.46]			
	m_t				0.06	0.80**	-0.13	-0.05	0.77**	-0.28			
					[0.29]	[2.06]	[-0.65]	[-0.19]	[1.78]	[-1.21]			
	R^2 (%)	1.73	0.53	2.30	0.02	4.27	0.11	1.75	4.35	2.74			

Table 8 Out-of-sample forecasting results

This table reports out-of-sample forecasting results using the first half of our data as a training sample. Column 2 (Column 3) displays out-of-sample forecasting results based on the combined fundamental (non-fundamental) predictor μ_t (m_t). μ_t is constructed from 7 individual macroeconomic predictors while m_t is extracted from 6 individual non-fundamental variables. Column 4 reports out-of-sample forecasting results using both μ_t and m_t as predictors. Column 5 presents results based on a shifting predictor, based on m_t during the high-sentiment regime and switching to μ_t during the low-sentiment regime. We specify results separately during the whole sample period, the high-sentiment and the low-sentiment regimes in Columns 2, 3 and 4. To reduce estimation error, at each period t we estimate the weights of individual predictors according to partial least squares analysis and set their weight at time t as zero if the product of the weight at time t and the average weight estimated from period 1 to $t-1$ is less than 0.05. R^2_{OS} statistics in percentage points are reported. High and low sentiment regimes are estimated based on a real-time regime switching approach. The statistical significance for R^2_{OS} is based on the p-value for the Clark and West (2007) out-of-sample MSPE-adjusted statistic for testing the null hypothesis that the competing forecasting model's equal expected square prediction error is equal to that of the historical benchmark forecasting model against the alternative hypothesis that the competing forecasting model's expected square prediction error is lower than that of the historical benchmark forecasting model. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

R^2_{OS} (%)	μ_t	m_t	$\mu_t \& m_t$	$I_{H,t} m_t + (1 - I_{H,t}) \mu_t$
Whole	-2.28	0.48	-1.32	1.38^{**}
High	-2.10	3.30^{*}	1.83	
Low	0.81^{*}	-0.90	0.52	

Table 9 Out-of-sample forecasting results using variables from Campbell and Thompson (2008)

This table reports out-of-sample forecasting power for the 11 variables in Table 2 of Campbell and Thompson (2008), using the first half of our data as a training sample. We use the "fixed coefficients" remedy described in Campbell and Thompson (2008). In contrast to Campbell and Thompson (2008), our sample period begins in July 1965 to be consistent with the sentiment data. R^2_{OS} statistics in percentage points are reported. High- and low-sentiment regimes are estimated based on a real-time regime switching approach. Statistical significance for R^2_{OS} is based on the p-value for the Clark and West (2007) out-of-sample MSPE-adjusted statistic for testing the null hypothesis that the competing forecasting model's expected square prediction error is equal to that of the historical benchmark forecasting model against the alternative hypothesis that the competing forecasting model's expected square prediction error is lower than that of the historical benchmark forecasting model. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

	Whole	High	Low
Dividend-price ratio	-0.37	1.10	-1.16
Earnings-price ratio	0.79*	1.20*	0.44
Smoothed earnings-price ratio	0.59	1.06	0.23
Dividend-price ratio + growth	0.63**	-0.14	0.90**
Earnings-price ratio + growth	0.80**	-0.32	1.19**
Smoothed earnings-price ratio + growth	0.71**	-0.32	1.08**
Book-to-market ratio + growth	0.42	-0.55	0.77**
Dividend-price ratio + growth − real rate	0.30	0.22	0.22
Earnings-price ratio + growth − real rate	0.55**	0.12	0.61**
Smoothed earnings-price ratio + growth − real rate	0.44	0.07	0.48*
Book-to-market ratio + growth − real rate	0.09	-0.18	0.08

Table 10 Forecasting channel

Panel A (B) reports the results of forecasting dividend-price ratio dy^{12} (dividend growth g^{12}) using the combined fundamental predictor μ_t and combined non-fundamental predictor m_t together as regressors. We specify results for the whole sample period, the high-sentiment and the low-sentiment regimes. Regression coefficients, Newey-West t-statistics (with a lag of 12), and R^2s in percentage points are reported. $*, **$, and $***$ indicate significance based on bootstrapped p-values at the $10\%, 5\%$, and 1% levels, respectively. dy^{12} is used as a proxy for discount rate while g^{12} is used as a proxy for cash flow. μ_t is constructed from the 7 macroeconomic categories described in Jurado, Ludvigson and Ng (2015). m_t is extracted from 6 individual non-fundamental predictors, including three time series momentum proxies, one anchoring variable and two moving average indicators. High- and low-sentiment regimes are estimated based on the regime switching approach. The sample period spans from 1965.07 to 2010.12.

dy^{12}	Regimes	β_1	β_2	R^2
	Whole	-0.78***	-0.33*	98.91
		[-4.40]	[-1.55]	
	High	-0.56**	-0.79***	99.41
		[-2.49]	[-2.48]	
	Low	-0.89***	-0.12	98.63
		[-4.17]	[-0.40]	
g^{12}	Regimes	β_1	β_2	R^2
	Whole	-0.08	0.09*	0.74
		[-1.14]	[1.33]	
	High	0.06	0.01	5.68
		[0.73]	[0.11]	
	Low	-0.08	0.06	0.33
		[-0.92]	[0.76]	