Market Sentiment and Paradigm Shifts in Equity Premium Forecasting

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Abstract

There is a recent debate and even a doubt about whether fundamental economic variables can predict equity premium or not. Some remedies seem working well and help in restoring the confidence on predictability. However, we show that those remedies are fragile and irrelevant in some sense. The predictability is gone again, even with those remedies utilized, once market sentiment kicks in to distort the fundamental link between economic variables and equity premium. In contrast, without using any remedies, economic variables still show predicting power as long as sentiment stays low to not distort the link. In addition, we show that many non-fundamental predictors, such as time-series momentum and 52-week high, lose their power when sentiment is low since their power depends on behavioral activities significant only in high sentiment periods. As about 80% (20%) times can be classified as low (high) sentiment periods in our framework, fundamental predictors seem a more prevalent force than non-fundamental predictors in terms of forecasting equity premium. Nevertheless, investors can be better-off by utilizing both type of predictors though need to conduct a paradigm shift between fundamental predictors in low sentiment periods and non-fundamental predictors in high sentiment periods.

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

Keywords: Investors sentiment, Return forecast, Time-series momentum, 52-week high, Economic predictors

I. Introduction

Although the literature has provided theoretical justifications, intuitive reasons, and extensive empirical evidences for the forecasting ability of fundamental macroeconomic variables, there is a recent debate and even a doubt on the predicting power of fundamental macroeconomic variables (ECON variables; hereafter) (e.g., Cooper and Gulen, 2006; Welch and Goyal, 2008; Campbell and Thompson, 2008; Rapach, Strauss and Zhou, 2010). Moreover, some non-fundamental variables (NONFUND variables; hereafter), which are usually linked to behavioral justifications, are also recently found to be lack of robustness (e.g., Li and Yu, 2012).

Whether stock market returns or equity premium can be forecasted by certain predictors is an important question in financial economics (see Campbell and Thompson (2008) for a recent survey). Given the importance of return predictability and the set of recent influential studies debating on the predicting power of ECON variables and NONFUND variables, we aim to provide a unified answer to these debating studies by discussing and controlling for the impact of market sentiment.

First of all, why ECON variables do not have predicting power out-of-sample and their in-sample predicting power are also delicate and depending on a few years data as documented in Welch and Goyal (2008). The answer from us is that market sentiment can weaken the forecasting performance of the conventional macroeconomic variables by distorting the fundamental link between ECON variables and equity premium or expected market return.[1]

Some remedies, such as non-negativity constraint on the forecasted expected returns, are reported to work well to restore the predicting power of ECON variables. However, we show that these remedies are fragile and fail when stock market is going through a high investor sentiment period. The predictability is basically gone again even with the non-negativity constraint imposed when market sentiment is high. During high market sentiment periods, the fundamental link be-

[1]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 (2016) document that pervasive macro-related factors are priced in the cross-section of stock returns following low sentiment, but not following high sentiment.

tween ECON variables and expected equity return are distorted or broken. The predicting power then becomes too weak to be restored by those remedies. In contrast, during low market sentiment periods, the predicting power of ECON variables is significant even without those remedies. This is because the fundamental link is not distorted when sentiment stays low. The predicting power now becomes strong enough to be easily detected even without the help of those remedies. In this sense, those remedies are not relevant.

Therefore, the weak predicting performance of ECON variables found in Welch and Goyal (2008) is due to the lack of predicting power during periods when market sentiment is high. The remedies following Welch and Goyal (2008) improve the predicting power largely by addressing the issues of estimation errors/overfitting or parameter instability via imposing non-negativity constraint (Campbell and Thompson, 2008) or combining multiple forecasts (Rapach, Strauss and Zhou, 2010), etc. However, to our point of view, these remedies fail to address the key reason causing the seemingly weak predicting power of ECON variables documented in Welch and Goyal (2008), which is that the link between ECON variables and the expected market return, the underlying source of the predicting power, can be weakened significantly by market sentiment.

Secondly, recent studies report strong predictive power in forecasting excess market returns for various behavioral-bias-motivated NONFUND variables, such as time series momentum (Moskowitz, Ooi and Pedersen, 2012), anchoring variables (Li and Yu, 2012) and technical indicators (Brock, Lakonishok and LeBaron, 1992; Neely, Rapach, Tu and Zhou, 2014). However, some NONFUND variables, such as anchoring variables of Li and Yu (2012), turn out to be not robust.

Li and Yu (2012) motivate the predictability of their nearness to the 52-week high variable based on empirical evidence on psychological anchoring. However, they report that although nearness to the 52-week high based on DOW index does have significant predicting power, nearness to the 52-week high based on NYSE/AMEX total market value index turns out to have no forecasting power. This is really puzzling. Li and Yu (2012) provide strong argument and detailed explanations on why nearness to the 52-week high should have predicting power. The basic story is that investors tend to underreact to sporadic past news due to behavioral biases. Then, why the behavioral biases only matter when using Dow Jones Industrial Average index but not when using NYSE/AMEX total market value index to which Li and Yu (2012) do not provide a thorough explanation. Given there are many index funds tracking the performances of both Dow Jones Industrial Average index and NYSE/AMEX total market value index or their close proxies, it is kind of a puzzle to find underreaction in the Dow Jones Industrial Average index case but not for the NYSE/AMEX total market value index case.

In this paper, we address the puzzle from the perspective that a weak level of market sentiment can weaken the predictive strength of NONFUND variables by mitigating the impact of behavioral elements such as under-reaction and over-reaction (Barberis, Shleifer and Vishny, 1998; Hong and Stein, 1999). Indeed, when we split the sample into high and low sentiment periods, both nearness to the 52-week high based on DOW index and nearness to the 52-week high based on NYSE/AMEX index do have predicting power during high sentiment periods. In contrast, both of them do not have predicting power during low sentiment periods. Our results indicates that the ability of psychological anchors in predicting aggregate excess market return is not special for the Dow index only. Anchoring variables constructed based on other indices, no matter capturing market-wide information (e.g., Dow) or firm specific information (e.g., NYSE/AMEX), all present substantial predictive power in forecasting aggregate excess market return once we have understood and controlled the impact of market sentiment.

Overall, a strong level of market sentiment may significantly weaken the forecasting ability of ECON variables while a weak level of market sentiment may substantially deteriorate the predictive power of NONFUND variables. This provides a unified answer to why we observe the weak or lack of robust predicting performance in recent studies, such as Welch and Goyal (2008) and Li and Yu (2012). Once we have understood and controlled the impact of market sentiment, the underlying reason of these weakness and unrobustness, both ECON varibles and NONFUND variables turn out to have robust predicting power. The predicting power is independent from the prevalent remedies in recent literature or the specific index used, such as DOW or NYSE/AMEX.

Thirdly, in this paper, a regime-switching model is used (for the first time to our knowledge) to classify the time periods into two sentiment regimes, one with relatively high market sentiment while the other with relatively low market sentiment. In contrast, an ad hoc way of classifying sentiment regime is usually adopted in the existing studies. For example, one popular way is to split at the median level: above the median is classified as high sentiment regime while below the median is classified as low sentiment regime. Although such ad hoc way of classifying sentiment regime appears to be qualitatively similar in terms of capturing the idea that the market sentiment varies across high and low levels over time, it has certain limitations. For instance, splitting at the median would naively assume that sentiment is equally likely to prevail at a high or low level.

However, our proposed regime-switching model empirically indicates that there is about 80% (20%) times to be in low (high) sentiment regime. Then the equality assumption of being in high and low sentiment regimes could be a strong restriction and yield some potentially misleading implications. For instance, this will lead to a message that both ECON variables and NONFUND variables can offer comparable predictability given that either ECON variables or NONFUND variables can only predict returns in half of the times. This messages is not new in the sense that the existing literature seems also indicating both ECON variables and NONFUND variables can offer comparable predictability. However, by relaxing the equality assumption of being in high and low sentiment regimes, our study provides a new and unique evidence suggesting that ECON variables could be a more prevalent force than NONFUND variables in terms of the time periods of having predictive power. Moreover, we show that investors can be better-off by conducting paradigm shifts between fundamental predictors in low sentiment periods and non-fundamental predictors in high sentiment periods.

Finally, we propose a simple model to theoretically illustrate the mechanism of an asymmetric impact of sentiment on the performance of NONFUND predictors, such as time series momentum. More specifically, during high sentiment period, a noise investor tends to take long positions while a rational investor cannot arbitrage away mispricing due to short sale constraints. Therefore, price comprises a fundamental component and a mispricing component. However, as the noise investor observes new information, he corrects his beliefs through a learning process and the mispricing component is gradually removed accordingly. Consequently, the price gradually converges towards the fundamental component and momentum arises as a result. In contrast, during low sentiment period, the rational investor faces no constraints and the price is always adjusted immediately to its fundamental. Hence there is no momentum effect in low sentiment regime.

From a broad perspective, this paper is related to but also different from the literature on the impact of investor sentiment. Baker and Wurgler (2006, 2007) find that high investor sentiment predicts low returns in the cross-section, especially for stocks that are speculative and hard to arbitrage. Stambaugh, Yu and Yuan (2012) show that financial anomalies become stronger following high investor sentiment. Distinct from the studies which document the cross-sectional impact of sentiment, in this paper, we document that sentiment can have strong implications on aggregate market return predictability over time. Our findings are in line with the predictions of many prominent behavioral asset pricing theories, including Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) that all focus on a single risky asset, therefore having direct implications for time series rather than cross-sectional predictability. Our paper also closely resembles 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. In addition, this study 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), the idiosyncratic volatility puzzle (Stambaugh, Yu and Yuan, 2015), the momentum phenomenon (Antoniou, Doukas and Subrahmanyam, 2013), the slope of security market line (Antoniou, Doukas and Subrahmanyam, 2015) and hedge fund investment (Smith, Wang, Wang and Zychowicz, 2015).[2]

The rest of the paper is organized as follows. We present an econometric methodology in

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

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 VII concludes. In Appendix, we present a simple model to illustrate the intuition of sentiment-related forecasting power.

II. Econometric Methodology

In this section, we first follow the conventional predictive regression model under a single regime framework to analyse the overall return forecasting performance. Then, we implement a regime-dependent predictive regression model in order to examine the predictive performance conditional on different sentiment regimes. We also detail the method to identify sentiment regime and the procedures to construct both fundamental and non-fundamental predictors.

A. Single-regime predictive regression

To evaluate the overall return predictive performance for individual macroeconomic 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 the equity premium r_{t+1} is the excess return of a broad stock market index from the risk-free rate over the time period of t to $t+1$, $x_{i,t}$ is a macroeconomic predictor, and $\varepsilon_{i,t+1}$ is a zero-mean unforecastable term. Consequently the expected excess return based on 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 p-values using a wild bootstrap procedure which accounts for the persistence in predictors, correlations between equity premium and predictor innovations, as well as heteroskedasticity.

To examine the overall forecasting performance for individual non-fundamental variables, similarly, we follow the conventional regression model in the literature,

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

where $m_{j,t}$ is a non-fundamental predictor.

The forecasting power of individual predictors can be unstable across time since each one of them can be just one specific proxy (with noise) of some common fundamental condition (like the economy is doing well or doing badly) for macroeconomic variables or of some common trend condition (like the market is trending up or trending down) for non-fundamental variables. 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, respectively,

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

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 the extracted fundamental ECON variable from individual fundamental predictors and m_t is the extracted NONFUND variable from individual non-fundamental predictors by applying partial least squares procedure to individual fundamental and non-fundamental variables respectively.

To incorporate information from the entire set of fundamental and non-fundamental variables, we estimate parsimoniously a predictive regression based on the combined ECON variable μ_t in (4) and the combined NONFUND 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 stock market. Empirically, the market sentiment is not always high or always low, but more likely to shift between high and low sentiment regimes. Consequently, the forecasting performances of the two main categories of predictors, namely, fundamental economic variables and non-fundamental variables, may significantly depend on the level of investor sentiment. Motivated by this, we extend the above single-regime predictive regression to regime-dependent regression. As a consequence, we allow 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,

$$r_{t+1}^i = a_\mu^i + b_\mu^i \mu_t^i + \varepsilon_{t+1}^i, \qquad i = H, L \tag{7}$$

$$r_{t+1}^i = a_m^i + b_m^i m_t^i + \varepsilon_{t+1}^i, \qquad i = H, L \tag{8}$$

$$r_{t+1}^i = a^i + b_1^i \mu_t^i + b_2^i m_t^i + \varepsilon_{t+1}^i, \qquad i = H, L \tag{9}$$

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

We rely on 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}

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

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.[3] To back out unobservable regime from the data, we assume 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, a low sentiment period occurs.

C. Fundamental variables

For fundamental variables, we consider a wide range of macroeconomic series used in Jurado, Ludvigson and Ng (2015) as the macroeconomic fundamentals, where more than one hundred macroeconomic series 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 (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[4], we have seven categories of macroeconomic variables, including (1) output and income; (2) labour market; (3) housing; (4) consumption, orders and inventories; (5) money and credit; (6) exchange rates; and (7) prices. We implement principal component analysis (PCA) to derive 7 individual macroeconomic predictors from 7 categories of macroeconomic variables (denoted as $F_{jt},\ j = 1,2,\cdots,7$).[5] The seven extracted series may be treated as a set of representative macroeconomic predictors.[6]

[3]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 the refinement would not add much economic insight compared to the increased complexity and computational costs.

[4]We exclude these variables because they are financial variables which may contain sentiment related content.

[5]We take the first principal component from each category of macroeconomic variables as the first principal component usually captures a higher proportion of total variations in the individual proxies than the other principal components and incorporating more principal components will increase estimating noise and worsen the out-of-sample performance.

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

D. Non-fundamental variables

We collect a variety of behavioral/sentiment-related variables, which are frequently found to deliver significantly predictive ability in the forecasting literature but difficult to be explained by the rational finance theory, including the time series momentum (Moskowitz, Ooi and Pedersen, 2012), the anchoring variables (Li and Yu, 2012) and technical indicators (Neely, Rapach, Tu and Zhou, 2014).

For a large set of futures and forward contracts, Moskowitz, Ooi and Pedersen (2012) provide strong evidence for time series momentum that characterizes significantly positive predictability of the moving average of a security's own past returns. Following the literature, we use the moving averages of historical excess returns with different horizons as the momentum proxies in this paper. Particularly, we consider a vector of momentum variables with diversified horizons varying from 6 months to 12 months.[7] 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 the nearness to the Dow 52-week high and the 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 but opposite forecasting power for the aggregate stock market returns. More specifically, the nearness to the Dow 52-week high $x_{52,t}$ and the 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 $x_{52,t}$

[7] In this paper we consider the time series momentum variables with horizons up to 12 months following the time series momentum literature. We also consider other moving averages in (11) with longer time horizon and find that the loadings are positive up to 18 months and then become negative for longer horizons. Our results are not sensitive to the alternative choices.

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 at the last trading day of month t. 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 also construct the anchoring predictor $\hat{x}_{52,t}$, which is the nearness to the 52-week high orthogonal to the nearness to the historical high. And use $\hat{x}_{52,t}$ as one of our NONFUND variables. We expect $\hat{x}_{52,t}$ to be a more pure proxy for underreaction by removing potential overreaction part of it via controlling for nearness to the historical high.

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

Neely, Rapach, Tu and Zhou (2014) show that technical indicators display statistically and economically significant predictive power and complementary information in terms of macroeconomic variables. We also incorporate two moving-average (MA) indicators with 1-month short MA and 9- or 12-month long MA (denoted as $MA(1,9)$ and $MA(1,12)$ respectively) used 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 by 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 analyse monthly MA rules with $s = 1$ and $l = 9, 12$.[8]

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 or from various non-fundamental variables into one consensus combined variable. 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 used in (4) from the N_1 fundamental economic proxies $X_t = \{X_{1,t}, X_{2,t}, \cdots, X_{N_1,t}\}$, 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

[8] We find similar pattern if 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) by the variable $MA_{s,t} - MA_{l,t}$. The patterns are similar to but less significant than the "0/1" technical indicators (not reported here).

irrelevant to returns respectively, and $u_{i,t}$ 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, to 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 principle 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 PLS procedure to M_t. We refer this aligned approach to Huang et al. (2015) for details.[9]

[9]By comparing to the first principle 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 and hence the variables using PLS should outperform those using PCA.

III. Data Summary

A. Sentiment regimes

We estimate the regime switching parameters for sentiment by applying maximum likelihood estimation method (MLE) and report the result in Figure 1. The sentiment data spans from 1965:07 to 2010:12.[10]. The solid blue line in Figure 1 (a) depicts the estimated probability π_t of investor sentiment being at regime H (high sentiment). Generally, long periods of relative calm market sentiment is interrupted by short periods of extremely high sentiment, which occur at the end of 1960s, the first half of 1980s and the beginning of 2000. To help interpreting the asymmetry in high and low sentiment regimes, we may think of regime L as representing relatively normal sentiment states while regime H capturing more crazy sentiment phases which lead to steep increases in the level of market sentiment. Alternatively, we also follow Stambaugh et al. (2012) to define a high-sentiment month as one in which the value of BW sentiment index (Baker and Wurgler 2006, 2007) in the previous month is above the median value for the sample period, and a low-sentiment month that is 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). The numbers of high/low-sentiment months are $116/430$ (21.25% in high regime and 78.75% in low regime) based on Markov switching approach and $273/273$ (50% in high regime and 50% in low regime) based on the median level. The correlation between the two regimes estimated by the regime switching method and the median level is 0.54.

Figure 1 (b) and (c) depict the investor sentiment index from July of 1965 to December of 2010 where the shaded areas are the high sentiment months estimated by the regime switching approach in (b) and the median level in (c) respectively. Specifically, the high sentiment periods identified by regime switching model (10) coincide well with the anecdotal evidences, 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 mid 1980s (involving natural resource start ups in early 1980s after the second oil crises and the hightech and biotech booms in the first half of 1983), and

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

the Internet bubble occurring in the late 1990s and beginning of 2000s.

B. Data and Summary statistics

Consistent with existing literature on predicting aggregate market return, we measure 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.[11] Panel A of Table 1 reports summary statistics of monthly equity premium. The moments of excess market returns are different between high and low sentiment regimes. The mean of the excess market returns during high sentiment regime is -0.07%, which is much lower than its counterpart during low sentiment regime (0.41%). This pattern is consistent with the general hypothesis documented by the existing literature that high sentiment drives up the price and depresses the return. Moreover, the standard deviations of excess market returns across sentiment regimes are much closer, yielding a higher realized Sharpe ratio during low sentiment regime. The overall stock market displays weak time-series momentum alike pattern with a positive first-order autocorrelation of 0.06 whereas during high sentiment regime the market returns become more persistent with a first-order autocorrelation of around 0.10. 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 shows more stable patterns overall than the individual predictors: it displays higher average level, is slightly more volatile and less persistent during high sentiment regime. By contrast, the seven individual macroeconomic predictors F_i, $i = 1,2,3,4,5,6,7$ hardly exhibit consistent patterns across sentiment regimes possibly due to the noise in individual variables. Hence, we summarize information by extracting common components from various individual forecasting variables to alleviate the potential noise in each individual proxy.

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 PLS procedure to the seven fundamental variables F_{jt}, $j = 1,2,\cdots,7$, we

[11] The monthly data is from Center for Research in Security Press (CRSP).

obtain a combined ECON 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. Panel A of Figure 3 depicts the time series of the combined fundamental predictor μ_t, where the shaded areas are high sentiment regimes. Interestingly, for all of the three continuous high sentiment periods, μ_t reaches local minima near market sentiment peaks. The above equation (18) displays the estimated loadings for the 7 individual macroeconomic predictors F_{it}, $i = 1,2,3,4,5,6,7$ on the combined fundamental predictor μ_t. It reveals that macroeconomic factors extracted from labour 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 better forecast the equity risk premium than individual macroeconomic predictors. As shown later in Panel A of Table 3, the signs of the regression coefficients on the seven economic variables are consistent with the fact that each one of the seven economic variables is one specific proxy of some common fundamental economic conditions.

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

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

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 display a less smooth pattern than that of μ_t. In contrast to the findings based on μ_t, m_t arrives at local maxima near market sentiment peaks and drops abruptly as long as it turns into the high market 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 each of the individual non-fundamental variables. As shown later in Table 3, the extracted NONFUND variables forecast equity risk premium with 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 fundamental economic variables and non-fundamental variables for both the full sample and high/low sentiment regime determined by the Markov regime-switching approach (10). Our data spans from July of 1965 to December of 2010 because of availability of sentiment series. We address several robustness issues in Section C, such as the predictability of anchoring variables based on alternative indices, the removal of Oil shock period, sentiment regimes determined by median level and predictability during expansions. Furthermore, we conduct out-of-sample analysis in Section D.

A. Mispricing across sentiment regimes

We explore the distinct patterns of mispricing across high and low sentiment regimes using 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 simple average of the 17 long-short anomaly returns,[12] and report pricing errors (returns adjusted by benchmark factor models) during high and low sentiment regimes respectively in Table 2. The baseline regression is as follows:

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

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

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

The results in Table 2 reveal that pricing errors indicated by the long-short anomaly returns are generally higher following high sentiment. Specifically, the combined long-short benchmark-adjustment anomaly return earns 99 bps more per month following high sentiment using Carhart four-factor model as a benchmark. Furthermore, mispricing mainly comes from high sentiment regime, with average mispricing (measured as the combined long-short benchmark-adjustment anomaly return) in high-sentiment months accounting for 81% of overall average mispricing using Carhart four-factor model as the benchmark. The tendencies are consistent with the findings in Stambaugh et al. (2012) which use median level Baker and Wurgler sentiment index to differentiate high and low sentiment periods, showing 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 high and low sentiment regimes echoes our following findings that sentiment plays a pervasive role over time in affecting predictability.

B. In-sample predictive performances across sentiment regimes

We focus our empirical analysis on one-month horizon, with reasons in three aspects. 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). Last but not least, as market sentiment evolves through time, longer-horizon predictive regressions would include random combinations of high and low sentiment periods that would undoubtedly obscure the forecasting performance of predictors.

We start from examining the overall forecasting performances of ECON and NONFUND variables during full sample, and then compare the predictive strength of ECON and NONFUND variables during high and low sentiment regimes respectively. When ECON and NONFUND 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. We address this concern by computing p-values using a wild bootstrap procedure that accounts for complications in statistical inferences. Table 3 summarizes the differences in in-sample predictive relations between high and low sentiment regimes for ECON and NONFUND variables. Panels A and B in Table 3 report the regression coefficients, corresponding t-statistics and R^2s for the seven individual fundamental and six non-fundamental variables respectively. Panel C reports the regression results for the combined ECON and NONFUND variables. All the standard errors are adjusted for heteroskedasticity 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 lead to complementary patterns for ECON and NONFUND variables.

Firstly, economic variables, both the individual and the combined, perform well during whole sample and the low sentiment periods, but the predictive strength attenuates during high sentiment regime. Specifically, Panel A indicates that overall predictability of individual economic variables mainly concentrates in the low sentiment regime. Among the seven fundamental predictors, the fourth predictor F_{4t} has a sizeable in-sample R^2 statistics of 2.54% during low 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 insignificantly predicting future stock returns at conventional levels. This pattern still holds in Panel C for the combined ECON variable which is insignificant in the high periods, but significant with a t-statistic of 3.47 and R^2 of 2.51% over the total available sample, and a t-statistic of 3.85 and R^2 of 3.52% over the low sentiment periods. This supports our findings that, at individual predictor level, predictability of ECON variable is driven primarily by low sentiment periods. Furthermore, the coefficient estimate for the combined ECON variable is economically large. More explicitly one standard deviation increase in the combined ECON variable μ_t predicts an increase of 0.71% and 0.84% in expected market return over the whole sample and the low sentiment periods respectively.

Secondly, predictive performances of individual non-fundamental variables and the combined NONFUND variable are much stronger during high sentiment regime than during low sentiment regime. For instance, Panel B shows that the predictive coefficients of NONFUND variables at individual predictor level are, indeed, different across sentiment regimes, with larger predictive power occurs during high sentiment regime. Moreover, each of the six individual non-fundamental variables significantly forecasts equity risk premium in periods of high sentiment. Particularly, within the six individual non-fundamental variables, 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 rest non-fundamental predictors, with in-sample R^2 statistics ranging from 2.71% to 4.41% in periods of high sentiment. Nevertheless, we fail to find significant predictability from NONFUND variables in the low sentiment periods. This pattern extends to Panel C for the combined NONFUND variable, which is demonstrated by a significant t-statistics of 3.27 and R^2 of 4.07% during high sentiment regime and an insignificant t-statistics of 0.65 and R^2 of around 0.1% during low sentiment regime. This indicates that the predictability of NONFUND variable predominantly exists in high sentiment periods. In addition, when sentiment is high, one standard deviation increase in the combined NONFUND variable m_t corresponds to an increase of 0.89% in future excess market return, more than two times larger than that over entire sample period.[13]

Thirdly, as monthly stock returns inherently contain a substantial unpredictable component, a monthly R^2 near 0.5% can predict 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 exceed this 0.5% benchmark for regressions with both ECON variable μ_t and NONFUND variable m_t.[14]

We summarize in Figure 4 the cross-regime differences in correlations between excess market return and the two categories of the combined predictors, as well as regression coefficients, t-

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

[14] We also consider the case that m_t is orthogonalized to μ_t (or μ_t is orthogonalized to m_t) to eliminate the overlapping forecasting power and find the same patterns as in Table 3 (not reported here).

statistics and R^2s in percentage points based on the two categories of combined predictors. The first row in Figure 4 shows that μ_t is more highly correlated with excess market return during the low sentiment regime while m_t correlates more 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 categories of combined predictors μ_t and m_t, with higher beta, higher t-statistics and higher R^2 for fundamental predictor μ_t during low sentiment regime and higher beta, higher t-statistics and higher R^2 for non-fundamental predictor m_t during 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, which represent in-sample estimates of the expected equity premium. The expected equity premium for μ_t in Panel A of Figure 5 displays a relatively smooth pattern, in line with the picture in Panel A of Figure 3. The overall movements in the expected equity premium for m_t in Panel B of Figure 5 are relatively more abrupt, in line with the trend in Panel B of Figure 3. When information in μ_t and m_t is combined together in 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 reconciles the fluctuations in expected equity premium based on either μ_t or m_t alone.

To sum up, when the investor sentiment is shifting between high and low levels, our findings yield a few overall implications. Firstly, the economic variables indeed have strong forecasting ability as long as market sentiment is not high, otherwise the economic variables lose their predictive power while the predictability of the non-fundamental variables becomes strong. Secondly, the predictability of the non-fundamental variables tends to vanish away when the investor sentiment drops to a low level, while the economic variables obtain their predictive power back. The above patterns are further confirmed when using both ECON and NONFUND variables as predictors and the results are summarized in the last three columns in Panel C of Table 3. Moreover, with about 80% times of low sentiment periods, the results suggest that economic variables could be a more prevalent force than non-fundamental variables in terms of time periods with significant predictive power.

C. Discussion

In this section, we conduct various robustness analyses from Section C.1 to Section C.4 by constructing anchoring variable using alternative indices, addressing the effect of the Oil Shock recession from 1973 to 1975, considering an ad hoc way of classifying sentiment regimes, and examining the predictability during economic expansion and recession periods.

C.1 Discussion on the predictability of anchoring variable

Li and Yu (2012) find strong predictability of two psychological anchors, the nearness to the 52-week high $x_{52,t} = \frac{p_t}{p_{52,t}}$ and the nearness to the historical high $x_{max,t} = \frac{p_t}{p_{max,t}}$ using daily stock prices of Dow Jones Industrial Average index. The rational is that when the value of nearness to the 52-week high is small, or the current price level is far below the 52-week high, it is likely that the firm has experienced sporadic bad news in the recent past. A conservatism bias with psychological evidence suggests that investors could underreact to this bad news in the recent past. This underreaction story is also consistent with the experimental research on 'adjustment and anchoring bias'. For instance, past bad news can push a stock's price far below 52-week high, investors then may become reluctant to bid the price of the stock further down a lot even if the information justifies a large drop, leading to underreaction. Later, when the bad information is eventually absorbed and the underreaction is corrected, the price falls down to the correct level. This leads to a lower return in the next period. As a consequence, a smaller $x_{52,t}$ predicts a lower return or nearness to the 52-week high is expected to be positively associated with future returns.

In addition, if $x_{max,t}$ is large or 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 in the past. Then psychological evidenced representativeness indicates that investors could overreact to a series of good news, and this leads to subsequent lower returns in the future. As a consequence, a larger $x_{max,t}$ predicts a lower return or 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 also control the nearness to the historical high $x_{max,t}$ along with the nearness to the 52-week high $x_{52,t}$.

In addition, Li and Yu (2012) indicate that for the negative predictive power of nearness to the historical high, on top of the overreaction story, an explanation based on rational model with a mean-reverting state variable can not be ruled out. Given that nearness to the historical high $x_{max,t}$ could be partially a non-fundamental predictor and partially a fundamental predictor, the impact of market sentiment on the predictability of nearness to the historical high $x_{max,t}$ could be unclear. Hence, we focus on the the nearness to the 52-week high in our study.

In this section, on top of using the daily stock prices of Dow Jones Industrial Average index, we alternatively calculate the two psychological anchoring variables, the nearness to the 52-week high $x_{52,t}$ and the nearness to the historical high $x_{max,t}$ using daily NYSE/AMEX total market value index and stock prices of S&P 500 index, respectively. The three panels in Table 4 presents in-sample regression results of $x_{52,t}$ based on Dow Jones Industrial Average index, NYSE/AMEX total market value index and S&P 500 index, respectively, in predicting future monthly NYSE/AMEX value-weighted excess returns.[15]

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 Dow Jones Industrial Average index exhibits significant predictability during the whole sample period, the predictive power is only strong during the high sentiment regime but disappears in the low sentiment regime.

Panel B of Table 4 indicates that the predictive power of $x_{52,t}$ based on NYSE/AMEX total market value index is weak and not significant over the whole sample, same as reported in Li

[15]Following Li and Yu (2012), we control past return, the nearness to the historical high, historical high indicator, and 52-week high equal-historical high indicator in these regressions. In addition, in the other places, we follow Welch and Goyal (2008) to predict future monthly S&P 500 excess returns. Only in this table, for an easy comparison with Li and Yu (2012), we change to predict monthly NYSE/AMEX value-weighted excess returns.

and Yu (2012). Actually, this is kind of puzzling. Li and Yu (2012) provide strong argument and detailed explanations on why nearness to the 52-week high should have predicting power as summarized in the above. The basic story is that investors tend to underreact to sporadic past news due to behavioral biases. Then, why the behavioral bias only kicks in when using Dow Jones Industrial Average index but not when using NYSE/AMEX total market value index? Li and Yu (2012) do not provide any thorough discussion for the loss of predicting power of nearness to the 52-week high when Dow Jones Industrial Average index is replaced by NYSE/AMEX total market value index.[16]

Given there are many index funds tracking the performances of both Dow Jones Industrial Average index and NYSE/AMEX total market value index or their close proxies, it is really a puzzle to find underreaction in the Dow Jones Industrial Average index case but not for the NYSE/AMEX total market value index case. However, once conditional on a high sentiment regime, nearness to the 52-week high based on NYSE/AMEX total market value index becomes very strong and significant during the high sentiment regime, with a t-statistic of 3.76 almost three times higher than the t-statistic of 1.30 in the whole sample and the t-statistic of 1.37 in the low sentiment regime. Panel C of Table 4 reports the results for nearness to the 52-week high based on S&P 500 index, which supports the argument that the predicting power of nearness to the 52-week high is strong no matter which index used as long as market sentiment is high. All of these results indicate that the ability of psychological anchors in predicting aggregate excess market return is not special for the Dow index only. Anchoring variables constructed based on other indices, no matter capturing market-wide information (e.g., Dow) or firm specific information (e.g., NYSE/AMEX), all present substantial predictive power in forecasting aggregate excess market return once we understood and controlled for the impact of market sentiment.

[16]Li and Yu (2012) use "limited attention" to explain why nearness to the historical high has weaker predicting power when Dow Jones Industrial Average index is replaced by NYSE/AMEX total market value index. Li and Yu (2012) claim that Dow index represents more visible market-wide information and investors usually pay more attention to market-wide (Dow) rather than firm-specific information (NYSE/AMEX). However, they do not offer a thorough reason for the loss of predicting power for the other anchoring variable, the nearness to the 52-week high when DOW is replaced by NYSE/AMEX.

C.2 The effect of Oil shock period

We address the effect of the oil shock period in this section. Welch and Goyal (2008) comprehensively examine the forecasting powers of a large set of economic variables. They find that the predictive power of those economic variables seems largely depending on the period of the Oil Shock between 1973 and 1975 and most forecasting models have performed poorly in period after year 1975. To address this issue, we first examine the in sample 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 (although less significant) to those in Panel C of Table 3.

Next, we re-run the regressions by excluding the Oil Shock recession period from 1973 to 1975. Specifically, the sample period in Table 6 spans from 1965.07 to 2010.12, with the Oil Shock recession period from 1973 to 1975 excluded. Panel A of Table 6 shows that exclusion of this period does not alter our results greatly. The ECON variable still performs well in the whole sample and low sentiment regime while NONFUND variable still has significant forecasting power in the high sentiment regime. Moreover, after removing the 1973-75 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 in Table 3. Since the Oil Shock recession is within our low sentiment periods, the results for high sentiment regime are less affected.

C.3 Ad hoc way of classifying sentiment regimes

We alternatively re-estimate the regimes based on the median level. More specifically, we follow Stambaugh et al. (2012) to define a high-sentiment month as one in which the value of the BW sentiment index (Baker and Wurgler 2006, 2007) in the previous month is above the median value for the sample period, and the low-sentiment months as those with below-median values. Panel B of Table 6 reports the results when the regimes are determined by the median level. In regime H, comparing to the results in Panel C of Table 3, the coefficients and t-statistics become larger for ECON variable μ_t but smaller for NONFUND variable m_t. The reason seems straightforward. The high regime months according to the regime switching approach (10) increase from approximately 20% of the whole sample periods to around 50% when the regimes are determined by the median level. The sentiment in this additional 30% months is higher than the median but lower than in the 20% high regime. Therefore this additional 30% months lead to a smaller mean value of sentiment in the high regime based on 50%-50% cutoff, which is expected to strengthen the forecasting power of ECON variable while weakening the predictive strength of NONFUND variable.

C.4 Predictability during expansions

Enormous studies document the evidence that the predictive ability of economic variables concentrates in recession periods with little forecasting power during expansions. It is therefore interesting to see whether the forecasting patterns of the ECON and NONFUND variables are affected during business cycle expansions and recessions documented by National Bureau of Economic Research (NBER). The expansion periods are labelled as EXP and recession by REC. During the whole sample period from 07/1965 to 12/2010, 456 months are classified as EXP while 90 months are identified as REC. Figure 2 illustrates the NBER recession dummy from 07/1965 to 12/2010. For comparison, we also plot the high sentiment months estimated by the regime switching method (10) as the shaded area in Figure 2. Our sentiment regimes do not co-move much with business cycles, with a low correlation of 0.23 between NBER recession dummy and high sentiment dummy.

We re-run the regressions in Table 3 based on expansion periods only and detail the results in Table 7. The 'whole sample period' in Table 7 refers to the expansion periods and high/low months are the corresponding months in which investor sentiment is high/low during the expansion periods. We find similar predictive patterns over the expansion periods. The combined fundamental predictor μ_t is significant in both the whole expansion periods and low sentiment months while insignificant in the high sentiment months; the combined non-fundamental variable m_t is significant in the high sentiment months but insignificant in the whole expansion periods and the low sentiment months.

D. Out-of-sample analysis

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.[17] More importantly, some recent studies argue that out-of-sample forecasting performance of fundamental variables can be substantially improved by imposing some additional restrictions on forecasting regressions. It raises the question whether the fundamental variables still display poor out-of-sample performance during high sentiment periods even if we have added those recent remedies and whether the 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 fundamental and non-fundamental variables are indeed driven by the underlying behavioral force of investor sentiment rather than those additional remedies. Particularly, a high level of market sentiment distorts the link between fundamental variables and equity premium while it boosts the underlying behavioral activities such as underreactions and overreactions behind non-fundamental predictors. 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 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 the concern of look ahead bias,

[17] 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).

we use 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 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 at regime H (L) at time t, then we regress $\{R_s\}_{s=2}^{t}$ on $\{\mu_s\}_{s=1}^{t-1}$ and $\{m_s\}_{s=1}^{t-1}$ at regime H (L) and the out-of-sample forecast at regime H (L) at time $t+1$ is given by (21).

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

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,

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

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, and individual economic variables typically fail to outperform the historical average. 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 at regime H (L) is calculated using the out-of-sample forecasts at regime H (L) and realized returns r_{t+1} at the same time periods.

We select the first $1/2$ sample as the training sample. Panel A of Table 8 reports the differences in out-of sample predictive performances of ECON and NONFUND predictors across sentiment regimes.[18] The results have several implications. Firstly, when we use ECON variable as the only predictor, Column 3 shows that the R^2_{OS} is positive and exceeds the 0.5% benchmark (Campbell and Thompson, 2008) in the low sentiment regime, while it becomes negative in the high sentiment regime and also the whole sample period. This indicates that ECON variable has predictive power in low regime without imposing any prevalent remedies proposed in recent literature, while it underperforms the historical average benchmark in both the high sentiment regime and the full sample period. This collaborates our in sample results. Secondly, when we use NONFUND variable as the only predictor, Column 4 in Panel A shows that the NONFUND variable fails to outperform the historical average benchmark in low regime, as indicated by the corresponding negative R^2_{OS}. Column 4 also verifies that NONFUND variable tends to perform considerably better in high regime. This is indicated by observation that R^2_{OS} rises sharply from -0.90% in low sentiment regime to a positive value of 3.30% in high sentiment regime - an increase of more than four times, highlighting the importance of considering shifts in market sentiment in predicting stock returns. The complementary roles of the two major categories of predictors, fundamental and non-fundamental, infer that the two groups indeed capture different information relevant for predicting equity risk premium, supporting the findings in Neely et al. (2014). Additionally, we find that compared with using fundamental or non-fundamental information alone, or incorporating both of them, the out-of-sample predictability can be improved substantially when we consider a switching predictor combining both ECON and NONFUND variables with an sentiment regime indicator. Specifically, we take NONFUND variable m_t as predictor in high sentiment regime and ECON variable μ_t as forecasting variable in low sentiment regime. That is, we use $I_{H,t}m_t + (1 - I_{H,t})\mu_t$ as a predictor in (21), where $I_{H,t}$ is the indicator of regime H. Column 6 shows that the corresponding R^2_{OS} reaches a positive value of 1.38%. Furthermore, the R^2_{OS} of the switching predictor is greater than all the counterparts in Columns 3-5 during whole sample period. Therefore we claim that combining fundamental and non-fundamental predictors with information embedded in sentiment regimes

[18] To reduce estimation errors, at each period t we estimate the weights of individual predictors according to partial least squares analysis, and set the 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.

better captures the substantial fluctuations in equity risk premium than using either fundamental or non-fundamental predictor, or both of them.

Moreover, given the recent debate and doubt about whether fundamental economic variables can predict equity premium, some remedies are provided to restore the confidence on predictability. For instance, Campbell and Thompson (2008) provide some remedies by imposing certain economic rationale based constraints. One important constraint imposed in their paper is that the forecasted expected premium cannot be negative. They show that the predicting performance (especially out-of-sample) can be improved significantly once this non-negativity constraint is imposed. Following Campbell and Thompson (2008), we impose positive forecast constraint on out-of-sample forecasting analysis with the results reported in Panel B of Table 8. It shows that the predictability is gone again during high sentiment periods, even with the non-negativity constraint imposed. In contrast, Panel A also shows that economic variables do have predicting power during low sentiment periods, even without imposing the non-negativity constraint.

We adopt another remedy, the mean combination forecast approach in Rapach, Strauss and Zhou (2010), when carrying out out-of-sample forecasting analysis. The results are reported in Panel C of Table 8. Similarly, the results show that the predictability is gone again during high sentiment periods, even with the mean combination forecast approach utilized. In contrast, Panel A shows that economic variables do have predicting power during low sentiment periods, even without the mean combination forecast approach utilized. Overall, the market sentiment plays an important role given that it can distort the fundamental link between economic variables and equity premium. Without controlling this sentiment effect, the existing remedies, such as those in Campbell and Thompson (2008) and Rapach et al. (2010), are fragile.

V. Further Analysis

In this section, we first extend the aggregate market analysis to ten value-weighted portfolios of stocks sorted by firm size. Then we consider non-linear specifications on ”high” and ”low” sentiment effect. We also identify high and low sentiment regimes using purged sentiment index in Chu, Du and Tu (2016) to address the concern that Baker and Wurgler sentiment index contains component largely driven by business cycle and risk related factors. Finally, we explore the possible economic channels on the predictability of fundamental and non-fundamental variables.

A. Forecasting portfolios

The above analysis is based on the aggregate market index. It is interesting to know if the results still hold at portfolio level with different size. We obtain portfolio data from Kenneth R. French's Web site[19] and examine the returns on the ten value-weighted portfolios of stocks sorted by firm size. We focus on the combined ECON variable μ_t and the combined NONFUND variable m_t in Section IV.B to estimate single-regime predictive regression (6) in the whole sample and regime-dependent predictive regression (9) during high and low regimes for each portfolio. The results summarized in Table 9 reveal that, across all the ten portfolios, the forecasting strength of the combined ECON variable μ_t is strong in the whole sample period and especially during the low sentiment regime, but μ_t becomes less significant in the high sentiment regime. In contrast, the predictive ability of the combined NONFUND variable m_t is strong in the high regime, but weak in the low regime, according to the Newey-West t-statistics and empirical p-values. In addition, all the R^2 statistics exceed the 0.5% benchmark.

Baker and Wurgler (2006) investigate long-short spread portfolios formed on firm age (age), dividend to book equity (D/BE), external finance to assets (EF/A), earnings to book equity (E/BE), growth in sales (GS), property, plant and equipment to total assets (PPE/A), R&D to total assets (RD/A), stock return volatility (sigma), market equity (ME), and book to market equity (B/M). We also form the spread portfolios following the procedures exactly documented in Baker and Wurgler (2006) and examine the ECON and NONFUND variables in the whole sample, the high and low regimes. We find (not reported here) very similar patterns to the ten size portfolios reported in Table 9. In summary, the results imply that similar predictability pattern holds at portfolio level in

[19] *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*

addition to the aggregate market level.

B. Robustness on "High" and "Low" sentiment effect

We further employ several robustness checks on alternative specifications on "High" and "Low" sentiment effect.

We conduct in sample regressions by directly examining the sensitivity of aggregate market return to variation in investor sentiment in Table 10. We consider in sample regression with the interactive term of investor sentiment S_t and the combined fundamental μ_t (non-fundamental predictor m_t) as

$$r_{t+1} = \alpha + (\beta_0 + \beta_1 S_t)x_t + \varepsilon_{t+1}$$

where $x_t = \mu_t$ or $x_t = m_t$. We are particularly interested in the sign of the coefficient β_1 as it captures the effect of sentiment on the predictive performance for the two main categories of predictors. Table 10 documents that β_1 is significantly negative for the combined fundamental μ_t while it is significantly positive for the combined non-fundamental m_t, which is consistent with our main results in Table 3 that high sentiment deteriorates the predictive performance of fundamental variable while it boosts the forecasting power of non-fundamental variable.

Moreover, in order to explore the effects of high and low sentiment, we construct the positive part of sentiment $S_t^+ = \max\{S_t, 0\}$, and the negative part of sentiment $S_t^- = \min\{S_t, 0\}$ by following Shen, Yu and Zhao (2016). We replace S_t with S_t^+ and S_t^- respectively by conducting two types of in sample regressions separately: $r_{t+1} = \alpha + (\beta_0 + \beta_1 S_t^+)x_t + \varepsilon_{t+1}$ and $r_{t+1} = \alpha + (\beta_0 + \beta_1 S_t^-)x_t + \varepsilon_{t+1}$. Results in Table 10 show that β_1 is significantly positive for the interactive term of S_t^+ and m_t whereas β_1 is insignificant for the interactive term of S_t^- and m_t, suggesting that positive sentiment S_t^+ more strongly pushes up the behavioral actions such as underreactions and overreactions behind the combined non-fundamental predictor m_t than negative sentiment S_t^-. Regarding the combined fundamental predictor μ_t, the coefficient of the interactive term β_1 is negative under 10% significance level for both S_t^+ and S_t^-, suggesting that sentiment negatively affects the fundamental link between economic variables and equity premium.

Sibley, Wang, Xing and Zhang (2016) argue that Baker and Wurgler sentiment index contains component largely driven by business cycle and risk related factors. In this case, the time-varying predictive performance of fundamental and non-fundamental variables may be driven by fundamental related factors rather than behavioral component of sentiment. To address this concern, we identify high and low sentiment regimes using regime switching model (10) based on the purged sentiment index in Chu, Du and Tu (2016), which is purged from a comprehensive set of macroeconomic and risk related variables. In-sample regression results in Table 11 are consistent with our main results in Panel C of Table 3, supporting our main findings driven by behavioral related factor.

C. Forecasting channel

Having assessed the predictive power of both fundamental and non-fundamental variables, we now analyze the underlying sources of the observed differences in predictability across sentiment regimes. 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 aggregate stock market may stem from either the cash flow channel or the discount rate channel or both. We use dividend price ratio as our discount rate proxy, since the time variation in dividend price ratio is primarily driven by discount rates (Cochrane 2008, 2011). We use dividend growth as our cash flow proxy, which is 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 return 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^{12}_{t+1} is the log dividend growth rate, ρ is a positive log-linearization constant, and dy^{12}_{t+1} is the log dividend price ratio. Since g^{12}_{t+1} and dy^{12}_{t+1} represent cash flows and discount rates separately in our setting, the forecasting power of m_t and μ_t for g^{12}_{t+1} and dy^{12}_{t+1} would point to a cash flow channel or a discount rate channel. Accordingly, our study focuses on the following predictive regressions,

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

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

Table 12 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 whole sample period and low regime, while the predictive power becomes less significant in high regime. Neither μ_t nor m_t can predict time variation in cash flow. The evidences are in favour of the view that aggregate stock market predictability is derived from the time variation in discount rates (Fama and French, 1989; Cochrane 2008, 2011). Furthermore, we find discount rates can be predicted by m_t in high sentiment regime, supporting the implications in Campbell et al. (2010). The results suggests that the cross-regime predictive ability of fundamental and non-fundamental variables appears to come from the discount rate channel.

VI. Conclusion

The equity premium forecasting literature provides ample evidence of predictability for both fundamental economic variables and non-fundamental variables, such as time-series momentum. However, we show that the forecasting performances of these two main categories of forecasting variables could be affected significantly by the level of investor sentiment.

Empirically, we separate the time periods into two regimes, one with relatively high investor sentiment while the other with relatively low investor sentiment. Firstly, we find that the fundamental variables indeed have strong predicting power when the market sentiment is low while lose the forecasting power when investor sentiment is high. Secondly, we find that although the predictability of many famous non-fundamental predictors, such as nearness to the 52-week high, could be strong when investor sentiment is high, their predictability tends to vanish away when investor sentiment is low and behavioral actions have been moderated accordingly.

More importantly, there is a recent debate and even a serious doubt about whether fundamental economic variables can predict equity premium. Some remedies, such as the ones in Campbell and Thompson (2008) and Rapach, Strauss and Zhou (2010), are provided to restore the confidence on predictability. Nevertheless, market sentiment plays an important role given that it can distort the fundamental link between economic variables and equity premium. Without controlling this sentiment effect, we show that the existing remedies, such as the ones in Campbell and Thompson (2008) and Rapach, Strauss and Zhou (2010), are fragile. For instance, the predictability is gone again, even with those remedies utilized, once market sentiment kicks in to distort the fundamental link between economic variables and equity premium. In contrast, without using any remedies, economic variables still show predicting power as long as sentiment stays low to not distort the link.

In addition, the high sentiment regime is much less often to occur compared to the low sentiment regime. We find that high (low) sentiment regime represents about 20% (80%) of the whole sample. Consequently, although it seems that both fundamental variables and non-fundamental variables can offer strong and sometimes comparable predictability as indicated by the current literature, we provide a unique new finding, which indicates that fundamental variables could be a more prevalent force than non-fundamental variables in terms of the time periods to have predicting power for forecasting market returns.

Finally, with regime shifts in market sentiment, investors can be better-off by conducting paradigm shifts between fundamental predictors in low sentiment periods and non-fundamental predictors in high sentiment periods.

Appendix. A Simple Model

In this section, we present a simple model to show that short-sale constraints together with sentiment (noise) trading can give rise to time series momentum during high sentiment regime, while the price is adjusted to its fundamental immediately and there is no trend during low sentiment regime.

We consider a financial market with a risky asset in positive net supply. 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 they are risk neutral and subject to short-sale constraints.[20] 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 the volatility. Suppose the rational investor has correct prior belief about the mean value of D, i.e., $\mu_{R,D} = \mu_D$, while the noise investor believes $\mu_{N,D} = \mu_D(1 + e_N)$, where $e_N \sim N(\mu_e, \sigma_e)$ can be interpreted as sentiment. If $\mu_e = 0$, then the noise investor has rational belief and the price is determined by the expected payoff. In the following analysis, we assume $\mu_e \neq 0$, with $\mu_e > 0$ (< 0) corresponding to

[20] 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. But in multi-period environments, the optimal demands cannot be explicitly solved from the first order conditions, because of the nonlinear expectations caused by the short-sale constraints.

high (low) sentiment period.[21]

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 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 model of two periods with $T = 2$ for simplicity.[22] 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 different patterns during high and low sentiment periods respectively.

Case (I): $\mu_e < 0$, which amounts to a low sentiment state,

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

because $E_{N,0}[D] < E_{R,0}[D]$ and $E_{N,1}[D] < E_{R,1}[D]$. The prices are determined by the belief of

[21] We consider exogenous sentiment in our model because our concern is the impact of sentiment rather than the formation of sentiment. This is also consistent with the empirical analysis of this paper, 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).

[22] The two-period model can be easily extended to a multi-period case.

rational trader. In addition, under rational (or objective) belief,

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

Therefore, in low sentiment period, there is no autocorreltions in price changes since price at any given time has reflected its fundamental.

Case (II): $\mu_e > 0$, which corresponds to high sentiment periods,

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

because $E_{N,0}[D] > E_{R,0}[D]$ and $E_{N,1}[D] > E_{R,1}[D]$. The prices are determined by the belief of noise trader. 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 due to the gradual incorporation of information that adjusts the price towards the fundamental level. In other words, momentum is caused by the learning of noise traders.[23] Price is adjusted gradually and converges to its fundamental as information dominates priors eventually.[24]

In summary, during high sentiment period, noise investor tends to take long positions, but rational investor cannot arbitrage away mispricing due to short sale constraints. Price comprises a fundamental and a mispricing component. However, as noise investor learns more information gradually, he corrects his beliefs accordingly and hence momentum arises as information dominates priors gradually. In contrast, during low sentiment period, rational investor faces no con-

[23]This is, in spirit, similar to the findings in Diamond and Verrecchia (1987), who show that short-sale constraints reduces the adjustment speed of prices to private information.

[24]In one extreme case when $\sigma_e = 0$, we have $cov_{N,0}[P_2 - P_1, P_1 - P_0] = 0$ as well. Then there will be no price momentum as well as in the low sentiment case. However, in this case, the reason for no price momentum is that noise traders have a dogmatic prior belief and do not update its prior to adjust the price towards the fundamental level after observing new information.

straints and the price is always adjusted to its fundamental. Hence there is no momentum effect in low sentiment regime. Our model implies that short-sale constraints together with sentiment (noise) trading can give rise to momentum in high sentiment regime even without any behavioral preference hypothesis, e.g. cognitive dissonance as in Antoniou et al. (2013).[25]

[25] 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 sentiment being at high regime (solid blue line), and the regime estimated based on median level as in Stambaugh, Yu and Yuan (2012) (the red dots). The middle and bottom figures depict investor sentiment index from 1965:07 to 2010:12. The shaded area in the middle figure is the high sentiment months estimated by the regime switching approach while it is the high sentiment months estimated based on median level in the bottom figure.

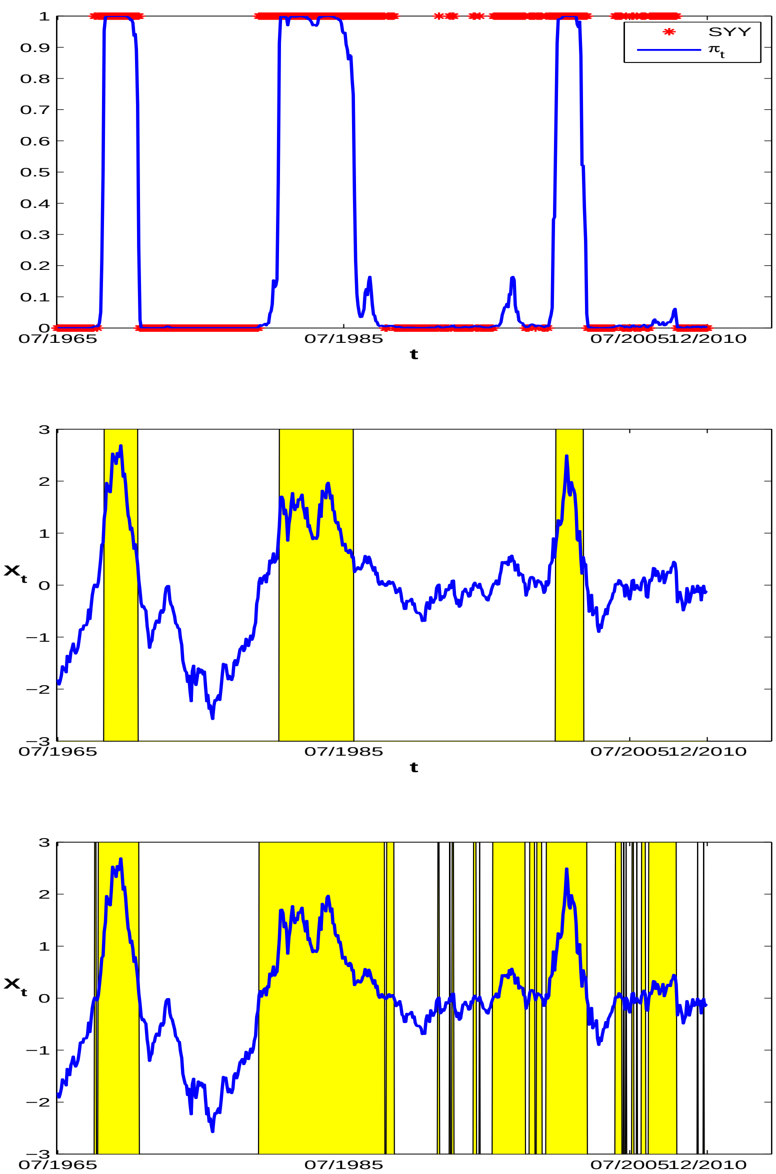

Figure 2. Times series of business cycle and investor sentiment regimes.

This figure plots the NBER recession dummy and high/low investor sentiment regimes. The shaded area is the high sentiment months estimated by the regime switching approach. The red dots represent NBER recession dates. Sample period is from July 1965 to December 2010.

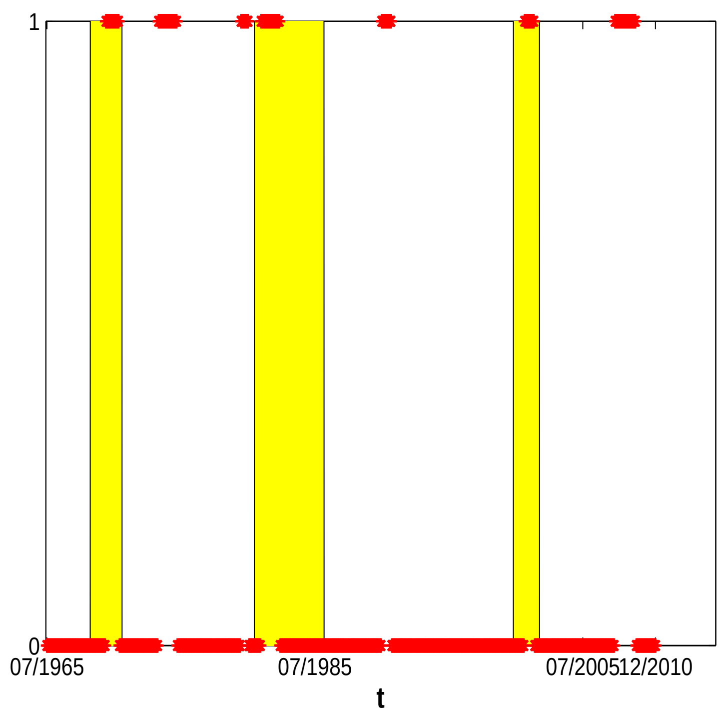

Figure 3. Times series of combined fundamental predictor μ_t and combined non-fundamental predictor m_t.

Panel A of figure 3 plots the combined fundamental predictor μ_t constructed from 7 categories of macroeconomic variables 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 is the high sentiment months estimated by the regime switching approach. Sample period spans from July 1965 to December 2010.

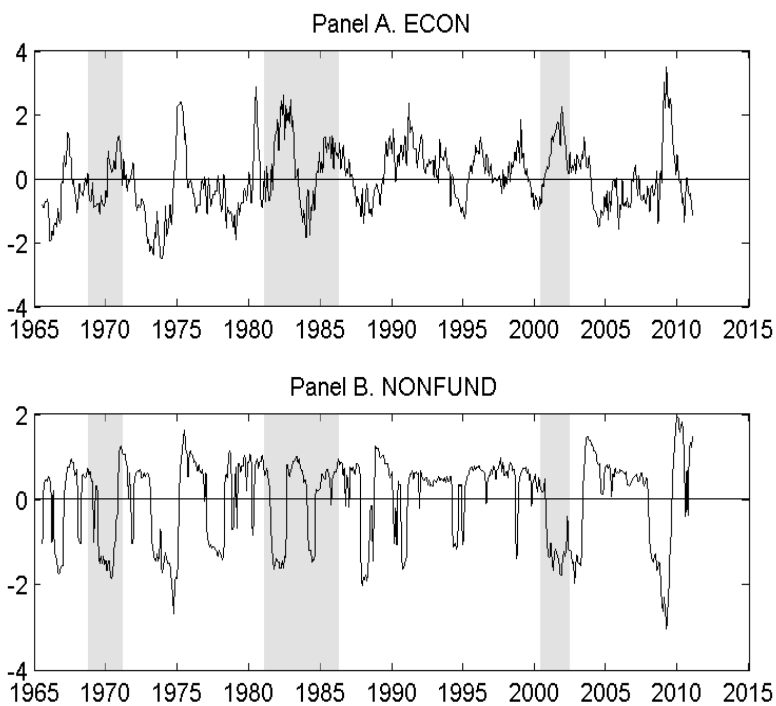

Figure 4. Correlations between predictors and equity premium as well as in sample predictive regression patterns.

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 whole sample (Bar 'whole'), high sentiment regime (Bar 'high') and low sentiment regime (Bar 'low'), respectively. The fourth bar in Panel A (B) depicts the difference in correlations based on μ_t (m_t) between high sentiment regime and low sentiment regime (Bar 'diff'). The first three bars in Panel C, E and G (Panel D, F and H) display coefficients, t-statistics and R squares in percentage points of in-sample predictive regressions based on μ_t (m_t) during whole sample (Bar 'whole'), high sentiment regime (Bar 'high') and low sentiment regime (Bar 'low'), respectively. The fourth bar in Panel C, E and G (Panel D, F and H) depicts the difference in coefficients, t-statistics and R squares in percentage points based on μ_t (m_t) between high sentiment regime and low sentiment regime (Bar 'diff'). μ_t is constructed from 7 macroeconomic categories in Jurado, Ludvigson and Ng (2015) whereas m_t is extracted from 6 non-fundamental variables including three time series momentum proxies, one anchoring variable and two moving average indicators. Sample period spans from July 1965 to December 2010.

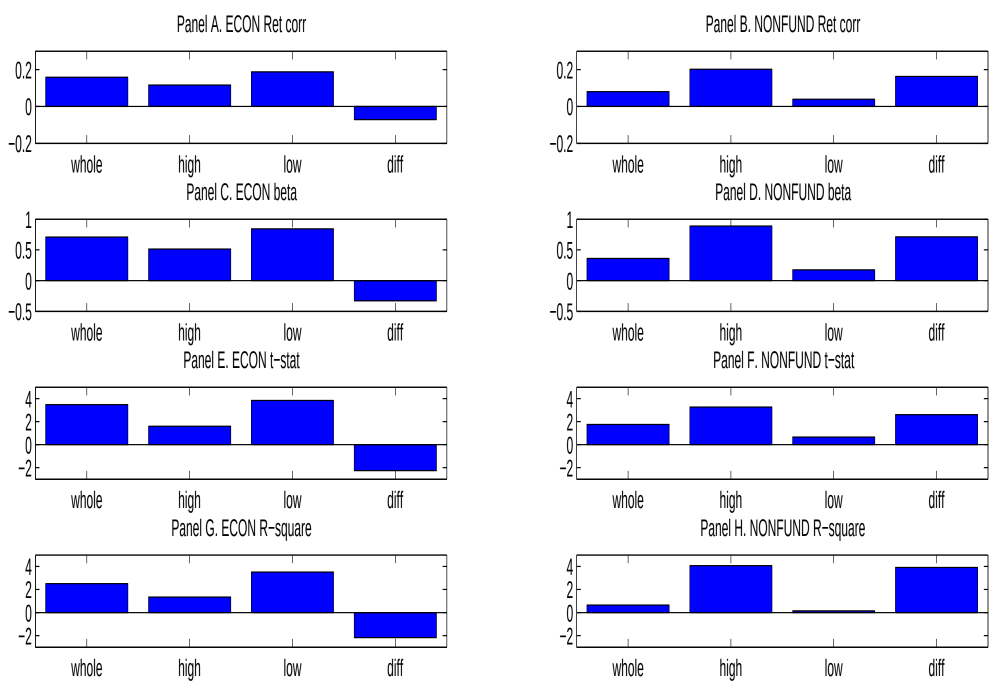

Figure 5. Times series of in sample equity premium forecasts based on combined fundamental predictor μ_t and combined non-fundamental predictor m_t.

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

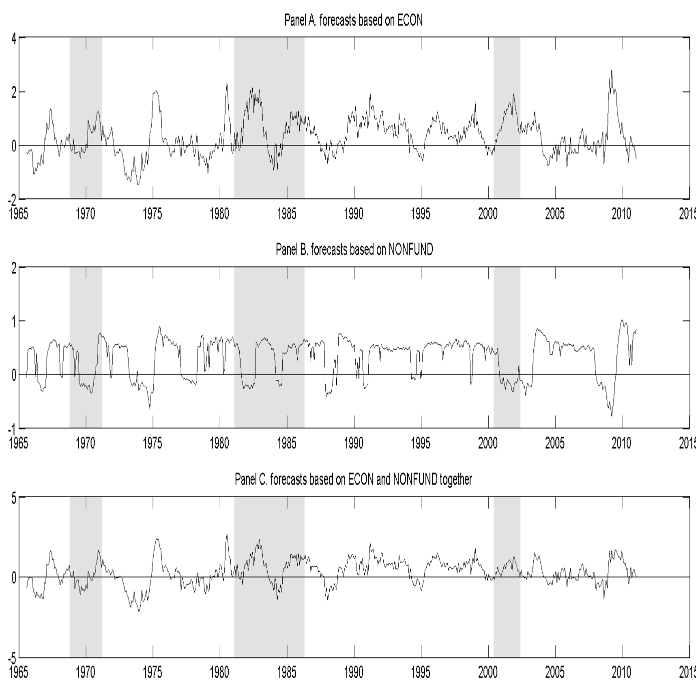

Table 1 Summary statistics

This table reports the summary statistics of the excess market return (the log return on the S&P 500 index in excess of the one-month T-bill rate) and fundamental predictors during whole sample, high sentiment regime and 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 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 7 macroeconomic categories 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, which represent 7 categories of macroeconomic variables in Jurado, Ludvigson and Ng (2015): (1) output and income; (2) labour market; (3) housing; (4) consumption, orders and inventories; (5) money and credit; (6) exchange rates; and (7) prices. Sharpe ratio is defined as the mean excess market return divided by its standard deviation. High and low sentiment regimes are estimated based on a regime switching approach over the sample period 1965.07 to 2010.12.

	Mean	Std	$\rho(1)$	Min	Max	SR
Panel A: excess market return						
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 predictor						
	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 as:

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

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

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

r_{t+1} is one of the anomaly long-short strategy returns from Novy-Marx and Velikov (2016). I_H is the high sentiment regime indicator while I_L is low sentiment regime dummy. The sample period is from 1965.08 to 2011.01 for all but Ohlsons O-score, return-on-book equity, failure probability and return-on-assets, whose data starts from 1973.07. Combination is the simple average of all the individual anomalies. All t-statistics are computed using White heteroskedasticity 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 whole sample, high sentiment regime and low sentiment regime, respectively. We consider 7 individual fundamental predictors from 7 categories of macroeconomic variables in Jurado, Ludvigson and Ng (2015) in Panel A, and 6 individual non-fundamental predictors including three time series momentum proxies, one anchoring variable and two moving average indicators in Panel B. Panel C presents in-sample regression results based on combined fundamental predictor μ_t extracted from the 7 individual macroeconomic predictors, combined non-fundamental predictor m_t extracted from 6 non-fundamental variables, as well as 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 at the $10\%, 5\%$ and 1% levels based on bootstrapped p-values, respectively. High and low sentiment regimes are estimated based on a regime switching approach. 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			
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 of $x_{52,t}$ (the nearness to the 52-week high variable) in predicting future monthly NYSE/AMEX value-weighted excess return with control variables including past return, the nearness to the historical high, historical high indicator, and 52-week high equal-historical high indicator. $x_{52,t}$ in Panels A, B and C is based on Dow Jones Industrial Average index, NYSE/AMEX total market value and S&P 500 index respectively. We report in each panel the regression coefficients, Newey-West t-statistics with a lag of 12, and R^2s in percentage points. 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 of in sample predictive regression for 1976:01-2005:12 following Welch and Goyal (2008). The combined fundamental predictor μ_t is constructed from 7 macroeconomic categories 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 at the $10\%, 5\%$ and 1% levels based on bootstrapped p-values, 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 removing the Oil Shock recession of from year 1973 to year 1975 based on the combined fundamental predictor μ_t and combined non-fundamental predictor m_t during whole sample, high sentiment regime and low sentiment regime, respectively. μ_t is constructed from 7 macroeconomic categories 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 a regime switching approach. Panel B reports in-sample regression results based on μ_t and m_t during whole sample, high sentiment and low sentiment periods, respectively, where high and low sentiment periods are determined by the median value of 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 at the $10\%, 5\%$ and 1% levels based on bootstrapped p-values, respectively. 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 period based on individual macroeconomic (non-fundamental) predictors. We consider 7 individual fundamental predictors from 7 categories of macroeconomic variables in Jurado, Ludvigson and Ng (2015) in Panel A, and 6 individual non-fundamental predictors including three time series momentum proxies, one anchoring variable and two moving average indicators in Panel B. 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 6 non-fundamental variables, as well as μ_t and m_t taken together as predictors. We present in each panel results during whole expansion period, high sentiment times in expansion period and low sentiment times in expansions, respectively. Regression coefficients, Newey-West t-statistics (with a lag of 12), and R^2s in percentage points are reported. $*, **$ and $***$ indicate significance at the $10\%, 5\%$ and 1% levels based on bootstrapped p-values, respectively. High and low sentiment regimes are estimated based on a 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			
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 $1/2$ data as training sample. Panel A reports out-of-sample forecasting results without remedies. Panel B reports out-of-sample forecasting results with positive forecast constraint in Campbell and Thompson (2008). Panel C reports out-of-sample forecasting results based on the mean combination forecast approach in Rapach, Strauss and Zhou (2010). Column 3 (Column 4) 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 5 reports out-of-sample forecasting results based on both μ_t and m_t as predictors. Column 6 presents results based on a shifting predictor which adopts m_t during high sentiment regime and switches to μ_t during low sentiment regime. We specify results separately during whole sample period, high sentiment regime and low sentiment regime in Columns 3, 4 and 5. To reduce estimation errors, at each period t we estimate the weights of individual predictors according to partial least squares analysis and set the 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.

Panel	R^2_{OS} (%)	μ_t	m_t	$\mu_t \& m_t$	$I_{H,t}m_t + (1-I_{H,t})\mu_t$
A:	whole	-2.28	0.48	-1.32	1.38
Without	high	-2.10	3.30	1.83	
remedies	low	0.81	-0.90	0.52	
B:	whole	-3.26	0.95	-1.93	1.27
Positive	high	-2.31	3.12	1.89	
constraint	low	0.72	0.24	0.23	
C:	whole	-0.15	0.17	0.05	0.61
Combined	high	-0.30	1.51	1.26	
forecast	low	0.35	-0.41	0.00	

Table 9 Forecasting cross-sectional portfolios

This table displays in-sample regression results of forecasting ten size portfolio returns using combined fundamental predictor μ_t and combined non-fundamental predictor m_t together as predictors during whole sample, high sentiment regime and low sentiment regime, respectively. μ_t is constructed from 7 macroeconomic categories in Jurado, Ludvigson and Ng (2015) and 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 at the 10%, 5% and 1% levels based on bootstrapped p-values, respectively. High and low sentiment regimes are estimated based on a regime switching approach. Sample period spans from 1965.07 to 2010.12.

	Regimes	μ_t	m_t	R^2 (%)		Regimes	μ_t	m_t	R^2 (%)
Small	whole	1.24***	0.77***	4.73	Dec 6	whole	0.94***	0.34*	3.28
		[4.66]	[2.43]				[4.17]	[1.27]	
	high	1.45***	1.91***	11.37		high	1.02**	1.30***	7.42
		[3.47]	[3.12]				[2.86]	[2.91]	
	low	1.30***	0.36	4.28		low	1.04***	-0.01	3.66
		[3.98]	[0.94]				[3.76]	[-0.04]	
Dec 2	whole	1.18***	0.55**	3.79	Dec 7	whole	0.98***	0.42*	3.80
		[4.52]	[1.74]				[4.24]	[1.49]	
	high	1.26**	1.79***	9.54		high	0.96**	1.16***	6.85
		[3.03]	[3.31]				[2.93]	[2.72]	
	low	1.26***	0.13	3.75		low	1.09***	0.12	4.16
		[3.72]	[0.33]				[3.92]	[0.32]	
Dec 3	whole	1.04***	0.42*	3.11	Dec 8	whole	0.87***	0.34*	3.15
		[4.16]	[1.39]				[4.11]	[1.29]	
	high	1.10**	1.51***	7.68		high	0.81**	1.12***	5.78
		[2.89]	[3.01]				[2.44]	[2.99]	
	low	1.13***	0.05	3.22		low	0.97***	0.06	3.53
		[3.58]	[0.12]				[3.84]	[0.17]	
Dec 4	whole	1.01***	0.41*	3.17	Dec 9	whole	0.81***	0.35*	3.28
		[4.08]	[1.40]				[4.00]	[1.37]	
	high	1.10**	1.52***	8.29		high	0.68**	1.02***	5.81
		[3.03]	[3.03]				[2.33]	[3.24]	
	low	1.10***	0.03	3.31		low	0.93***	0.09	3.81
		[3.48]	[0.07]				[3.98]	[0.25]	
Dec 5	whole	0.98***	0.40*	3.21	Big	whole	0.67***	0.39**	3.04
		[4.05]	[1.40]				[3.67]	[1.81]	
	high	1.03**	1.43***	7.87		high	0.53	0.93***	5.20
		[2.68]	[3.13]				[1.60]	[3.20]	
	low	1.08***	0.04	3.41		low	0.81***	0.15	3.56
		[3.67]	[0.10]				[3.82]	[0.52]	

Table 10 Sentiment index as continuous variable

This table presents in sample regression results taking Baker and Wurgler sentiment index S_t as a continuous variable. $S_t^+ = \max\{S_t, 0\}$ and $S_t^- = \min\{S_t, 0\}$ represent high and low sentiment respectively. The combined fundamental predictor μ_t is extracted from the 7 individual macroeconomic predictors while the combined non-fundamental predictor m_t is extracted from 6 non-fundamental variables. Regression coefficients, Newey-West t-statistics (with a lag of 12), and R^2s in percentage points are reported. $*, **$ and $***$ indicate significance at the $10\%, 5\%$ and 1% levels based on bootstrapped p-values, respectively. Sample period spans from 1965.07 to 2010.12.

	$r_{t+1} = \alpha + (\beta_0 + \beta_1 S_t)x_t + \varepsilon_{t+1}$	
	$x_t = \mu_t$	$x_t = m_t$
β_0	0.69***	0.36**
	[3.78]	[1.79]
β_1	-0.38**	0.25*
	[-1.94]	[1.48]
R^2 (%)	3.23	1.06

	$r_{t+1} = \alpha + (\beta_0 + \beta_1 S_t^+)x_t + \varepsilon_{t+1}$	
	$x_t = \mu_t$	$x_t = m_t$
β_0	0.89***	0.13
	[3.98]	[0.52]
β_1	-0.46*	0.54**
	[-1.46]	[2.51]
R^2 (%)	2.98	1.36

	$r_{t+1} = \alpha + (\beta_0 + \beta_1 S_t^-)x_t + \varepsilon_{t+1}$	
	$x_t = \mu_t$	$x_t = m_t$
β_0	0.42**	0.42**
	[1.88]	[1.60]
β_1	-0.65*	0.15
	[-1.94]	[0.42]
R^2 (%)	3.25	0.69

Table 11 In-sample predictive regressions based on purged sentiment index in Chu, Du and Tu (2016)

This table reports results of in sample predictive regression from 1965:01 to 2010:12 when high and low sentiment regimes are determined by the regime switching model based on the purged sentiment index in Chu, Du and Tu (2016). The combined fundamental predictor μ_t is constructed from 7 macroeconomic categories 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 at the $10\%, 5\%$ and 1% levels based on bootstrapped p-values, respectively.

	whole	high	low	whole	high	low	whole	high	low
μ_t	0.71***	0.58*	0.78***				0.72***	0.69**	0.78***
	[3.47]	[1.56]	[3.32]				[3.95]	[2.54]	[3.46]
m_t				0.36**	0.77**	0.19	0.38**	0.85**	0.19
				[1.77]	[2.21]	[0.85]	[1.68]	[2.16]	[0.83]
R^2 (%)	2.51	1.41	3.37	0.65	2.44	0.21	3.23	4.36	3.58

Table 12 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 separately during whole sample period, high sentiment regime and low sentiment regime in each panel. Regression coefficients, Newey-West t-statistics (with a lag of 12), and R^2s in percentage points are reported. $*, **$ and $***$ indicate significance at the $10\%, 5\%$ and 1% levels based on bootstrapped p-values, respectively. dy^{12} is considered as a proxy for discount rate while g^{12} is considered as cash flow proxy. μ_t is constructed from 7 macroeconomic categories 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 a regime switching approach. 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]	