Investor Sentiment and Paradigm Shifts in Equity Return Forecasting

Abstract

This study investigates the impact of investor sentiment on excess equity return forecasting. A high (low) investor sentiment may weaken the connection between fundamental economic (behavioral-based non-fundamental) predictors and market returns. We find that although fundamental variables can be strong predictors when sentiment is low, they tend to lose their predictive power when investor sentiment is high. Non-fundamental predictors perform well during high-sentiment periods while their predictive ability deteriorates when investor sentiment is low. These paradigm shifts in equity return forecasting provide a key to understanding and resolving the lack of predictive power for both fundamental and non-fundamental variables debated in recent studies.

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

I. Introduction

The predictability of the stock market return by fundamental macroeconomic variables has been debated in recent studies (e.g., Comin and Gertler, 2006; Welch and Goyal, 2008; Campbell and Thompson, 2008; Rapach, Strauss and Zhou, 2010). However, none of these studies have examined the impact of investor sentiment, which can cause prices to deviate from their fundamentals and weaken the connection between the fundamental economic predictors and the stock market return.[1] As a result, fundamental predictors may be doomed to perform badly when sentiment is high. Moreover, given that the performance of behavioral-based non-fundamental predictors (e.g., Li and Yu, 2012) originates from behavioral biases, they may also be doomed to fail during low-sentiment periods when behavioral biases tend to become insignificant.[2]

This study examines the impact of investor sentiment on the capacity of fundamental and non-fundamental predictors to explain the time-series predictability of aggregate stock market return. We find that fundamental variables indeed tend to lose their predictive power when sentiment is high even though they can be strong predictors when sentiment is low.[3] Regarding non-fundamental behavioral-based predictors, we also find that they do not predict the market return well when sentiment is low, while they can have significant forecasting power during high-sentiment periods. Furthermore, as detailed below, the investor-sentiment-based paradigm shifts in return forecasting provide a key to understanding and resolving the lack of forecasting power for both fundamental and non-fundamental variables debated in recent studies.

Welch and Goyal (2008) find that the predictive ability of the fundamental variables documented in the literature is questionable. As discussed above, fundamental predictors may be doomed to fail when investor sentiment is high. Therefore, this study seeks to enhance our understanding regarding why there is a lack of forecasting power for fundamental predictors as documented in Welch and Goyal (2008).

In addition, one serious issue raised by Welch and Goyal (2008) is that the in-sample predictive power of economic variables does not remain robust out-of-sample. Some remedies, such as the fixed coefficients approach in Campbell and Thompson (2008), have been proposed to restore economic variables' out-of-sample forecasting power. Essentially, such methods are based on theoretically-motivated restrictions from

[1]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. We refer to the work of Richard Thaler for more details on the impact of behavioral biases on financial markets.

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

[3]Following recent studies, such as Stambaugh, Yu and Yuan (2012, 2015), we use Baker and Wurgler sentiment index as the measure of investor sentiment in our study.

rational economic models.[4] However, when investor sentiment is high, these rational economic models may no longer hold; hence, the remedies based on these models will also be doomed to fail.[5] Indeed, we find that these remedies do not work well during high-sentiment periods. In contrast, during low-sentiment periods, we find that these economic-model-based constraints can improve the forecasting ability of the fundamental variables, such as the growth-adjusted price-scaled predictors. Therefore, economic-model-based remedies are not sufficient if the sentiment effect is not controlled, while they can be useful if the sentiment effect is properly controlled.

Moreover, Welch and Goyal (2008) show that even for the in-sample forecasting case, the forecasting power of the fundamental predictors proposed in the literature seems limited to the oil crisis of 1973–1975, with most forecasting variables performing poorly since 1975. In contrast, we find that fundamental variables remain strong predictors in low-sentiment periods, even after 1975. In addition, many studies, such as Rapach, Strauss and Zhou (2010) and Henkel, Martin and Nardari (2011), find that return predictability is significant only during economic recessions, accounting for 20%–30% of the time, and insignificant for 70%–80% of the time during economic expansions, again suggesting that the documented return predictability is limited. However, we find that fundamental variables perform well during all low-sentiment periods, which represent about 80% of our sample period and include 83% of all expansionary periods.[6]

In addition to the fundamental predictors of the market return, some recent studies report that various behavioral-bias-motivated non-fundamental variables have strong predictive ability. For instance, Li and Yu (2012) propose some anchoring variables based on potential under-reactions to sporadic past news due to psychological anchoring biases. However, they show that, although one anchoring variable (the Dow Jones Industrial Average index's nearness to its 52-week high) has significant predictive power, another anchoring variable (the NYSE/AMEX total market value index's nearness to its 52-week high) has none. Li and Yu (2012) hypothesize that the Dow index is more visible than the NYSE/AMEX index and that investors have limited attention. Nevertheless, given that many index funds track the performance of both the Dow index

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

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

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

and the NYSE/AMEX index or their close proxies, it is puzzling to find such substantial differences in predictive power.

By splitting our sample into high- and low-sentiment periods, we find that both anchoring variables turn out to have strong predictive power during high-sentiment periods, but not during low-sentiment periods. Again the paradigm shifts in return forecasting help to understand and resolve this puzzle for anchoring variables. We also examine other non-fundamental predictors, including time series momentum (Moskowitz, Ooi and Pedersen, 2012) and technical indicators (Brock, Lakonishok and LeBaron, 1992; Neely, Rapach, Tu and Zhou, 2014). These non-fundamental predictors also have strong predictive power during high-sentiment periods but not low-sentiment periods.[7]

Overall, we show that a key to understanding and resolving the lack of forecasting power of both fundamental and non-fundamental variables as debated in recent studies may be the investor-sentiment-based paradigm shifts. As for fundamental variables, when investor sentiment is low (high), the link between fundamental variables and the market return (e.g., Campbell and Shiller, 1988; Cochrane, 2008) tend (not) to hold, and hence the fundamental predictors tend (not) to perform well. As for non-fundamental variables, their forecasting power originates from investor behavioral biases. When investor sentiment is high (low), investor behavioral biases are also high (low) and hence non-fundamental variables tend (not) to perform well.

In addition, to the best of our knowledge, this paper is the first to use a regime-switching model to formally classify time periods into high- and low-sentiment regimes. The model indicates that the low-sentiment regime represents about 80% of the whole sample. Accordingly, fundamental (non-fundamental) variables are likely to have significant predictive power only during the 80% (20%) of low-sentiment (high-sentiment) periods. As a result, our approach indicates that fundamental variables may function more frequently as effective predictors of the market return than non-fundamental variables do. In fact, there is a lack of studies comparing the effectiveness of fundamental versus non-fundamental predictors across time, to which this paper contributes. In contrast, the existing studies usually adopt ad hoc approaches to classify sentiment regimes. For example, one popular approach is to split the sentiment index at the median: periods above the median are classified as the high-sentiment regime and periods below the median are classified as

[7] In Section VI, we propose a model by combining short-sale constraints and sentiment regimes. This model provides a simple yet rigorous framework for understanding the underlying economic channel of the paradigm shifts in forecasting stock returns, which is the time-varying dominance of irrational investors during the high sentiment regime and rational investors during the low sentiment regime.

the low-sentiment regime. Although the ad hoc median cut approach appears to be qualitatively similar in capturing the idea that sentiment varies over time, it assumes that sentiment is high for 50% of the time and low for the remaining 50% of the time. This may yield misleading implications. For instance, the median cut approach may suggest that both fundamental and non-fundamental predictors have forecasting power 50% of the time.

Finally, this paper adds to the growing literature regarding the asymmetric effect of sentiment on many asset price behaviors. Firstly, most studies examine the impact of sentiment on the cross-sectional relation between firm characteristics and returns at the firm level. For instance, Stambaugh, Yu and Yuan (2012) document that anomaly returns are more significant in high sentiment periods. Antoniou, Doukas and Subrahmanyam (2016) show that larger beta stocks earn smaller returns during optimistic high sentiment periods. More recently, Shen, Yu and Zhao (2017) document that pervasive macro-related factors are priced in the cross-section of stock returns following low sentiment, but not following high sentiment.[8] Secondly, there appears to be only one study (Yu and Yuan, 2011) that focuses on the time series relation between market equity premium and market volatility (a fundamental type variable) across high and low sentiment regimes.[9] The present study contributes to the literature by examining the impact of sentiment on the time-series relation between future aggregate market return and both fundamental and non-fundamental variables under a single unified framework.

The rest of the paper is organized as follows. We present the econometric methodology in Section II. Sentiment regimes and predictors are summarized in Section III. Section IV reports the main empirical findings, and Section V provides further analysis on forecasting channels. In Section VI, we present a theoretical model to formalize the intuition of sentiment impact on forecasting and Section VII concludes. In the Appendix, we provide some discussions on additional model implications.

[8]This strand of literature relies on behavioral and psychological explanations by combining two prominent concepts, investor sentiment and short-selling constraints. Particularly, Antoniou, Doukas and Subrahmanyam (2013) argue that the cognitive dissonance caused by news that contradicts investor sentiment gives rise to under-reaction, which is strengthened mainly during high-sentiment periods due to short-selling constraints, raising the profits from cross-sectional momentum. There are other studies, including the idiosyncratic volatility puzzle (Stambaugh, Yu and Yuan, 2015) and hedge fund investment (Smith, Wang, Wang and Zychowicz, 2016).

[9]Shen et al. (2017) slightly touch on the time series relation topic by documenting once in their paper (Panel B of Table 8) that the negative relation between investor sentiment (a non-fundamental type variable) and market equity premium is more significant when sentiment is positive.

II. Econometric Methodology

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

A. Single-regime predictive regression

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

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

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

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

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

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

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

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

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

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

and

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

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

To incorporate information from the entire set of fundamental and non-fundamental variables, we parsimoniously estimate a predictive regression based on the combined fundamental variable μ_t in (4) and non-fundamental variable m_t in (5),

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

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

B. Regime-dependent predictive regression

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

More specifically, we run the following regime shifting predictive regressions,

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

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

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

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

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

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

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.[10] To back out the unobservable regimes from the data, we assume that the market is at regime H at time t if the probability of staying in this regime $\pi_t := Prob(\rho_t = H|S_t) \geq 0.5$; otherwise, we assume time t is a low-sentiment period.

C. Fundamental variables

Although price-scaled variables such as the dividend-price ratio are normally considered as fundamental variables in return forecasting, these variables also depend on price, which can potentially be affected by investor sentiment. Cassella and Gulen (2018) treat the dividend-price ratio as a behavioral variable and find evidence of stronger predictive ability when the degree of behavioral bias is higher. Our analyses (presented in Table 4 and discussed in Section IV.C.1) also indicate that the price-scaled predictors perform like behavioral non-fundamental predictors. Therefore, to conduct an accurate analysis on the impact of investor sentiment on the return forecasting powers of fundamental versus non-fundamental variables, we do not use the variables from Campbell and Thompson (2008) and Rapach et al. (2010) as fundamental predictors in our analysis.

Instead, we consider a wide range of fundamental macroeconomic variables used in Jurado, Ludvigson and Ng (2015), where more than one hundred macroeconomic variables are selected to represent broad categories of macroeconomic time series. This can guard against data mining of reporting a few significant fundamental predictors. In order to effectively incorporate information from a large number of macroeco-

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

nomic variables into a smaller set of forecasting variables, we extract some common factors from the 132 macroeconomic series in Jurado et al. (2015). More specifically, after excluding 21 time series of bond and stock market data,[11] the 132 series are organized into seven categories according to priori information, including: (i) output and income; (ii) labour market; (iii) housing; (iv) consumption, orders, and inventories; (v) money and credit; (vi) exchange rates; and (vii) inflation. We implement principal component analysis (PCA) to derive seven individual macroeconomic predictors from these seven categories of macroeconomic variables (denoted as $F_{jt},\ j = 1,2,\cdots,7$).[12] The seven extracted series may be treated as a set of representative macroeconomic predictors.[13]

D. Non-fundamental variables

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

For a large set of futures and forward contracts, Moskowitz, Ooi and Pedersen (2012) provide strong evidence for the existence of time series momentum that characterizes significantly positive predictive ability of the moving average of a security's own past returns. Following the literature, we define momentum as the moving averages of historical excess returns (e.g., Neely, Rapach, Tu and Zhou, 2014; Goyal and Jegadeesh, 2018). We consider different momentum variables with time horizons varying from 6 to 12 months. That is,

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

Li and Yu (2012) use nearness to the Dow 52-week high and nearness to the Dow historical high as proxies for the degree to which investors under- and over-react to news, respectively, and show that the former (latter) positively (negatively) predicts the market return. More specifically, nearness to the Dow

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

[12] We take the first principal component of each category of macroeconomic variables to capture a higher proportion of total variations in the individual proxies than the other principal components. Incorporating more principal components increases estimating noise and may worsen out-of-sample performance.

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

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

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

where p_t denotes the level of the Dow Jones Industrial Average index at the end of day t, and $p_{52,t}$ and $p_{max,t}$ represent its 52-week high and historical high at the end of day t, respectively. The value at month t is defined as the value on the last trading day of month t. Given that there might be some salient information in recent past news such that the stock price is very close to its 52-week high, nearness to the 52-week high may also partially proxy for overreaction. Therefore, we also construct the anchoring predictor $\hat{x}_{52,t}$, which is nearness to the 52-week high orthogonal to nearness to the historical high. We use $\hat{x}_{52,t}$ as one of our non-fundamental variables, and expect it to be a more accurate proxy for under-reaction. Other anchoring variables based on alternative stock indices will also be constructed in the same way later in Section IV.C.4 for comparison.

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

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

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

where

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

p_t is the level of a stock price index, and s (l) is the length of the short (long) MA ($s < l$). We denote the moving-average indicator with lengths s and l as MA(s,l). Intuitively, the MA rule detects changes in stock price trends because the short MA is more sensitive to recent price movement than the long MA. We analyze monthly MA rules with $s=1$ and $l=9,12$.[14]

E. Extracting combined predictors

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

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

and N_2 non-fundamental proxies

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

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

To extract μ_t, which is used in equation (4), from the N_1 fundamental economic proxies $X_t = \{X_{1,t}, X_{2,t}, \cdots, X_{N_1,t}\}$, we assume that $X_{i,t} (i=1,2,\cdots,N_1)$ has a factor structure

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

where $\gamma_{i,1}$ and $\gamma_{i,2}$ are the factor loadings measuring the sensitivity of the fundamental economic proxy $X_{i,t}$ to μ_t and the common approximation error component δ_t of all the N_1 proxies that is irrelevant to returns, respectively. $u_{i,t}$ is the idiosyncratic noise associated with proxy $X_{i,t}$ only. By imposing the above factor structure on the proxies, we can efficiently estimate the collective contribution of X_t to μ_t, and, at the same time, eliminate the common approximation error δ_t and the idiosyncratic noise $u_{i,t}$. In general, μ_t can also be estimated as the first principal component analysis (PCA) of the cross-section of X_t. However, as discussed

[14] We find a similar pattern when using other technical indicators considered in Neely et al. (2014). In order to be consistent with the time series momentum and anchoring variables, we also replace the "0/1" technical indicators from Neely et al. (2014) with the variable $MA_{s,t} - MA_{l,t}$. The patterns are similar to but less significant than the "0/1" technical indicators.

in Huang, Jiang, Tu and Zhou (2015), the PCA estimation is unable to separate δ_t from μ_t and may fail to generate significant forecasts for returns which are indeed strongly predictable by μ_t. The PLS approach extracts μ_t efficiently and filters out the irrelevant component δ_t in two steps. In the first step, we run N_1 time-series regressions. That is, for each $X_{i,t}$, we run a time-series regression of $X_{i,t-1}$ on a constant and realized return,

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

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

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

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

Similarly, the non-fundamental variable m_t is extracted by applying the PLS procedure to M_t. For more details on this aligned approach, we refer to Huang et al. (2015).[15]

III. Data Summary

A. Sentiment regimes

We estimate the regime switching model (10) for sentiment by applying the maximum likelihood estimation method (MLE) and report the results in Figure 1. The sentiment data spans from 1965:07 to 2010:12.[16] The solid blue line in the upper panel depicts the estimated probability π_t of a high-sentiment regime H over time. Generally, long periods of relatively low investor sentiment are interrupted by short periods of extremely high sentiment, which occur at the end of the 1960s, the first half of the 1980s and the beginning of the 2000s. We assume that regime L represents periods of relatively normal time with low sentiment, while regime H captures more irrational phases, which lead to steep increases in the level of market sentiment. The high-sentiment periods identified by the regime-switching approach coincide well with anecdotal

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

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

evidence, such as the "Nifty Fifty" episode between the late 1960s and early 1970s, the speculative episodes associated with Reagan era optimism from the late 1970s through the mid-1980s (involving natural resource startups in early 1980s after the second oil crisis and the high-tech and biotech booms in the first half of 1983), and the Internet bubble of the late 1990s/early 2000s.

Alternatively, we also follow Stambaugh, Yu and Yuan (2012) to define a high-sentiment month as one in which the value of the Baker and Wurgler's (2006, 2007) sentiment index in the previous month is above the median value for the sample period, and a low-sentiment month as one in which the index is below the median value. The middle and lower panels depict the investor sentiment index from July 1965 to December 2010. The shaded areas are the high-sentiment months estimated by the regime-switching approach in the middle panel and the median cut approach in the lower panel, respectively. Using the regime-switching approach, we find 116 (430) high (low) sentiment months in our sample (21.25% and 78.75% of the total, respectively). In contrast, defining high- and low-sentiment regimes based on the median level yields 273 high-sentiment months and 273 low-sentiment months. The correlation between the estimates from the regime switching approach and the median cut approach is 0.54.

B. Data and summary statistics

Following the literature, we measure the excess stock market return as the difference between the log return on the S&P 500 (including dividends) and the log return on a risk-free bill.[17] Panel A of Table 1 reports summary statistics for the monthly excess market return. The moments of the excess market returns differ between high- and low-sentiment regimes. The mean of the excess market returns during the high sentiment regime is -0.07%, much lower than its counterpart during the low-sentiment regime (0.41%). This pattern is consistent with the general consensus in the existing literature that high sentiment drives up prices and depresses future returns. In contrast, the standard deviations of the excess market returns are similar across the two regimes, yielding a higher realized Sharpe ratio during the low sentiment regime. The overall stock market displays weak time-series momentum with a positive first-order autocorrelation of 0.06; during the high-sentiment regime, the market returns become more persistent with a first-order autocorrelation of around 0.10.

To examine the forecasting performance of combined fundamental and non-fundamental predictors, we consider seven individual fundamental variables and six individual non-fundamental variables. Applying the

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

PLS procedure to the seven fundamental variables F_{jt} ($j = 1,2,\cdots,7$), we obtain a combined fundamental variable μ_t,

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

where each underlying individual proxy is standardized. The summary statistics of the combined fundamental predictor and individual fundamental predictors are reported in Panels B and C of Table 1. The combined fundamental predictor is more stable than the individual predictors overall. It has a higher average and is slightly more volatile and less persistent during the high-sentiment regime than during the low-sentiment regime. In contrast, the seven individual macroeconomic predictors F_i ($i = 1,2,3,4,5,6,7$) do not exhibit consistent patterns across the sentiment regimes, possibly due to the noise in the individual variables. Hence, we summarize information by extracting common components from various individual forecasting variables to alleviate the potential noise in each individual proxy.

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

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

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

where each underlying individual variable is standardized. The loadings on the momentum, psychological anchor, and moving average proxies are all positive. Panel B of Figure 2 plots the time series of the combined non-fundamental predictor m_t. It is evident that the time series of m_t displays a less smooth pattern than that of μ_t. In contrast to μ_t, m_t reaches local maxima near the market sentiment peaks and drops abruptly as it enters the low-sentiment periods. Equation (19) shows that a number of individual non-fundamental variables load relatively strongly on m_t, including time series momentum proxy M_t^6, anchoring variable $\hat{x}_{52,t}$, and moving average indicators $MA(1,9)$ and $MA(1,12)$. Consequently, m_t reflects a wide variety of individual non-fundamental variables and potentially captures more useful predictive information than any single non-fundamental variable. As shown in Table 3, the extracted non-fundamental variables forecast the market return with a positive sign, consistent with individual proxies.

IV. Main Empirical Results

In this section, we examine the forecasting performance of the fundamental economic variables and non-fundamental variables for both the full sample and the high-/low-sentiment regimes determined using the Markov regime-switching approach. Our data spans from July 1965 to December 2010, a period determined by the availability of the sentiment series. In Subsection A, we show that mispricing is much more significant during the high-sentiment regime than the low-sentiment regime. In Subsection B, we analyze the in-sample predictive performances across sentiment regimes. In Subsection C, we address several important issues regarding the lack of predictive power for both fundamental and non-fundamental variables as debated in recent studies, including some economic-theory-based remedies, the lack of predictive ability after the oil shock of 1973–1975, predictability during expansions, and the lack of predictive ability of the anchoring variables based on alternative indices, sentiment regimes determined by median cut approach, etc. Finally, in Subsection D, we conduct out-of-sample analysis.

A. Mispricing across sentiment regimes

We explore the distinct patterns of mispricing across the high- and low-sentiment regimes using the regime switching approach described in Sections II.B and III.A. We consider 17 long-short anomaly returns from Novy-Marx and Velikov (2016) as well as a combination strategy that takes a simple average of all 17 long-short anomaly returns,[18] and report pricing errors (returns adjusted by benchmark factor models)

[18]There are 32 long-short strategy returns in Novy-Marx and Velikov's (2016) data library. We consider 17 of these anomalies (after excluding anomalies related to risk factors).

during the high- and low-sentiment regimes, respectively, in Table 2. The baseline regression is as follows:

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

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

The results in Table 2 reveal that the pricing errors indicated by the long-short anomaly returns are generally higher following high-sentiment periods. Specifically, the combined long-short benchmark-adjusted anomaly return is 99 bps higher per month following high-sentiment periods, using the Carhart four-factor model as a benchmark. Furthermore, the mispricing mainly stems from the high-sentiment regime, with average mispricing (measured as the combined long-short benchmark-adjusted anomaly return) in the high-sentiment months accounting for 81% of overall average mispricing benchmarked on the Carhart (1997) four-factor model. We interpret periods of high sentiment as periods when the market is dominated by unsophisticated investors, and the illustrative model in Section VI describes how sentiment, together with short-sale constraints, affects the dominance of different investors, which further affects return predictability. The observed tendencies are consistent with the findings in Stambaugh et al. (2012), who use the median level of the Baker and Wurgler sentiment index to differentiate high- and low-sentiment periods and show that combining market-wide sentiment with short-sale constraints leads to greater mispricing in the cross-section following high-sentiment periods. The difference in the degree of mispricing across the high- and low-sentiment regimes echoes the literature, suggesting that investor sentiment could drive prices away from their fundamentals. As a result, investor sentiment may break the link between economic predictors and the market return from time to time.

B. Predictive performances across sentiment regimes

We focus our empirical analysis on the one-month horizon for two main reasons. First, 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). Second, as market sentiment evolves through time, longer-horizon predictive regressions would include random combinations of the high- and low-sentiment periods that would undoubtedly obscure predictors' forecasting performance. Nevertheless, as a robustness check, we also examine the predictive performances over longer horizons in Section C.6 and find the results are similar.

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

First, both the individual and combined economic fundamental variables perform well over the whole sample and during the low-sentiment periods, but their predictive strength is attenuated during the high-sentiment regime. Panel A indicates that the overall predictability of the individual economic variables is mainly concentrated on the low-sentiment regime. F_2, F_3, F_4, and F_7 have significant unconditional forecasting power when using the whole sample data.[19] However, none of these variables have significant conditional forecasting power over the high-sentiment periods (at 5% significance level). Their forecasting power is conditional and limited in the low-sentiment periods. F_1, F_5, and F_6 do not have significant unconditional forecasting power over the whole sample, low- or high-sentiment periods. In sum, fundamental variables may or may not have strong forecasting power. While they are strong predictors, their forecasting power tends to be limited in the low-sentiment periods. During the high-sentiment periods, they tend to lose their forecasting power.

This pattern holds in Panel C for the combined fundamental variable, which is insignificant in the high-sentiment periods, but significant over the whole sample (with t-statistic of 3.47 and R^2 of 2.51%), and

[19]The negative forecasting power of F_2 is consistent with Santos and Veronesi (2006) showing that labour income negatively forecasts stock return. The negative sign for F_4 can be consistent with Campbell and Cochrane (1999) and Cochrane (2011) showing that the consumption surplus ratio—a measure of how current consumption compares to past consumption—can negatively forecast future stock market returns.

the low-sentiment periods (with t-statistic of 3.85 and R^2 of 3.52%). This supports our above findings that, at the individual predictor level, the predictive ability of the fundamental variable concentrates in the low-sentiment periods. Furthermore, the coefficient estimated for the combined fundamental variable is economically large. A one-standard-deviation increase in the combined fundamental variable μ_t predicts increases of 0.71% and 0.84% in the expected market return over the whole sample and the low-sentiment periods, respectively.

Second, the predictive performances of the individual non-fundamental variables and the combined non-fundamental variable are much stronger during the high-sentiment regime than during the low-sentiment regime. Out of the six non-fundamental predictors, only two (the anchoring variable $\hat{x}_{52,t}$ and moving average predictor $MA(1,12)$) have significant unconditional forecasting power over the whole sample at 5% significance level. However, neither of them has significant conditional forecasting power over the low-sentiment periods. Their forecasting power is conditional and limited in the high-sentiment periods. Regarding the remaining four non-fundamental predictors, three have significant conditional forecasting power over the high-sentiment periods while none has conditional forecasting power over the low-sentiment periods (at 5% significance level). In sum, non-fundamental variables are usually strong predictors when sentiment is high; however, they do not predict the market return well when sentiment is low.

In Panel C, this pattern extends to the combined non-fundamental variable,[20] whose coefficient is significant during the high-sentiment regime (t-statistic of 3.27 and R^2 of 4.07%) but insignificant during the low-sentiment regime (t-statistic of 0.65 and R^2 of approximately 0.1%). This indicates that the combined non-fundamental variable is able to forecast the market return predominantly in the high-sentiment periods. In fact, when sentiment is high, a one-standard-deviation increase in the combined non-fundamental variable m_t corresponds to an increase of 0.89% in the future excess market return, more than twice as large as that for the entire sample period.[21]

Third, the results show complementary patterns for the fundamental and non-fundamental variables. In fact, Panel C shows that the sum of R^2s when using fundamental and non-fundamental variables alone to

[20]Sentiment itself can be considered as a non-fundamental variable. By combining the sentiment variable with the 6 non-fundamental variables in Table 3 and comparing with the results in Panel C of Table 3 for the combination variable of the 6 non-fundamental variables, we find (the results are not reported here) that the new combined non-fundamental predictor has stronger predictive power in high sentiment regimes (with higher coefficient, higher t-statistic, and higher R^2 statistic). Regarding the low sentiment regimes, there is not much change due to the fact that the sentiment predictor is insignificant in the low sentiment regime.

[21]We find the same pattern when simply using principal components to extract the combined predictors from the individual proxies. We also consider the case in which m_t is orthogonal to μ_t (or μ_t is orthogonal to m_t) to eliminate the overlapping forecasting power and find the same patterns as in Table 3 (results not reported here).

forecast return approximately equals the R^2 when using both. This holds for the whole sample and both high- and low-sentiment regimes, confirming that fundamental and non-fundamental variables complement each other in return predictability. As monthly stock returns contain a substantial unpredictable component, a monthly R^2 near 0.5% can signal an economically significant degree of return predictability (e.g., Campbell and Thompson, 2008). Based on our empirical findings, all R^2s over the sample period for regressions with both fundamental variable μ_t and non-fundamental variable m_t exceed this 0.5% benchmark.

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

Figure 5 further illustrates the complementary roles of fundamental predictor μ_t and non-fundamental predictor m_t. Panels A and B in Figure 5 show in-sample forecasts of the monthly market return for μ_t and m_t, respectively. The expected market return predicted by μ_t (Panel A of Figure 5) displays a relatively smooth pattern, in line with Panel A of Figure 2. The movements in the expected market return predicted by m_t (Panel B of Figure 5) are relatively more abrupt, in line with the trend in Panel B of Figure 2. When the information from μ_t and m_t is combined (Panel C of Figure 5), the expected equity return rises to lower levels before extremely high-sentiment dates relative to that in Panel B, while it falls to a lower extent after entering extremely high sentiment periods, indicating that the complementary information in μ_t and m_t reduces the fluctuations in the expected market return predicted by μ_t or m_t alone.

In summary, when the investor sentiment is shifting between high- and low-sentiment regimes, our findings yield several implications. First, economic variables have strong forecasting ability when sentiment is low, but lose predictive power when it is high. Secondly, the predictability of the non-fundamental variables tends to peak when sentiment is high and vanish when sentiment is low. Using both the fundamental and non-fundamental variables as predictors confirms these patterns. Moreover, because low-sentiment regimes account for about 80% of the sample period, the results suggest that fundamental variables may function more frequently as effective predictors of the market returns compared to non-fundamental variables.

C. Further discussions

In this subsection, we first show (in Subsections C1-C4) that the above documented paradigm shifts in equity return forecasting based on sentiment regimes may provide a key to understanding and resolving the lack of predictive power for both fundamental and non-fundamental variables as debated in recent studies. We then provide additional discussion on alternative sentiment regimes based on non-parametric approach (in Subsection C5), return predictability over longer horizons (in Subsection C6), alternative variables determining regimes (in Subsection C7), and some interpretations regarding potential reasons behind the regime switching in sentiment (in Subsection C8).

C.1 Economic-theory-based remedies

One serious issue raised by Welch and Goyal (2008) is that the in-sample predictive power of economic variables does not remain robust out-of-sample. Some recent studies, such as Campbell and Thompson (2008), have proposed certain economic-theory-based remedies to restore the out-of-sample forecasting power of economic variables. Essentially, these remedies, such as the fixed coefficients approach, are based on theoretically motivated restrictions from rational economic models. However, these rational economic models may no longer hold when investor sentiment is high; hence, the remedies based on these models will also be doomed to fail during high sentiment periods.

Table 4 reports out-of-sample forecasting results of the eleven variables in Table 2 of Campbell and Thompson (2008) for the cases without any constraint and with the "fixed coefficients" restriction developed in Campbell and Thompson (2008). The "fixed coefficients" restriction sets the coefficient of a given single predictor to one – the value implied by a simple steady-state model (e.g., Gordon, 1962). With the "fixed coefficients" restriction, the out-of-sample R^2s (R^2_{OS}) are reported in Columns 5 to 7.

We first examine the growth-adjusted price-scaled ratios, calculated as the sum of each price-scaled ratio plus its corresponding growth rate. For instance, the growth-adjusted dividend-price ratio is equal to the dividend-price ratio plus the dividend growth rate. Without any remedy, Columns 2 to 4 show that all eleven variables have negative R^2_{OS}s for the whole sample period and both regimes, consistent with the literature. Campbell and Thompson (2008) document that the out-of-sample predictive ability of the ratios can be substantially improved by the "fixed coefficient" restriction. For instance, for the dividend-price ratio, this restriction essentially assumes that the expected return is equal to dividend-price ratio plus dividend growth, which is hence the best predictor of the expected return in the next period.

Rows 5 to 8 (in the middle panel) show that the R^2_{OS}s of the growth-adjusted price-scaled predictors are generally much higher in the low-sentiment regime than in the high-sentiment regime after imposing the "fixed coefficient" restriction. The R^2_{OS}s of all four growth-adjusted price-scaled predictors are all positive and exceed 0.5% during the low-sentiment regime, while are all negative during the high-sentiment regime. The same pattern can be found in Rows 9 to 12 (in the lower panel), where the risk-free rate of return is deducted from the growth-adjusted price-scaled ratios. This shows that economic-model-based remedies can help to improve the predictive performance of fundamental variables (the performance is better for the constrained case compared to the unconstrained case) during the low-sentiment regime but fail to do so during the high-sentiment regime.

In addition, Rows 2 to 4 (in the upper panel) show that all the three price-scaled predictors (namely dividend-price ratio, earnings-price ratio, and smoothed earnings-price ratio) tend to perform better in the high-sentiment regime than in the low-sentiment regime. Therefore, the results in Table 4 indicate that price-scaled predictors perform more like behavioral non-fundamental predictors, and also perform more like fundamental variables after being adjusted for growth. As a result, price-scaled predictors may constitute a type of hybrid predictor, consisting of both "fundamental" and "behavioral" elements. To conduct a precise analysis of the impact of investor sentiment on the market return forecasting powers of fundamental versus non-fundamental variables, we do not consider the price-scaled variables in Campbell and Thompson (2008) and Rapach et al. (2010) as fundamental variables in our analysis.[22]

C.2 The effect of the oil shock period

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

[22] Although the price-scaled variables are normally considered as fundamental variables, they may also be partially sentiment-driven since they depend on price, which can be affected by sentiment. For instance, Cassella and Gulen (2018) propose a behavioral explanation for the forecasting power of the price-scaled variables and show that this power depends on the degree of extrapolation bias: it is strong when the degree of extrapolation bias is high, but disappears as the degree of extrapolation bias decreases.

Panel C of Table 3 (though less significant), showing that both fundamental and non-fundamental predictors still have forecasting power after 1975 (conditioning on sentiment).

Next, we re-run the regressions over the entire sample period (July 1965 to December 2010), excluding only the years 1973–1975. Panel B of Table 5 shows that exclusion of this period does not substantially alter our results. The fundamental variable still performs well in the whole sample and the low sentiment regime, while the non-fundamental variable still has significant forecasting power in the high-sentiment regime. After removing the 1973-1975 oil shock period, both the t-statistics and R^2 become slightly weaker for the fundamental variable in the whole-sample and the low-sentiment regime, compared to Panel C of Table 3. Since the oil shock occurs within our low-sentiment periods, the results for the high-sentiment regime are less affected.

C.3 Predictability during expansions

A large number of studies present evidence that the predictive ability of economic variables is concentrated in recession periods, and there is little forecasting power during expansions. It is therefore interesting to see whether the forecasting patterns of both the fundamental and non-fundamental variables are affected by business cycle expansions and recessions. We label the National Bureau of Economic Research (NBER) expansion periods as EXP and recessions as REC. During the whole sample period, from July 1965 to December 2010, 456 months are classified as EXP while 90 months are identified as REC (see Figure 3). For comparison, we also plot the high-sentiment months estimated by the regime switching approach as the shaded areas in Figure 3. Our sentiment regimes do not co-move substantially with the business cycles: the correlation between the NBER recession dummy and the high-sentiment dummy is only 0.23.

We re-run the regressions in Table 3 for expansion periods only and detail the results in Panel C of Table 5. The “whole sample period” in Panel C of Table 5 refers to the aggregate of the expansion periods; the “high/low periods” are the months within these expansion periods during which investor sentiment is high or low. We find similar predictive patterns over the expansion periods. The combined fundamental predictor μ_t is significant for both expansions as a whole and low-sentiment months and insignificant in the high-sentiment months; the combined non-fundamental variable m_t is significant in the high-sentiment months but insignificant over all expansion periods and low-sentiment months.

C.4 The predictive ability of anchoring variables

Li and Yu (2012) document that nearness to the 52-week high $x_{52,t}$ has strong predictive ability when calculated using daily stock prices of the Dow Jones Industrial Average index. They contend that, when prices are far below the 52-week high (i.e. nearness to the 52-week high has a low value), it is likely that the firm has recently experienced sporadic bad news. Based on psychological evidence, conservatism bias suggests that investors may under-react to such bad news. This under-reaction hypothesis is also consistent with the experimental research on adjustment and anchoring bias. In particular, when bad news pushes a stock's price far below the 52-week high, investors may become reluctant to bid the price further down, even if the news justifies a large drop; this leads to under-reaction. Later, when the bad news is absorbed and the under-reaction is corrected, the price falls to the correct level. This leads to a lower return in the subsequent period. Consequently, a lower $x_{52,t}$ predicts a lower return, or, put differently, nearness to the 52-week high is expected to be positively associated with future returns.[23]

We calculate the psychological anchoring variables using the daily prices of the Dow Jones Industrial Average index, the NYSE/AMEX total market value index, and the S&P 500 index, respectively. The three panels in Table 6 present in-sample regression results for $x_{52,t}$, calculated using these three indices as a predictor of future monthly NYSE/AMEX value-weighted excess returns.[24]

Panel A of Table 6 echoes the results in Panel B of Table 3. More specifically, although the anchoring variable $x_{52,t}$ based on the Dow Jones Industrial Average index exhibits significant predictive power during the whole sample period, this power is driven by the high-sentiment regime and disappears in the low-sentiment regime.

Panel B of Table 6 indicates that the predictive power of $x_{52,t}$ based on the NYSE/AMEX total market value index is weak and insignificant over the whole sample, which is consistent with Li and Yu (2012). However, this finding is puzzling, as Li and Yu (2012) provide a strong argument and detailed explanation regarding this predictive power, wherein investors tend to underreact to sporadic past news due to behavioral biases. However, why does this behavioral bias only kick in when using the Dow Jones Industrial Average

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

[24]Following Li and Yu (2012), we control for past return, nearness to the historical high, a historical high indicator, and a "52-week high equal-historical high" indicator in these regressions. In addition, we predict monthly NYSE/AMEX value-weighted excess returns in Table 6 to facilitate an easy comparison with Li and Yu (2012). In all other analyses, we follow Welch and Goyal (2008) and predict future monthly S&P 500 excess returns.

index and not the NYSE/AMEX total market value index? Li and Yu (2012) do not provide a thorough discussion of this loss of predictive power.[25]

Given that many index funds track both the Dow Jones Industrial Average index and the NYSE/AMEX total market value index or their close proxies, the "limited attention" hypothesis seems to be an insufficient explanation for the results, which reveal the under-reaction only exists when using the Dow index to calculate nearness to the 52-week high. Our results show that accounting for investor sentiment sheds light on this puzzle. During the high-sentiment regime, nearness to the 52-week high based on the NYSE/AMEX total market value index has strong and statistically significant predictive ability, with a t-statistic of 3.76. This is almost three times higher than the t-statistic of 1.30 for the whole sample and the t-statistic of 1.37 for the low-sentiment regime. This is also true for nearness to the 52-week high calculated based on the S&P 500 index (see Panel C of Table 6), indicating that the predictive power of nearness to the 52-week high is strong regardless of indices used as long as market sentiment is high. Overall, these results indicate that the ability of psychological anchors to predict aggregate market return is not exclusive to the Dow index. Anchoring variables constructed based on other indices, no matter if they capture market-wide or firm-specific information, also present substantial predictive power once we control for the impact of market sentiment.

C.5 Non-parametric approach to classify sentiment regimes

In this subsection, we study alternative sentiment regimes based on a non-parametric approach in the form of the commonly used median cut approach. As shown in Panels D and E of Table 5, when the regimes are determined by the commonly used non-parametric naive median cut or a specific non-parametric 20% cut (matching the approximate 20% high-sentiment regime periods indicated by our regime switching model), we are still able to observe the pattern of paradigm shifts in equity return forecasting between fundamental (in low regime) and non-fundamental predictors (in high regime). This indicates that the results of this study are not likely due to over-fitting of the parametric regime switching model proposed in this study.

Moreover, comparing the results in Panel D for median cut to the main results in Panel C of Table 3, the t-statistics become larger for fundamental variable μ_t but smaller for non-fundamental variable m_t in regime H. The reason seems straightforward: the median definition classifies 50% of the sample as high-regime

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

periods, a substantial increase from the regime switching approach, under which high-regime periods only comprise 20% of the sample. Thus, for 30% of the months in the sample, sentiment is above the median but below the high-sentiment threshold set by the regime switching approach. These months decrease the mean value of sentiment in the high-sentiment periods defined using the 50%–50% cutoff. This, in turn, strengthens the forecasting power of the fundamental variable while weakening the predictive strength of the non-fundamental variable.

In addition, the main reason to use a regime switching model is that the median cut approach may be problematic. As shown in the bottom panel of Figure 1, the shifts between high- and low-sentiment regimes become quite frequent in the latter part of the Baker and Wurgler sentiment index sample period. Very often, high-sentiment regimes last for just two or three months, followed by low-sentiment regimes of similar duration. However, there do not appear to be any corresponding major events that would trigger such frequent sentiment shifts. In contrast, as shown in the middle panel of Figure 1, under the regime switching model, there is no such seemingly unreasonable volatile swings in sentiment.

C.6 Return predictability over longer horizons

Given that short-horizon return predictability is usually magnified at longer horizons (Campbell, Lo and MacKinlay, 1997; Cochrane, 2011), we also explore longer-horizon regressions and report the results in Table 7.

As expected, the fundamental variable tends to have stronger predictive power at longer horizons. Particularly, in the high sentiment regime, the fundamental variable becomes significant at 3 month and 6 month horizons while it is insignificant at the 1 month horizon. This indicates that even the connection between fundamental predictors and market returns can be weakened over the high sentiment regime as the increasing power of the fundamental variable at longer horizons may cause the coefficient to become significant. However, at 9 month and 12 month horizons, the fundamental variable becomes insignificant again during the high sentiment regime. This may be due to the fact that the connection between fundamental predictors and market returns is weakened more heavily at 9 month and 12 month horizons, and this weakened connection effect dominates the strengthened forecasting power effect. Nevertheless, similar to the 1 month horizon case, the significance levels and the R^2 statistics for the high sentiment regime are always smaller than those for the low sentiment regime. This supports the key finding of this study that the connection between fundamental predictors and market returns can be weakened when sentiment is high.

As for the non-fundamental variable, it demonstrates increasing predictive power when the 1 month horizon is extended to a 3 month horizon. However, as horizon increases further from 3 months to 12 months, the predictive power of the non-fundamental variable tends to decrease, becoming less significant at 9 month and 12 month horizons. This seems consistent with the fact that non-fundamental predictors likely capture temporary market trends and hence may not work well for longer horizons. For example, the significant predictive ability of the time series momentum variable over short horizons disappears for horizons greater than 1 year, e.g., Moskowitz et al. (2012). However, similar to the 1 month horizon case, the significance levels and the R^2 statistics for the high sentiment regime are always greater than those for the low sentiment regime. This supports the key point of this study that the connection between non-fundamental predictors and market returns can be strengthened when sentiment is high.

C.7 Alternative variables determining regimes

There may be a concern that alternative variables, such as the consumption surplus ratio and TED spread (a proxy for capital or funding constraints), could also affect the time-varying return predictability. In this subsection, we examine the impact of alternative measures.

We first use credit spread (CRDSPRD) as a proxy for capital or funding constraints. CRDSPRD is computed as the monthly credit spread (the difference between BAA corporate bond yields and AAA corporate bond yields obtained from the St. Louis Federal Reserve). Higher credit spread could increase the cost of margin capital. The sample covers 1965:07–2010:12. When CRDSPRD is used to determine the regimes, the results are reported in Panel A of Table 8.[26] The fundamental variable significantly forecasts returns in both regimes while the non-fundamental variable does not forecast returns in either regime. This finding may not be that surprising. Firstly, CRDSPRD is more like a “rational variable”. Regardless of whether it is high or low, the connection between the fundamental predictor and market returns is not likely to be weakened. Hence, the fundamental variable can be a strong predictor for both high- and low-CRDSPRD regimes. Secondly, given that CRDSPRD tends to be a “rational variable”, when it is high, the connection between the non-fundamental predictor and market returns is unlikely to be strengthened much. Indeed, we find that

[26]For these alternative variables, the high and low regimes are determined by being above or below median level. Use of the Markov regime switching model can be difficult for many alternative measures, which often have much shorter sample periods (such as 90 monthly observation) compared to more than 500 monthly observations in the case of Baker and Wurgler sentiment index. For comparison, please refer to Panel D of Table 5 in which the high and low regimes are also determined by being above or below median level of the Baker and Wurgler sentiment index. Consistent with the sentiment index, we use the level of these alternative variables to determine regimes. We also study the 1-month change in CRDSPRD following Akbas et al. (2016) and find similar results when regimes are determined by the change in CRDSPRD.

the non-fundamental variable does not forecast returns in the high-CRDSPRD regime. Hence, when the regimes are determined by the alternative measure CRDSPRD, we do not observe the pattern of paradigm shifts in equity return forecasting between fundamental (in low regime) and non-fundamental predictors (in high regime).

We then use the TED spread as an alternative proxy for capital or funding constraints. We compute the TED spread as the difference between the three-month LIBOR and the three-month T-Bill rate. As in other studies using the TED spread (e.g., Nyborg and Östberg, 2014), the sample period starts from 1986:01 due to data availability. The results are reported in Panel B of Table 8. Similar to the CRDSPRD case, when the regimes are determined by the level of the TED spread, we do not observe the pattern of paradigm shifts in equity return forecasting between fundamental (in low regime) and non-fundamental predictors (in high regime).[27] Like the CRDSPRD, the TED spread appears to measure market friction and is more or less a "rational variable". Therefore, when it is high, the connection between fundamental economic (non-fundamental behavioral-based) predictors and market returns is unlikely to be weakened (strengthened).

In addition, we use the FEARS index constructed in Da, Engelberg and Gao (2015) to measure investors' fear. [28] We use the monthly average of the daily FEARS index to obtain a monthly FEARS index. The high (low) regime refers to low (high) FEARS periods. The results are reported in Panel C of Table 8. Similar to the Baker and Wurgler sentiment index case, when the regimes are determined by the level of the FEARS index, we observe the pattern of paradigm shifts in equity return forecasting between fundamental (in low regime) and non-fundamental predictors (in high regime). This is not surprising since the FEARS index is an alternative measure of investor sentiment as claimed by Da et al. (2015). Nevertheless, the FEARS index has rather short sample period compared with the Baker and Wurgler sentiment index. The relatively longer sample is one main reason for many studies (including this one) to use the Baker and Wurgler sentiment index instead of alternative sentiment measures with shorter sample periods.

Furthermore, the consumption surplus ratio proposed in Campbell and Cochrane (1999) varies with the business cycle and could affect the time-varying return predictability. We use the consumption surplus ratio to determine the regimes and the results are reported in Panel D of Table 8. The fundamental variable significantly forecasts returns in both regimes while the non-fundamental variable does not forecast returns

[27] Note that different from the above CRDSPRD case in which we have the same sample period as for the sentiment index case, the results for the whole sample for the TED case are different from Table 3 due to the different sample periods used for the TED case. The sample period used for Table 3 is 1965:07-2010:12 while the sample period used here is 1986:01 to 2010:12. This difference exists for two of the following three alternative measures since their sample periods are also different from 1965:07-2010:12.

[28] We download the data over 2004:07–2010/12 from Zhi Da's webpage `https://www3.nd.edu/~zda/`.

in either regime. Hence, when the regimes are determined by the level of the consumption surplus ratio, we do not observe the pattern of paradigm shifts in equity return forecasting between fundamental (in low regime) and non-fundamental predictors (in high regime). Similar to the CRDSPRD case and the TED case, this finding may not be that surprising since the consumption surplus ratio is also a "rational" type variable. As a result, when it is high, the connection between fundamental economic (non-fundamental behavioral-based) predictors and market returns is not likely to be weakened (strengthened).

Finally, we examine aggregate disagreement as another alternative "behavioral variable". Following Yu (2011), we calculate the aggregate disagreement as the cross-sectional value-weighted average of analyst forecast standard deviations of long-term earnings-per-share growth rate. The results are reported in Panel E of Table 8. When the regimes are determined by the level of the aggregate disagreement, both the fundamental and non-fundamental predictors tend to be more significant in the high aggregate disagreement regime. One potential reason may be that the high aggregate disagreement regime is related to a more volatile period of the market and/or economic recessions. Some studies have documented that the forecasting power of fundamental predictors tends to concentrate in volatile/recession periods. As for the non-fundamental predictors, they should be more significant in the regime when the aggregate disagreement, a "behavioral variable", is high. Nevertheless, we still do not observe the pattern of paradigm shifts in equity return forecasting between fundamental (in low regime) and non-fundamental predictors (in high regime). Cen, Lu and Yang (2013) and Cen, Wei and Yang (2017) provide an elegant theoretical framework and solid empirical analysis to show that sentiment and disagreement may affect stock returns in different ways, even though they interact closely.

Overall, when alternative measures are used to determine the high/low regimes, we do not observe a similar pattern of paradigm shifts in equity return forecasting between fundamental (low regime) and non-fundamental predictors (high regime) as we observe across high/low sentiment regimes. The only exception is the FEARS index. Nevertheless, the FEARS index has rather short sample period compared with the Baker and Wurgler sentiment index.

C.8 Some potential reasons behind the regime switching in sentiment

The regime switching in sentiment regimes can be caused by time-varying dominance of rational/irrational investors as discussed in the literature. For instance, Barberis, Greenwood, Jin and Shleifer (2018) show that, due to random allocation of attention to different signals, the composition of behavioral-bias-driven investors and rational investors "waves" over time. The large literature of heterogeneous agent models (e.g., Brock and Hommes, 1997; Hommes, 2013) shows that the evolutionary selection based on relative performance can generate time-varying dominance between rational and irrational investors. In addition, Lof (2015) directly estimates the heterogeneous agent models and shows that the fraction of rational/irrational investors can vary dramatically over time. When irrational (rational) investors dominate, we may observe high (low) investor sentiment. Thus, the time-varying dominance of rational/irrational investors can lead to the observed regime switching in investor sentiment.[29]

D Out-of-sample forecasting performance

Although the in-sample analysis provides more efficient parameter estimates and thus more precise return forecasts by utilizing all available data, Welch and Goyal (2008), among others, argue that out-of-sample tests seem more relevant for assessing genuine return predictability in real time and avoiding the in-sample over-fitting issue.[30] We expect that the regime-dependent predictive performances of both fundamental and non-fundamental variables are driven by the underlying behavioral force of investor sentiment. Particularly, a high level of market sentiment distorts the link between fundamental variables and the market return while enhancing the underlying behavioral activities behind non-fundamental predictors, such as under-reaction and overreaction. Hence, it is of interest to investigate the robustness of out-of-sample predictive performance conditional on investor sentiment.

The key requirement for out-of-sample forecasts at time t is that we can only use information available up to t in order to forecast market return 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 concerns of look-ahead bias, we use a real-time sentiment index to estimate the regimes. Following Baker and Wurgler (2006), we form the sentiment index at time t by taking the first principal component of the six measures of investor sentiment up to time t. The six

[29] The alternation of investors' aggregate expectations in overoptimistic and overpessimistic states is also found in laboratory experiments, e.g, Hommes, Sonnemans, Tuinstra and van de Velden (2005).

[30] 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).

measures are the closed-end fund discount, the number and the first-day returns of IPOs, NYSE turnover, the equity share in total new issues, and the dividend premium. At each time t, we use the recursively estimated sentiment index $\{X_s\}_{s=1}^{t}$ to estimate the regimes during time periods $1:t$. If the market is in regime H (L) at time t, then we regress $\{R_s\}_{s=2}^{t}$ on $\{\mu_s\}_{s=1}^{t-1}$ and $\{m_s\}_{s=1}^{t-1}$ in regime H (L), and the out-of-sample forecast in regime H (L) at time $t+1$ is given by (21).

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

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

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

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

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

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

We select the first half of the sample as the training sample. Table 9 reports the differences in out-of sample predictive performances of the fundamental and non-fundamental predictors across sentiment regimes.[31] The results have several implications. First, when we use the fundamental variable as the only predictor, Column 2 shows that the R_{OS}^2 is 0.81% in the low-sentiment regime, exceeding the 0.5% benchmark (Campbell and Thompson, 2008), but becomes negative in the high-sentiment regime (−2.10%) and in the whole sample period (−2.28%). This indicates that the fundamental variable has predictive power in

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

the low-sentiment regime even without imposing any of the remedies proposed in recent literature, as we expected. However, this variable underperforms the historical average benchmark in the full sample period as documented in the previous literature, and also in the high-sentiment regime, which is also intuitively expected. This is consistent with our in-sample results.

Second, when we use the combined non-fundamental variable as the single predictor, Column 3 in Panel A shows that it fails to outperform the historical average benchmark in the low-sentiment regime, with a negative R^2_{OS} of -0.90%. Column 3 also verifies that the non-fundamental variable performs considerably better in the high-sentiment regime, as expected, with a positive R^2_{OS} of 3.30% – a nearly fourfold increase from the low-sentiment regime. This stark difference again highlights the importance of considering shifts in market sentiment in predicting stock market return.[32]

Additionally, we find that compared with using fundamental or non-fundamental information alone, or incorporating both of them unconditionally as reported in Column 4, the out-of-sample predictability can be substantially improved when we consider a predictor that switches between the fundamental and non-fundamental variables conditional on the sentiment regime. Specifically, we use $I_{H,t}m_t + (1 - I_{H,t})\mu_t$ as a predictor in (21), where $I_{H,t}$ is an indicator of regime H. That is, we use non-fundamental predictor m_t conditional on being in the high-sentiment regime and switch to fundamental predictor μ_t in the low-sentiment regime. Column 5 shows that the corresponding R^2_{OS} reaches 1.38%, the largest across Panel A for the whole sample period. Therefore, shifting between fundamental and non-fundamental predictors conditional on sentiment regimes outperforms both using the fundamental or non-fundamental predictor alone and using both of them unconditionally. This is because the former approach incorporates the impact of sentiment on market return forecasting while all of the latter methods ignore it.

V. Forecasting Channel

In this section, we explore the possible economic channels driving the predictive ability of the fundamental and non-fundamental variables. Valuation models suggest that stock prices are determined by both future expected cash flows and discount rates. From this perspective, the ability of fundamental and non-fundamental variables to forecast the aggregate stock market may stem from the cash flow channel, the

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

discount rate channel, or both. We use dividend price ratio as our discount rate proxy, since its time variation is primarily driven by discount rates (Cochrane 2008, 2011). We use dividend growth as our cash flow proxy as this variable has been widely examined and used in similar studies in the literature (Campbell and Shiller, 1988; Lettau and Ludvigson, 2005; Huang et al., 2015).

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

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

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

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

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

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

VI. A Theoretical Model

In this section, we present a model to illustrate that the combination of short-sale constraints and sentiment may lead to time series momentum during the high-sentiment regime but not during the low-sentiment regime.

We consider a financial market populated by two types of investors: rational investors and irrational investors indexed by $i = R, I$ respectively. We assume that all investors are risk neutral and subject to short-sale constraints.[33]

There is a risky asset with a positive net supply. The final payoff D of the risky asset is normally distributed

$$D \sim N(\mu_D, \sigma_D^2). \tag{26}$$

Before observing any signals, investors have prior beliefs about the final payoff D of the risky asset,

$$D \sim N\big(\mu_{i,D}, \sigma_D^2\big), \qquad i = R, I. \tag{27}$$

For simplicity, we assume that investors have homogeneous and correct beliefs about volatilities. We also assume that rational investors have a correct prior belief about the mean value of D, i.e.,

$$\mu_{R,D} = \mu_D.$$

However, irrational investors are subject to exogenous sentiment shocks. We assume that the sentiment shock follows different distributions during the high-sentiment regime and low-sentiment regime. More specifically, during the high-sentiment regime, sentiment e^H follows a continuous uniform distribution $e^H \sim U(\underline{e}^H, \overline{e}^H)$, where the minimum and maximum values $\underline{e}^H$ and $\overline{e}^H$ satisfy $0 < \underline{e}^H < \overline{e}^H$. During the low-sentiment regime, sentiment follows $e^L \sim U(\underline{e}^L, \overline{e}^L)$ with $\underline{e}^L < \overline{e}^L < 0$. The exogenous sentiment changes irrational investors' prior belief about the mean value of D:

$$\mu_{I,D} = \mu_D(1 + e^k), \qquad k = H, L.$$

[33] 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 investors in a one-period model; however, in multi-period environments, the optimal demands cannot be explicitly solved from the first order conditions due to the nonlinear expectations caused by the short-sale constraints.

As a result, irrational investors are overoptimistic (overpessimistic) during the high- (low-) sentiment regime by noting that the high sentiment e^H is positive while the low sentiment e^L is negative. We assume that rational investors know which sentiment regime the market is at.[34]

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

$$s_t = D + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma^2_{\varepsilon,t}), \tag{28}$$

where D, e^k, and ε_t are mutually independent. In order to show the momentum effect, we consider $T = 2$ for simplicity.[35] Due to the difference in priors, investors hold different posterior beliefs about the distribution of D at time 1:

$$E_{R,1}[D] = \beta s_1 + (1-\beta)\mu_D, \quad E_{I,1}[D] = \beta s_1 + (1-\beta)\mu_D(1+e^k)$$

where

$$\beta = \frac{1/\sigma^2_{\varepsilon,1}}{1/\sigma^2_D + 1/\sigma^2_{\varepsilon,1}}. \tag{29}$$

We normalize the time discount rate to zero. Type-i investors are willing to pay $P^i_t = E_{i,t}[D]$ at time t for a unit of the asset, and price at time t is given by

$$P_t = \max_{i=R,I} \{P^i_t\}. \tag{30}$$

Now we study return dynamics during high- and low-sentiment regimes.

Case (I) Low-sentiment regime. In this case, irrational investors with prior of $\mu_D(1+e^L)$, where $e^L \leq 0$, have lower expectations about the payoff than the rational investors. Therefore, equilibrium prices are determined by the belief of rational investors and reflect fundamentals. Equilibrium prices are given by

$$P_0 = P^R_0 = \mu_D, \qquad P_1 = P^R_1 = \beta s_1 + (1-\beta)\mu_D, \qquad P_2 = D. \tag{31}$$

[34]We consider exogenous sentiment in our model because we are concerned with the impact of sentiment rather than its formation. This is also consistent with this paper's empirical analysis, in which the sentiment is exogenously given. The interaction between price and sentiment has been studied in the theoretical literature, e.g., Barberis, Greenwood, Jin and Shleifer (2015) and Li and Liu (2019), in which sentiment shock is triggered by past market returns. In addition, we simply assume that rational investors know the sentiment regime, which is, indeed, easier to be estimated than sentiment itself. In our model, rational investors can realize that the market is at a low (high) sentiment regime if they hold (do not hold) the risky asset.

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

Price differences over the two periods are given, respectively, by

$$P_1 - P_0 = \beta s_1 - \beta \mu_D = \beta(D - \mu_D) + \beta \varepsilon_1,$$
$$P_2 - P_1 = D - [\beta s_1 + (1-\beta)\mu_D] = (1-\beta)(D - \mu_D) - \beta \varepsilon_1.$$

Under the rational (or objective) belief,

$$cov_{R,0}[P_2 - P_1, P_1 - P_0] = \beta(1-\beta)\sigma_D^2 - \beta^2 \sigma_{\varepsilon,1}^2 = 0, \tag{32}$$

where the last equality is due to (29). In this case, there are no autocorrelations in price changes since asset prices respond to new information immediately and correctly.

Case (II) High-sentiment regime. During the high-sentiment regime, irrational investors with prior of $\mu_D(1+e^H)$ $(> \mu_D)$ are overoptimistic. As a result, asset prices are set by irrational investors and feature behavioural bias:

$$P_0 = P_0^I = \mu_D(1+e^H), \qquad P_1 = P_1^I = \beta s_1 + (1-\beta)\mu_D(1+e^H), \qquad P_2 = D. \tag{33}$$

Price differences over the two periods are given, respectively, by

$$P_1 - P_0 = \beta(D - \mu_D) + \beta \varepsilon_1 - \beta \mu_D e^H,$$
$$P_2 - P_1 = (1-\beta)(D - \mu_D) - \beta \varepsilon_1 - (1-\beta)\mu_D e^H.$$

In this case, prices exhibit momentum:

$$cov_{R,0}[P_2 - P_1, P_1 - P_0] = \beta(1-\beta)\mu_D^2 \sigma_{e^H}^2 = \frac{1}{12}\beta(1-\beta)\mu_D^2(\bar{e}^H - \underline{e}^H)^2 > 0. \tag{34}$$

Indeed, biased belief causes prices to gradually incorporate information. As new information comes and (eventually) dominates priors, asset price gradually converges to the fundamental value. As a result, momentum arises.[36]

[36]This is, in spirit, similar to the findings in Diamond and Verrecchia (1987), who show that short-sale constraints reduce the speed at which prices adjust to private information. In one extreme case of $\sigma_{e^H} = 0$, we have $cov_{R,0}[P_2 - P_1, P_1 - P_0] = 0$. In this case, there will be no price momentum. However, the reason for the lack of price momentum differs from the low-sentiment periods: sentiment investors hold a dogmatic prior belief and do not update it to adjust the price toward the fundamental level after observing new information.

In summary, when sentiment is high, irrational investors tend to initially overvalue the stock and take long positions. In contrast, rational investors cannot arbitrage away the overpricing due to short-sale constraints. As the information about the true value of the stock comes and dominates priors over time, the stock price is gradually adjusted downwards to the true value, giving rise to momentum. In contrast, when sentiment is low, irrational investors tend to undervalue the stock but cannot take short position due to short-sale constraints. Therefore, the stock price will be always set by rational investors and there is no momentum in this case. Overall, the influences of heterogeneous agents, namely, the irrational and rational investors, take their turns in our proposed model. As a consequence, non-fundamental predictors, such as momentum variables, may (may not) work well during high (low) sentiment periods when the influence of irrational (rational) investors dominates.[37] Therefore, the proposed model provides a simple yet rigorous framework for understanding the underlying economic channel of the paradigm shifts in forecasting stock returns, which is the time-varying dominance of irrational investors during the high sentiment regime and rational investors during the low sentiment regime.

Moreover, the proposed model capturing the economic channel of time-varying composition of the irrational and rational investors can also have additional implications besides the paradigm shifts in returns forecasting (see the Appendix).

VII. Conclusion

We propose a regime-switching model to examine paradigm shifts in stock market return forecasting. We find that fundamental economic variables forecast the market return well only when sentiment is low. They lose their predictive power when sentiment is high, since their connection with aggregate market return can be weakened during high sentiment periods. In contrast, non-fundamental variables predict the market return well only when sentiment is high but not when it is low, since their performance relies on behavioral biases that tend to become insignificant during low-sentiment periods. Moreover, the sentiment-based paradigm shifts in aggregate market return forecasting provide a key to understanding and resolving the lack of predictive power for both fundamental and non-fundamental variable as debated in recent studies.

[37] We assume that investors are risk neutral in our setting for tractability. As a result, this model does not provide direct evidence that fundamental predictors may (may not) work well during low (high) sentiment periods when the influence of rational (irrational) investors dominates. Nevertheless, this model indicates that the price is determined (not determined) by the fundamentals during a low (high) sentiment regime when rational (irrational) investors dominate. This may be considered as a form of indirect supporting evidence that fundamental predictors may (may not) work well during low (high) sentiment periods.

Appendix. Some Additional Implications of the Model

The proposed model in Section VI may have some additional implications besides the paradigm shifts in returns forecasting.

First, during high-sentiment periods, our model implies that the sentiment investor sets the price and there is a time series momentum over the decline from P_0 to P_1 and followed by a continuation decline from P_1 to P_2. This implies a slow diffusion of negative news when sentiment is high. This implication has been tested by Antoniou et al. (2013) and Stambaugh et al. (2012). Particularly, Stambaugh et al. (2012) "consider a setting in which the presence of market-wide sentiment is combined with the argument that overpricing should be more prevalent than underpricing, due to short-sale impediments." They find that the short leg of momentum strategy is more profitable during high-sentiment periods. In our model, when sentiment is high, it is likely to see a decline from the initially overvalued P_0 (due to an upward biased prior) to a less overvalued P_1 (due to incorporation of an unbiased signal from the true distribution). This decline in price from P_0 to P_1 indicates a loser portfolio. By shorting it, we can make profit when the follow-up decline from overvalued P_1 to fairly valued P_2 occurs. However, when sentiment is low, if there is a decline from P_0 to P_1, it will be due to the incorporation of bad news by rational investors while the bad news is randomly sampled from the true distribution of the payoff D. In this case, we do not expect a follow-up decline from P_1 to P_2 given that P_1 is correctly priced and the change from P_1 to P_2 will be independent from the past change from P_0 to P_1 as proved mathematically in our model. Therefore, our model implication is consistent with the asymmetry in the short leg of the momentum anomaly across sentiment regimes documented by Stambaugh et al. (2012), wherein the short leg of momentum strategy is more profitable during high-sentiment periods than during low-sentiment periods. Please note that although our model is about time series momentum, Moskowitz and Grinblatt (1999) show that time series momentum across time and the momentum anomaly across-section, such as in Stambaugh et al. (2012), are closely related.

In addition, our model implies that the impact of the momentum effect should be stronger for firms with larger σ_{e^H} as indicated by our model: $cov_{R,0}[P_2 - P_1, P_1 - P_0] = \beta(1-\beta)\mu_D^2\sigma_{e^H}^2 > 0$. Dividing both sides of the equation by μ_D^2 to standardize the momentum effect across firms, this implies that the higher the σ_{e^H}, the larger the momentum effect. Therefore, our model implies that time series momentum and the associated cross-sectional momentum anomaly should be stronger for firms that are more difficult to value (larger σ_{e^H}, such as small and growth firms) than for firms that are less difficult to value (smaller σ_{e^H}, such as large and matured firms). This implication of our model is consistent with the literature.

Moreover, our model shows that, when sentiment is high, stock tends to be overvalued and followed by lower returns in the future. This implication is consistent with the literature, e.g., Baker and Wurgler (2006) and Huang et al. (2015).

Therefore, besides deepening our understanding on the economic channel of the paradigm shifts between fundamental and non-fundamental predictors, our proposed model seems able to provide a framework for understanding some existing observations in the literature as well.

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

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

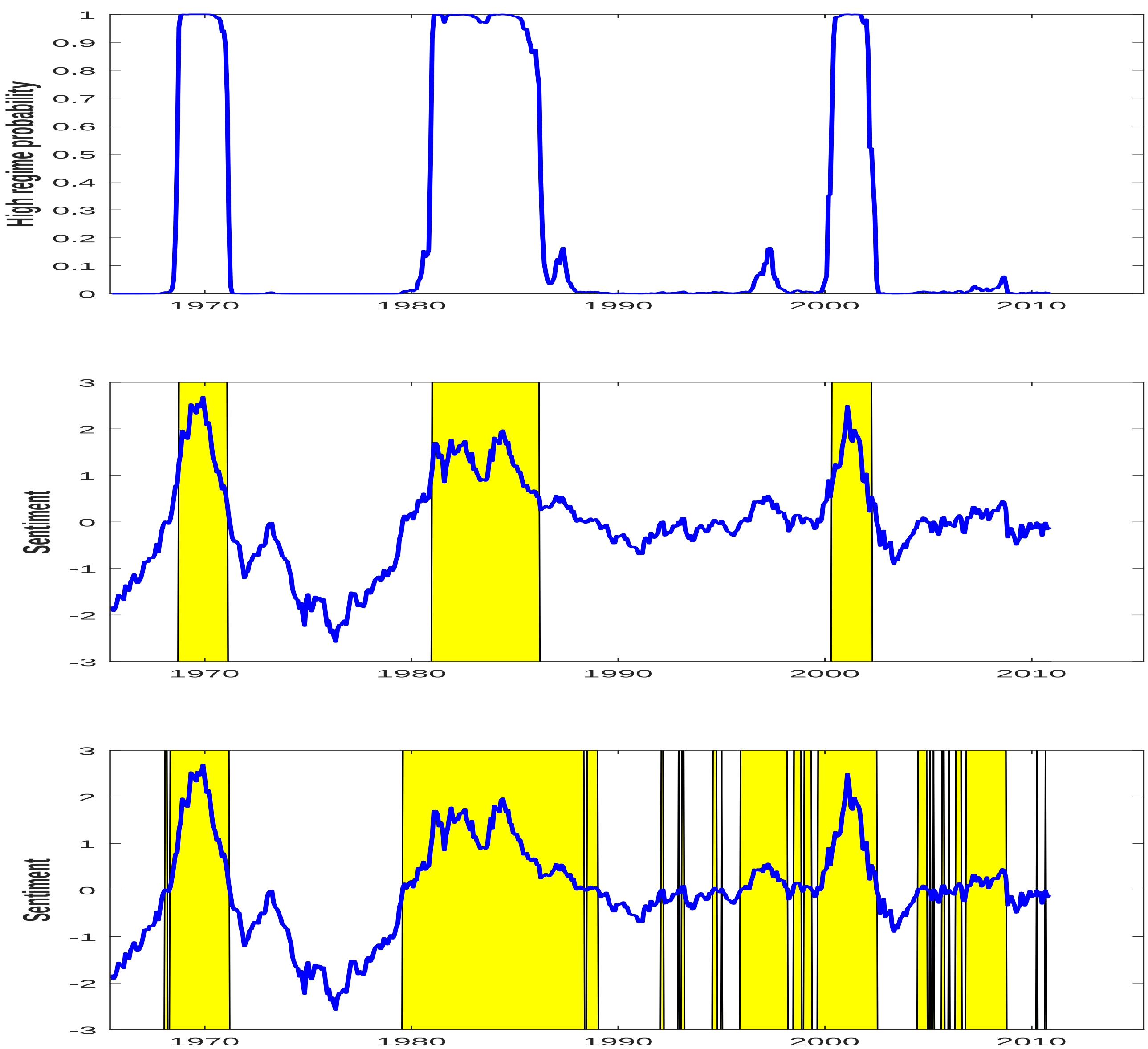

Figure 2. Times series of combined fundamental predictor μ_t and combined non-fundamental predictor m_t.

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

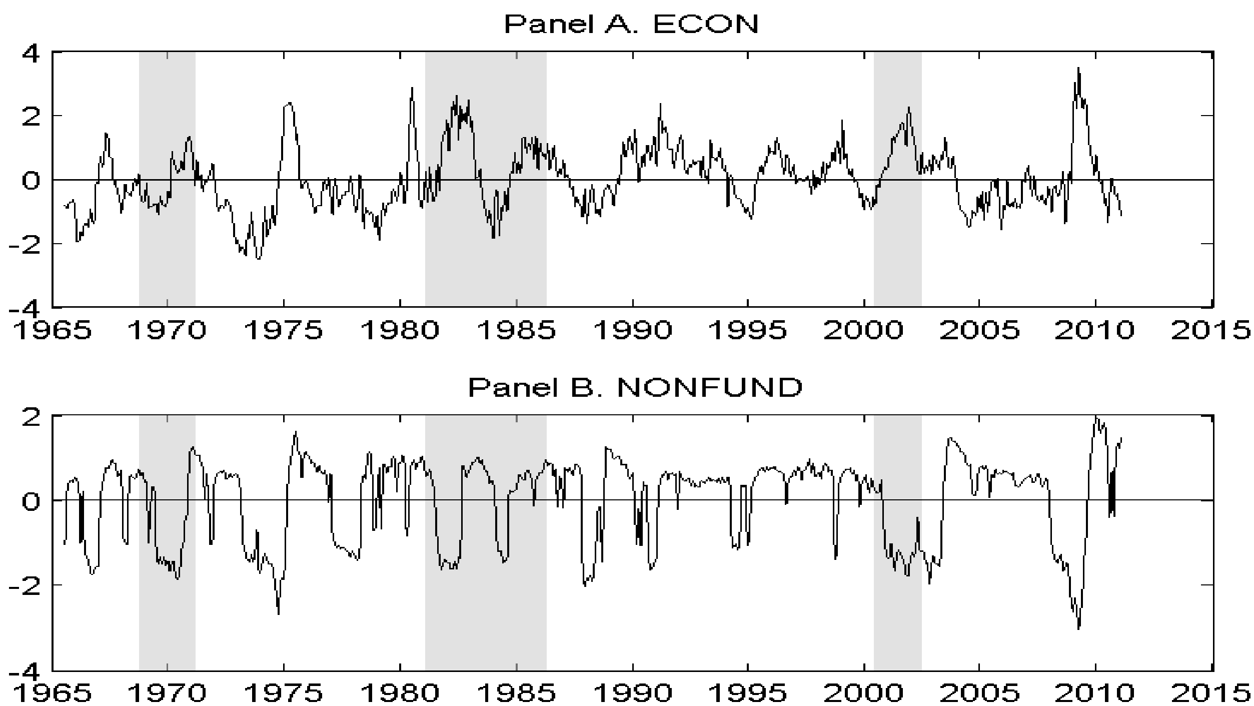

Figure 3. Times series of business cycle and investor sentiment regimes.

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

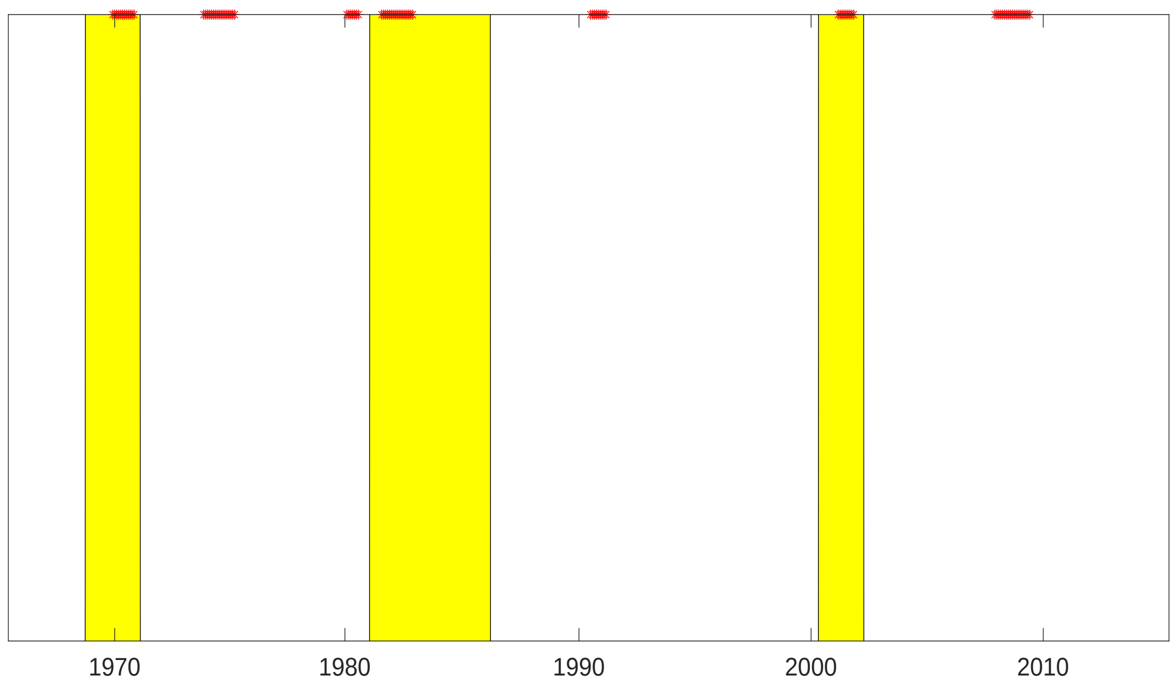

Figure 4. Correlations between predictors and excess market return and in-sample predictive regression patterns.

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

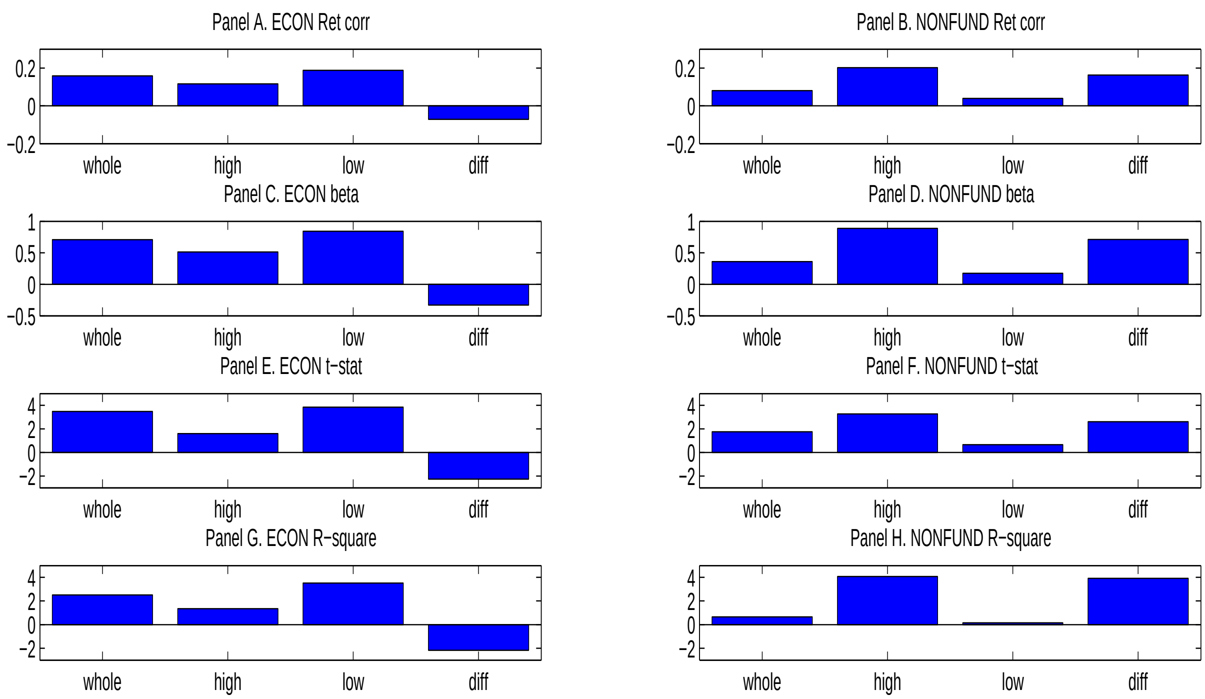

Figure 5. Time series of in-sample excess market return forecasts based on combined fundamental predictor μ_t and combined non-fundamental predictor m_t.

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

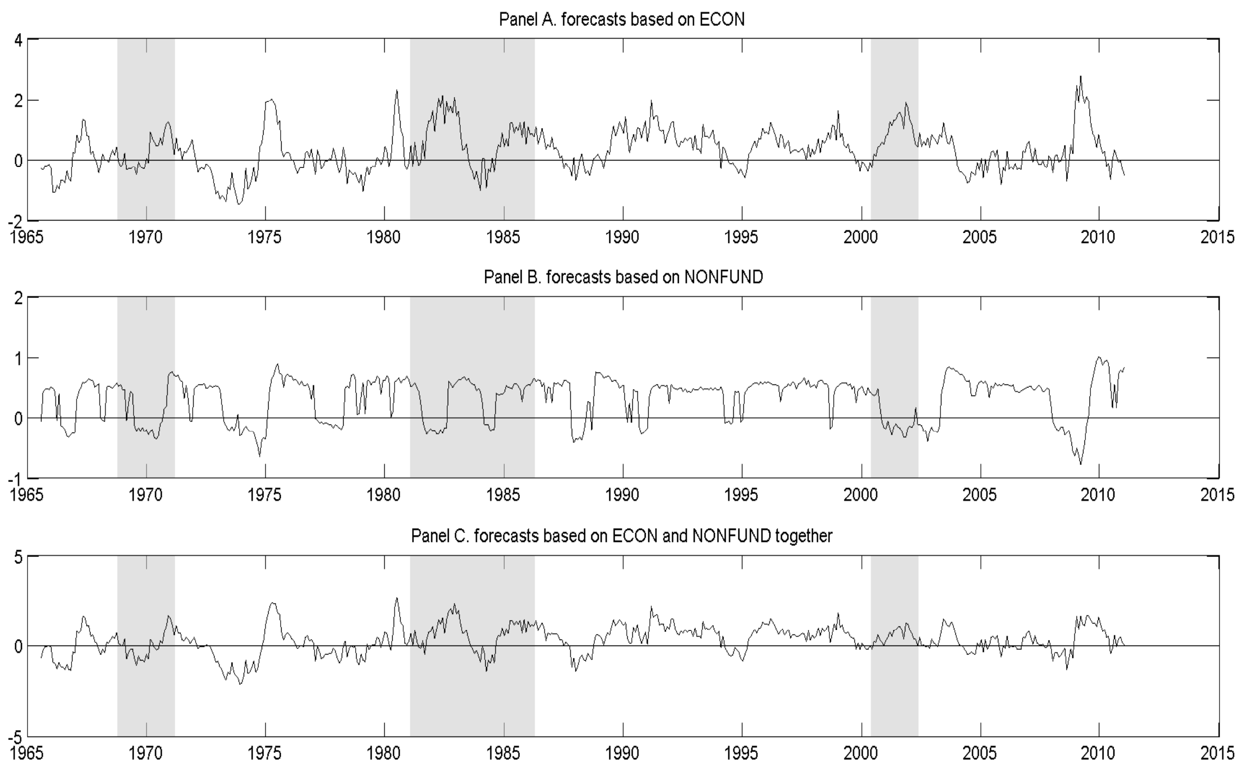

Table 1 Summary statistics

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

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

Table 2 Mispricing during high and low sentiment regimes

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

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

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

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

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

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

Table 3 In-sample predictive regressions

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

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

Table 3 In-sample predictive regressions—Continued

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

Table 4 Out-of-sample forecasting results using variables from Campbell and Thompson (2008)

This table reports out-of-sample forecasting power for the 11 variables in Table 2 of Campbell and Thompson (2008), using the first half of our data as a training sample. Our sample period begins in July 1965 to be consistent with the sentiment data. R^2_{OS} statistics in percentage points are reported for the cases without any constraint and with the "fixed coefficients" remedy described in Campbell and Thompson (2008). High- and low-sentiment regimes are estimated based on a real-time regime switching approach. Statistical significance for R^2_{OS} is based on the p-value for the Clark and West (2007) out-of-sample MSPE-adjusted statistic for testing the null hypothesis that the competing forecasting model's expected square prediction error is equal to or larger than that of the historical benchmark forecasting model against the alternative hypothesis that the competing forecasting model's expected square prediction error is lower than that of the historical benchmark forecasting model. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

	unconstrained			fixed coefficients		
	Whole	High	Low	Whole	High	Low
Dividend-price ratio	-3.21	-2.77	-3.65	-0.37	1.10	-1.16
Earnings-price ratio	-1.31	-0.16	-1.86	0.79*	1.20*	0.44
Smoothed earnings-price ratio	-1.80	-1.78	-1.89	0.59	1.06	0.23
Dividend-price ratio + growth	-0.59	-2.93	0.07	0.63**	-0.14	0.90**
Earnings-price ratio + growth	-0.60	-0.58	-0.90	0.80**	-0.32	1.19**
Smoothed earnings-price ratio + growth	-1.06	-1.93	-0.88	0.71**	-0.32	1.08**
Book-to-market ratio + growth	-2.13	-6.90	-0.62	0.42	-0.55	0.77**
Dividend-price ratio + growth − real rate	-0.48	-2.43	0.09	0.30	0.22	0.22
Earnings-price ratio + growth − real rate	-0.58	-0.51	-0.88	0.55**	0.12	0.61**
Smoothed earnings-price ratio + growth − real rate	-1.00	-1.76	-0.85	0.44	0.07	0.48*
Book-to-market ratio + growth − real rate	-2.17	-6.12	-0.70	0.09	-0.18	0.08

Table 5 Further discussions

This table displays in-sample regression results under several different cases based on the combined fundamental predictor μ_t and combined non-fundamental predictor m_t over the whole sample, the high-sentiment and the low-sentiment regimes, respectively. Panel A reports results of in-sample predictive regressions for the period 1976.01:2005.12, following Welch and Goyal (2008). Panel B presents in-sample regression results excluding the oil shock recession of 1973:1975. Panel C presents in-sample regression results during expansion periods, and the high- and low-sentiment portions of the expansion periods respectively. Panel D reports in-sample regression results when high- and low-sentiment periods are determined by the median value of the Baker and Wurgler sentiment index. Panel E uses the 20th percentile of sentiment to separate the whole sample into two regimes: we consider the months with sentiment value higher than (or equal to) the 20th percentile as high sentiment periods and the remaining months as low sentiment periods. The combined fundamental predictor μ_t is constructed from the 7 macroeconomic categories described in Jurado, Ludvigson and Ng (2015) and the combined non-fundamental predictor m_t is extracted from 6 individual non-fundamental predictors, including three time series momentum proxies, one anchoring variable, and two moving average indicators. High- and low-sentiment regimes in Panels A, B and C are estimated based on the regime switching approach. Regression coefficients, Newey-West t-statistics (with a lag of 12), and R^2s in percentage points are reported in each panel. $*, **$ and $***$ indicate significance based on bootstrapped p-values at the 10%, 5%, and 1% levels, respectively.

Panel		Whole	High	Low	Whole	High	Low	Whole	High	Low
A	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
B	μ_t	0.51***	0.54	0.57***				0.54***	0.62*	0.58***
		[2.86]	[1.60]	[3.19]				[3.30]	[1.92]	[3.29]
	m_t				0.28*	0.91***	0.02	0.34*	0.97***	0.05
					[1.31]	[3.31]	[0.07]	[1.45]	[3.40]	[0.17]
	R^2 (%)	1.36	1.50	1.78	0.42	4.29	0.00	1.97	6.29	1.80
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
D	μ_t	0.71***	0.47*	0.94***				0.72***	0.53**	0.94***
		[3.47]	[1.71]	[3.39]				[3.95]	[2.29]	[3.49]
	m_t				0.36**	0.62**	0.12	0.38**	0.66**	0.10
					[1.77]	[2.10]	[0.46]	[1.68]	[2.08]	[0.43]
	R^2 (%)	2.51	0.96	5.29	0.65	1.64	0.08	3.23	2.82	5.36
E	μ_t	0.71***	0.55	0.84***				0.72***	0.68*	0.83***
		[3.47]	[1.52]	[3.85]				[3.95]	[1.87]	[3.91]
	m_t				0.36**	0.70***	0.21	0.38**	0.81***	0.16
					[1.77]	[2.65]	[0.78]	[1.68]	[2.66]	[0.53]
	R^2 (%)	2.51	1.57	3.56	0.65	2.50	0.22	3.23	4.85	3.69

Table 6 Anchoring variables constructed based on alternative indices

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

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

Table 7 Return predictability over longer horizons

This table displays results of predictive regressions of holding-period excess returns over longer horizons onto the combined fundamental predictor μ_t and combined non-fundamental predictor m_t over the whole sample and different regimes. μ_t is constructed from the 7 macroeconomic categories described in Jurado, Ludvigson and Ng (2015). m_t is extracted from the 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 in each panel. $*, **$ and $***$ indicate significance based on bootstrapped p-values at the $10\%, 5\%$, and 1% levels, respectively. High- and low-sentiment regimes are estimated based on the regime switching approach. The sample period spans from 1965.07 to 2010.12.

		Whole	High	Low	Whole	High	Low	Whole	High	Low
3 month	μ_t	1.97***	2.06**	2.24***				2.00***	2.36**	2.22***
		[3.68]	[2.31]	[4.41]				[4.15]	[3.11]	[4.52]
	m_t				0.95*	2.21***	0.45	1.02*	2.49***	0.35
					[1.63]	[3.26]	[0.58]	[1.62]	[3.35]	[0.43]
	R^2 (%)	6.06	6.12	8.07	1.41	7.04	0.33	7.68	14.96	8.27
6 month	μ_t	3.78***	4.67**	4.17***				3.84***	5.05**	4.13***
		[3.71]	[2.49]	[4.42]				[4.04]	[2.93]	[4.55]
	m_t				1.65*	2.98**	0.92	1.77*	3.52**	0.73
					[1.69]	[2.28]	[0.73]	[1.68]	[2.33]	[0.58]
	R^2 (%)	10.34	13.22	13.55	1.96	5.38	0.66	12.59	20.67	13.97
9 month	μ_t	5.07***	6.26*	5.63***				5.11***	6.56**	5.58***
		[3.35]	[2.00]	[4.04]				[3.58]	[2.21]	[4.19]
	m_t				2.00*	2.84	1.28	2.12*	3.42*	0.98
					[1.56]	[1.30]	[0.78]	[1.53]	[1.39]	[0.61]
	R^2 (%)	12.08	14.80	16.50	1.89	3.05	0.85	14.20	19.19	16.99
12 month	μ_t	5.98***	6.78	6.71***				5.95***	6.71	6.64***
		[3.11]	[1.62]	[3.75]				[3.24]	[1.61]	[3.93]
	m_t				2.11*	2.98	1.42	2.01	2.81	0.96
					[1.47]	[1.06]	[0.78]	[1.32]	[0.87]	[0.55]
	R^2 (%)	12.69	12.59	17.81	1.58	2.43	0.80	14.13	14.75	18.17

Table 8 Determining Regimes Using Alternative Variables

This table displays regression results of the combined fundamental predictor μ_t and combined non-fundamental predictor m_t over the whole sample and different regimes as determined by alternative variables. High- and low-regimes are determined by median cut (a non-parametric method). The regimes are determined by the credit spread, the TED spread, FEARS, the consumption surplus ratio, and disagreement in Panels A, B, C, D and E, respectively. The credit spread over 1965:07–2010:12 is computed as the monthly credit spread (the difference between BAA corporate bond yields and AAA corporate bond yields); the TED spread is computed as the difference between the three-month LIBOR and the three-month T-Bill rate runs from 1986:01 to 2010:12; the FEARS index is constructed as per Da et al. (2015) and covers 2004:07–2010/12; the consumption surplus ratio defined by Campbell and Cochrane (1999) runs from 1965:07-2010:12; and the disagreement is defined as the cross-sectional value-weighted average of analyst forecast standard deviations of long-term earnings-per-share growth rate as in Yu (2011) and runs from 1981:12 to 2010:12. μ_t is constructed from the 7 macroeconomic categories described in Jurado, Ludvigson and Ng (2015). m_t is extracted from the 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 in each panel. $*, **$ and $***$ indicate significance based on bootstrapped p-values at the $10\%, 5\%$, and 1% levels, respectively.

Panel		Whole	High	Low	Whole	High	Low	Whole	High	Low
A: Credit Spread	μ_t	0.71***	0.79***	0.54**				0.72***	0.84***	0.49**
(funding constraints)		[3.47]	[3.69]	[1.75]				[3.95]	[4.26]	[1.98]
	m_t				0.36**	0.28	0.47*	0.38**	0.39	0.41
					[1.76]	[0.81]	[1.31]	[1.68]	[1.02]	[1.17]
	R^2 (%)	2.51	2.58	1.87	0.65	0.32	1.44	3.23	3.19	2.96
B: TED	μ_t	0.21	0.41	0.01				0.32	0.48*	0.14
(funding constraints)		[0.89]	[1.33]	[0.03]				[1.31]	[1.55]	[0.54]
	m_t				0.31	0.30	0.29	0.40*	0.38	0.34
					[0.97]	[0.54]	[0.97]	[1.13]	[0.65]	[1.11]
	R^2 (%)	0.21	0.58	0.00	0.46	0.30	0.60	0.91	1.06	0.72
C: FEARS (fear measure)	μ_t	0.34	-0.85	1.69**				1.05*	0.25	2.09**
		[0.66]	[-1.71]	[3.33]				[1.97]	[0.41]	[3.33]
	m_t				0.74**	1.55*	0.22	1.22**	1.72*	1.03**
					[1.32]	[2.30]	[0.34]	[2.01]	[1.96]	[2.06]
	R^2 (%)	0.56	2.71	15.90	3.51	9.02	0.27	7.58	9.16	20.92
D: Consumption surplus ratio	μ_t	0.71***	0.63**	0.61***				0.72***	0.61**	0.76***
		[3.47]	[2.32]	[2.94]				[3.95]	[2.26]	[3.60]
	m_t				0.36**	0.19	0.43	0.38**	0.10	0.61
					[1.76]	[0.67]	[1.13]	[1.68]	[0.36]	[1.49]
	R^2 (%)	2.51	1.91	2.11	0.65	0.18	0.95	3.23	1.99	3.79
E: Disagreement	μ_t	0.33	0.53	-0.03				0.45*	0.96**	-0.04
		[1.43]	[1.38]	[-0.15]				[1.91]	[2.79]	[-0.15]
	m_t				0.36*	0.56*	0.01	0.46**	0.99**	0.01
					[1.24]	[1.32]	[0.02]	[1.43]	[2.03]	[0.03]
	R^2 (%)	0.46	1.09	0.01	0.61	1.23	0.00	1.39	4.17	0.01

Table 9 Out-of-sample forecasting results

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

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

Table 10 Forecasting channel

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

Panel A: 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]	
Panel B: 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]	