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Investor Sentiment and Paradigm Shifts in Equity Return Forecasting

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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 nonfundamental) 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 nonfundamental variables debated in recent studies.

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Keywords: return predictability • economic predictors • non-fundamental predictors • regime-switching • behavioral biases

1. Introduction

The predictability of the stock market return by fundamental macroeconomic variables has been debated in recent studies (e.g., Comin and Gertler 2006, Campbell and Thompson 2008, Welch and Goyal 2008, Rapach et al. 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 nonfundamental 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 nonfundamental 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 nonfundamental 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, 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 nonfundamental 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, 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 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 et al. (2010) and Henkel et al. (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 nonfundamental 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 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 nonfundamental predictors, including time series momentum

(Moskowitz et al. 2012) and technical indicators (Brock et al. 1992, Neely et al. 2014). These nonfundamental 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 nonfundamental 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 nonfundamental variables, their forecasting power originates from investor behavioral biases. When investor sentiment is high (low), investor behavioral biases are also high (low) and hence nonfundamental 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 (nonfundamental) 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 nonfundamental variables do. In fact, there is a lack of studies comparing the effectiveness of fundamental versus nonfundamental 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 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 nonfundamental 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 et al. (2012) document that anomaly returns are more significant in high sentiment periods. Antoniou et al. (2016) show that larger beta stocks earn smaller returns during optimistic

high sentiment periods. More recently, Shen et al. (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 nonfundamental variables under a single unified framework.

The rest of the paper is organized as follows. We present the econometric methodology in Section 2. Sentiment regimes and predictors are summarized in Section 3. Section 4 reports the main empirical findings. Section 5 presents a theoretical model to formalize the intuition of sentiment impact on forecasting and Section 6 concludes. In an online appendix, we provide some additional discussions on return predictability over longer horizons (Appendix A.1), more implications of the theoretical model (Appendix A.2), out-of-sample forecasting performance (Appendix A.3), and forecasting channel (Appendix A.4).

2. 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 nonfundamental predictors.

2.1. 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,

$$r_{t+1} = \alpha + \beta_i x_{i,t} + \epsilon_{i,t+1}, \quad (1)$$

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 $\epsilon_{i,t+1}$ is zero-mean unforecastable noise. The expected excess return based on the macroeconomic variables can be estimated by

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

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 nonfundamental variables,

$$r_{t+1} = a + b_j m_{j,t} + \epsilon_{j,t+1}, \quad (3)$$

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

The forecasting power of individual fundamental predictors can be unstable across time, because 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 nonfundamental 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 nonfundamental predictor m_t , as follows:

$$r_{t+1} = \alpha_\mu + \beta_\mu \mu_t + \epsilon_{\mu,t+1}, \quad (4)$$

and

$$r_{t+1} = \alpha_m + \beta_m m_t + \epsilon_{m,t+1}, \quad (5)$$

where $\epsilon_{\mu,t+1}$ and $\epsilon_{m,t+1}$ 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 nonfundamental predictors by applying the partial least squares procedure described in Section 2.5.

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

$$r_{t+1} = a + b_\mu \mu_t + b_m m_t + \epsilon_{t+1}, \quad (6)$$

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

2.2. 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 nonfundamental 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,

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

$$r_{t+1}^i = a_m^i + b_m^i m_t^i + \varepsilon_{t+1}^i, \quad i = H, L \quad (8)$$

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

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}

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

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 $\pi_t := \text{Prob}(\rho_t = H | S_t) \geq 0.5$; otherwise, we assume time t is a low-sentiment period. Tu (2010) applies a similar regime-switching model on stock returns.

2.3. 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 4.3.1) also indicate that the price-scaled predictors perform like behavioral nonfundamental predictors. Therefore, to conduct an accurate analysis on the impact of investor sentiment on the return forecasting powers of fundamental versus nonfundamental 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 et al. (2015), where more than 100 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 macroeconomic 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) labor 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} , $j = 1, 2, \dots, 7$).¹² The seven extracted series may be treated as a set of representative macroeconomic predictors.¹³

2.4. Nonfundamental Variables

We collect a variety of behavioral/sentiment-related variables, including time series momentum (Moskowitz et al. 2012), anchoring variables (Li and Yu 2012), and technical indicators (Neely et al. 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 et al. (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 et al. 2014, Goyal and Jegadeesh 2018). We consider different momentum variables with time horizons varying from 6 to 12 months. That is,

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

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 overreact to news, respectively, and show that the former (latter) positively (negatively) predicts the market return. More specifically, nearness to the Dow 52-week high $x_{52,t}$ and nearness to the Dow historical high $x_{\max,t}$ are defined as

$$x_{52,t} = \frac{p_t}{p_{52,t}}, \quad x_{\max,t} = \frac{p_t}{p_{\max,t}}, \quad (12)$$

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

nonfundamental 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 4.3.4 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 nonfundamental 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 nonfundamental variable.

Neely et al. (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,

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

where

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

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

2.5. 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 nonfundamental variables into two consensus combined variables. In general, at period t ($t = 1, \dots, T$), we derive combined fundamental and nonfundamental predictors using N_1 fundamental economic proxies

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

and N_2 nonfundamental proxies

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

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

$$X_{i,t} = \gamma_{i,0} + \gamma_{i,1}\mu_t + \gamma_{i,2}\delta_t + u_{i,t}, \quad i = 1, 2, \dots, N_1, \quad (15)$$

where $\gamma_{i,1}$ and $\gamma_{i,2}$ are the factor loadings measuring the sensitivity of the fundamental economic proxy $X_{i,t}$ to μ_t and the common approximation error component δ_t of all the N_1 proxies that is irrelevant to returns, respectively. $u_{i,t}$ is the idiosyncratic noise associated with proxy $X_{i,t}$ only. By imposing the above factor structure on the proxies, we can efficiently estimate the collective contribution of X_t to μ_t , and, at the same time, eliminate the common approximation error δ_t and the idiosyncratic noise $u_{i,t}$. In general, μ_t can also be estimated as the first principal component analysis (PCA) of the cross-section of X_t . However, as discussed in Huang et al. (2015), the PCA estimation is unable to separate δ_t from μ_t and may fail to generate significant forecasts for returns that 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,

$$X_{i,t-1} = \eta_{i,0} + \eta_{i,1}r_t + v_{i,t-1}, \quad t = 1, 2, \dots, T, \quad (16)$$

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),

$$X_{i,t} = c_t + \mu_t \hat{\eta}_{i,1} + w_{i,t}, \quad i = 1, 2, \dots, N_1, \quad (17)$$

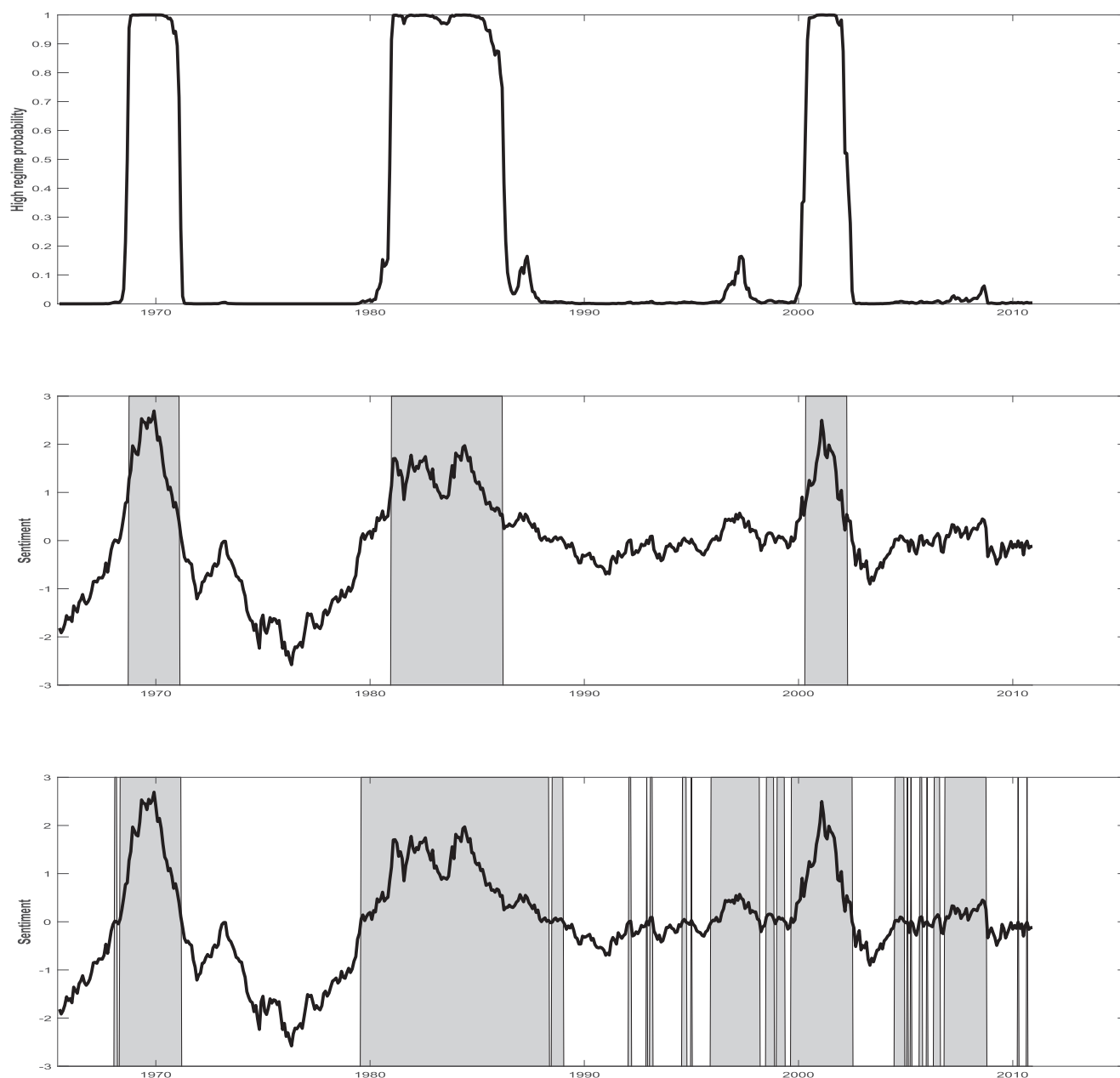
where the regression slope μ_t in (17) is the extracted μ_t .

Similarly, the nonfundamental 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

3. Data Summary

3.1. 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 span from July 1965 to

Figure 1. Time Series of Investor Sentiment and High/Low Sentiment Regimes

Notes. The upper panel plots the estimated probability of the high-sentiment regime (solid line). The middle panel depicts the investor sentiment index from July 1965 to December 2010, with high-sentiment months estimated using the regime switching approach shaded in grey. The bottom figure also depicts the investor sentiment index, with high-sentiment months estimated using the median cut approach as per Stambaugh et al. (2012) shaded in grey.

December 2010.¹⁶ The solid 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 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 et al. (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 in Figure 1 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.

3.2. 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 nonfundamental predictors, we consider seven individual fundamental variables and six individual nonfundamental variables. Applying the PLS procedure to the seven fundamental variables F_{jt} ($j = 1, 2, \dots, 7$), we obtain a combined fundamental variable μ_t ,

$$\begin{aligned} \mu_t = & -0.11F_{1t} - 0.25F_{2t} + 0.25F_{3t} - 0.34F_{4t} - 0.18F_{5t} \\ & - 0.12F_{6t} - 0.32F_{7t}, \end{aligned} \quad (18)$$

where each underlying individual proxy is standardized. The summary statistics of the combined fundamental

Table 1. Summary Statistics

| 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 | |
| F_7 | | | | | | |
| 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 | |

Notes. 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, Std, $\rho(1)$, Min, and Max of the combined fundamental predictor μ_t constructed from the seven macroeconomic categories described in Jurado et al. (2015). Panel C presents the Mean, Std, $\rho(1)$, Min, and Max of each of the seven individual macroeconomic predictors F_i , $i = 1, 2, 3, 4, 5, 6, 7$, respectively: (1) output and income; (2) labor market; (3) housing; (4) consumption, orders, and inventories; (5) money and credit; (6) exchange rates; and (7) inflation. The SR 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 July 1965 to December 2010 and shown in the middle panel of Figure 1.

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) 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,

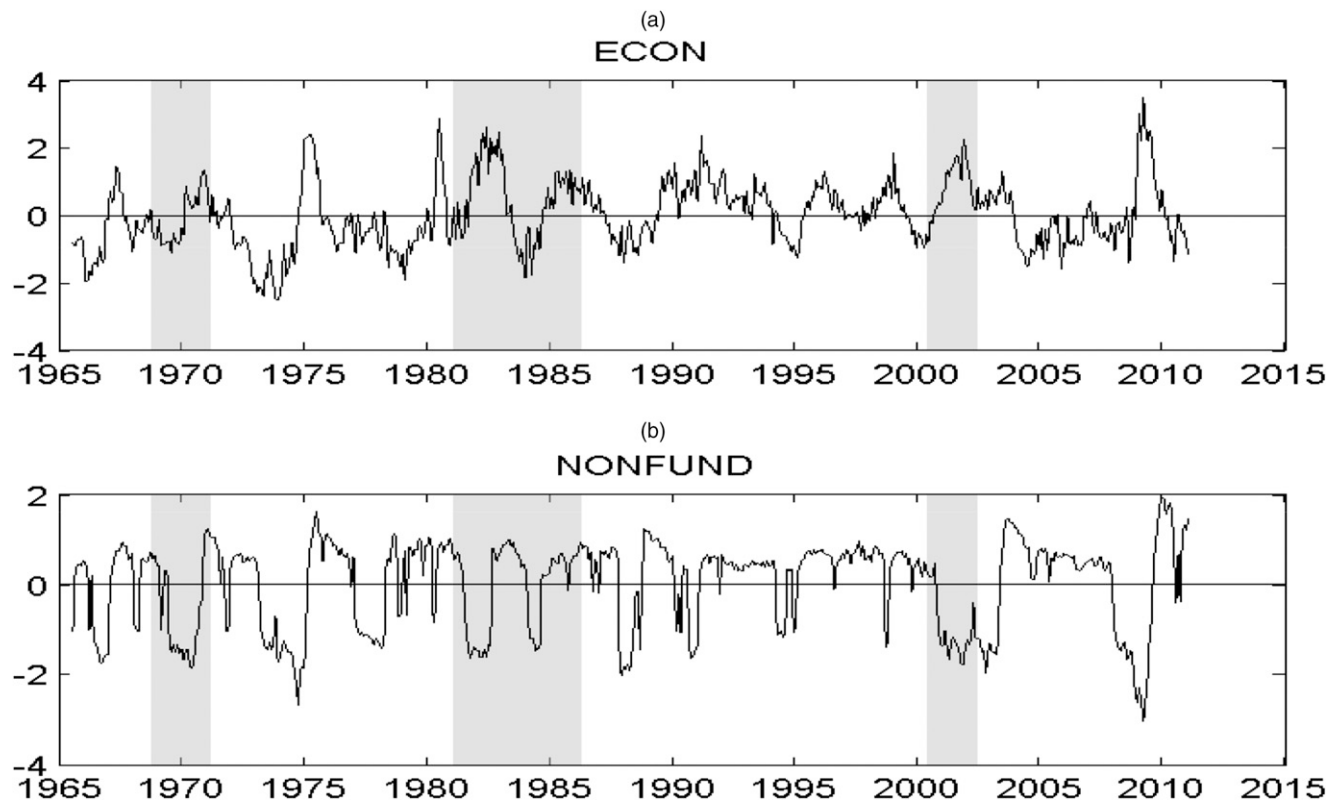
consumption, and inflation load relatively heavily on μ_t , indicating that the combined fundamental predictor primarily captures common fluctuations in various fundamental information, which may help μ_t to forecast the market return better than the individual macroeconomic predictors. As shown in Panel 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 nonfundamental variables, we generate a combined nonfundamental variable m_t ,

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

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 nonfundamental 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

Figure 2. Times Series of Combined Fundamental Predictor μ_t and Combined Nonfundamental Predictor m_t



Notes. Panel (a) plots the combined fundamental predictor μ_t , constructed from seven categories of macroeconomic variables described in Jurado et al. (2015). Panel (b) plots the combined nonfundamental predictor m_t extracted from six individual nonfundamental 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.

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 nonfundamental 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 nonfundamental variables and potentially captures more useful predictive information than any single nonfundamental variable. As shown in Panel B of Table 3, the extracted nonfundamental variables forecast the market return with a positive sign, consistent with individual proxies.

4. Main Empirical Results

In this section, we examine the forecasting performance of the fundamental economic variables and nonfundamental variables for both the full sample and the high-/low-sentiment regimes determined using the Markov regime-switching approach. Our data span from July 1965 to December 2010, a period determined by the availability of the sentiment series. In Section 4.1, we show that mispricing is much more significant during the high-sentiment regime than the low-sentiment regime. In Section 4.2, we analyze the in-sample predictive performances across sentiment regimes. In Section 4.3, we address several important issues regarding the lack of predictive power for both fundamental and nonfundamental 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, alternative sentiment regimes based on nonparametric approach, and alternative variables determining regimes. Some potential reasons behind the regime switching in sentiment is also discussed.

4.1. 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 2.2 and 3.1. 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) during the high- and low-sentiment regimes, respectively, in Table 2. The baseline regression is as follows:

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

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 5 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.

4.2. 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 et al. 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 Online Appendix A.1 and find the results are similar.

Table 2. Mispricing During High and Low Sentiment Regimes

| Anomaly | Panel A: | | | | Panel B: | | | |
|-----------------------------|---------------------------|--------|------------|--------|--------------------------------|--------|------------|--------|
| | Carhart four-factor model | | | | Fama French three-factor model | | | |
| | 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 (rebalanced: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 <i>F</i> -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 (rebalanced: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 <i>O</i> -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 |

Notes. 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 August 1965 to January 2011 for all variables except Ohlson's *O*-score, return-on-book equity, failure probability, and return-on-assets, for which data are available from July 1973. Combination is the simple average of all the individual anomalies. All *t*-statistics are computed using White heteroscedasticity robust standard errors.

We start by examining the overall forecasting performances of the fundamental and nonfundamental 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 nonfundamental variables are highly persistent, the well-known Stambaugh (1999) bias potentially inflates the *t*-statistic for regression coefficients in (4)–(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 nonfundamental variables. Panels A and B in Table 3 report the regression coefficients, the corresponding *t*-statistics, and R^2 s for the seven fundamental and six nonfundamental variables, respectively. Panel C reports the regression results for

the combined fundamental and nonfundamental 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

Table 3. In-Sample Predictive Regressions

| Panel | | Whole | High | Low | Whole | High | Low | Whole | High | Low | Whole | High | Low |
|-------|------------------|-------------------|-------------------|-------------------|--------------------|-------------------|--------------------|---------------------|-------------------|---------------------|---------------------|------------------|---------------------|
| A | F_{1t} | −0.20 [−0.79] | 0.08 [0.25] | −0.35 [−1.09] | | | | | | | | | |
| | F_{2t} | | | | −0.44** [−1.99] | −0.57* [−1.84] | −0.51** [−1.90] | | | | | | |
| | F_{3t} | | | | | | | 0.45** [2.01] | 0.05 [0.10] | 0.59** [2.39] | | | |
| | F_{4t} | | | | | | | | | | −0.59*** [−2.83] | −0.34 [−1.00] | −0.71*** [−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 [−1.47] | −0.06 [−0.19] | −0.37 [−1.60] | | | | | | | | | |
| | F_{6t} | | | | −0.20 [−1.13] | −0.28 [−0.72] | −0.16 [−0.79] | | | | | | |
| | F_{7t} | | | | | | | −0.56*** [−2.84] | −0.74* [−2.15] | −0.58*** [−2.52] | | | |
| | R^2 (%) | 0.51 | 0.02 | 0.69 | 0.21 | 0.40 | 0.13 | 1.60 | 2.78 | 1.65 | | | |
| Panel | | Whole | High | Low | Whole | High | Low | Whole | High | Low | Whole | High | Low |
| B | M_t^6 | 0.18 [1.00] | 0.73*** [3.17] | 0.01 [0.03] | | | | | | | | | |
| | M_t^9 | | | | 0.08 [0.37] | 0.38** [1.76] | −0.04 [−0.14] | | | | | | |
| | M_t^{12} | | | | | | | 0.16 [0.73] | 0.21* [0.88] | 0.11 [0.37] | | | |
| | $\hat{x}_{52,t}$ | | | | | | | | | | 0.34** [1.91] | 0.87** [2.31] | 0.22 [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* [1.38] | 0.88** [2.83] | 0.08 [0.28] | | | | | | | | | |
| | $MA(1,12)$ | | | | 0.43** [1.99] | 0.93*** [3.08] | 0.25 [0.87] | | | | | | |
| C | R^2 (%) | 0.41 | 4.00 | 0.03 | 0.95 | 4.41 | 0.30 | | | | | | |
| | μ_t | 0.71*** [3.47] | 0.51 [1.59] | 0.84*** [3.85] | | | | 0.72*** [3.95] | 0.64* [2.03] | 0.83*** [3.88] | | | |
| | m_t | | | | 0.36** [1.77] | 0.89*** [3.27] | 0.18 [0.65] | 0.38*** [1.68] | 0.97*** [3.36] | 0.13 [0.43] | | | |
| | R^2 (%) | 2.51 | 1.36 | 3.52 | 0.65 | 4.07 | 0.15 | 3.23 | 6.13 | 3.61 | | | |

Notes. Panel A (B) displays in-sample regression results based on individual macroeconomic (nonfundamental) predictors over the whole sample, the high-sentiment, and the low-sentiment regimes, respectively. Panel A shows seven individual fundamental predictors from the seven categories of macroeconomic variables described in Jurado et al. (2015). Panel B shows six individual nonfundamental 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 seven individual macroeconomic predictors, the combined nonfundamental predictor m_t extracted from the six nonfundamental 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^2 s in percentage points are reported. High- and low-sentiment regimes are estimated based on the regime switching approach. The sample period spans from July 1965 to December 2010.

*, ** and *** indicate significance based on bootstrapped p -values at the 10%, 5% and 1% levels, respectively.

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. Although 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 the low-sentiment periods (with t -statistic of 3.85 and R^2 of 3.52%). This supports our 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 nonfundamental variables and the combined nonfundamental variable are much stronger during the high-sentiment regime than during the low-sentiment regime. Out of the six nonfundamental 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 nonfundamental 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, nonfundamental 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 nonfundamental 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 nonfundamental 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 nonfundamental 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 nonfundamental variables. In fact, Panel C shows that the sum of R^2 s when using fundamental and nonfundamental variables alone to 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 nonfundamental 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^2 s over the sample period for regressions with both fundamental variable μ_t and nonfundamental variable m_t exceed this 0.5% benchmark.

In Figure 3, 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^2 s in percentage points. The first row of Figure 3 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 3 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 nonfundamental predictor m_t during the high-sentiment regime.

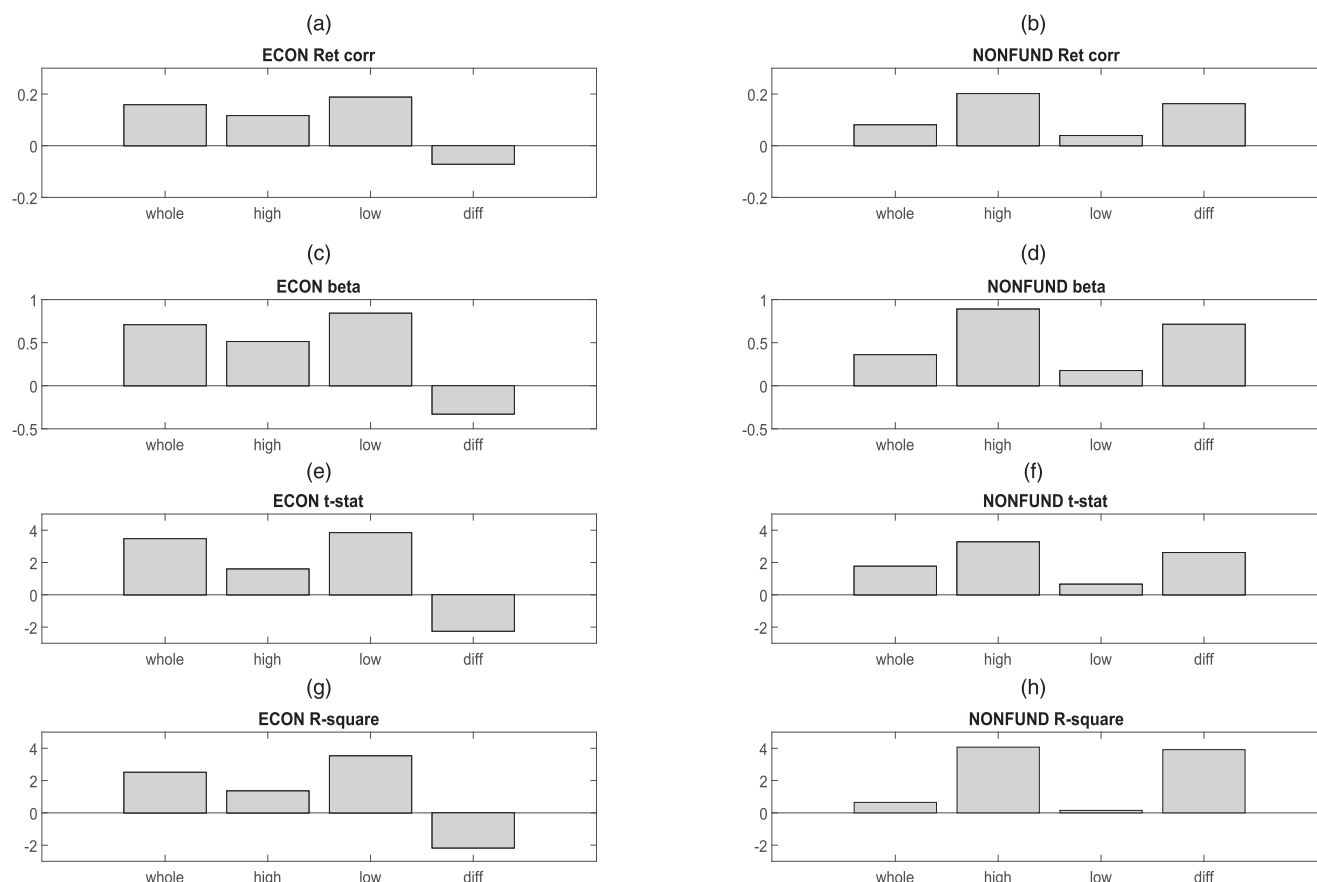
Figure 4 further illustrates the complementary roles of fundamental predictor μ_t and nonfundamental predictor m_t . Panels (a) and (b) in Figure 4 show in-sample forecasts of the monthly market return for μ_t and m_t , respectively. The expected market return predicted by μ_t (Panel (a) of Figure 4) 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 4) 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 4), 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 nonfundamental variables tends to peak when sentiment is high and vanish when sentiment is low. Using both the fundamental and nonfundamental 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 with nonfundamental variables.

4.3. Further Discussions

In this section, we first show 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

Figure 3. Correlations Between Predictors and Excess Market Return and In-Sample Predictive Regression Patterns



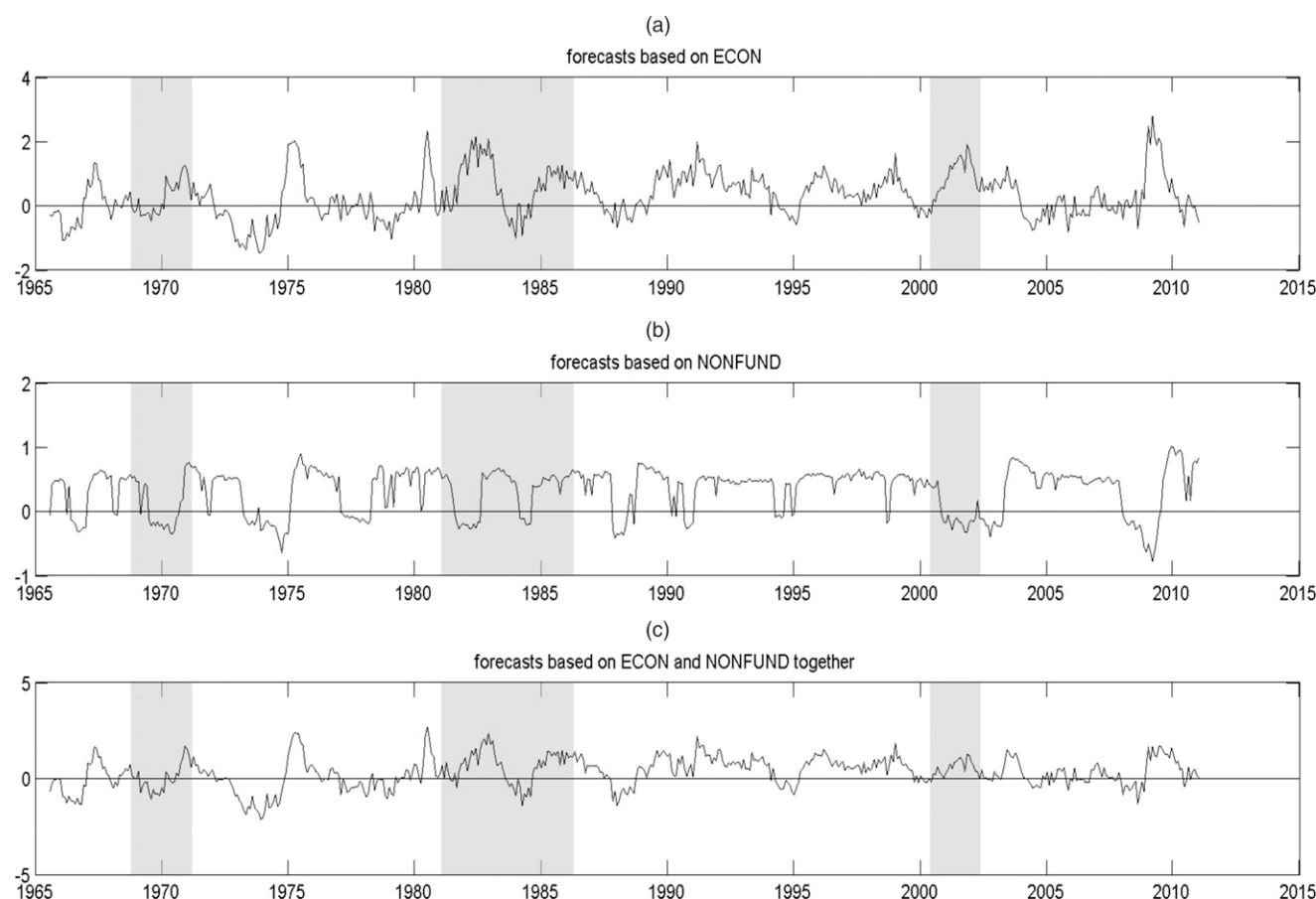
Notes. The first three bars in Panel (a), (b) display correlations between the combined fundamental predictor μ_t (the combined nonfundamental predictor m_t) and excess market return during the whole sample period, the high-sentiment regime, and the low-sentiment regime, respectively. The fourth bar 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^2 s 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^2 s in percentage points between the high-sentiment and low-sentiment regimes. μ_t is constructed from the seven macroeconomic categories described in Jurado et al. (2015). m_t is extracted from the six nonfundamental 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.

power for both fundamental and nonfundamental variables as debated in recent studies. We then provide some discussions on the robustness of the main findings including alternative sentiment regimes based on nonparametric approach and alternative variables determining regimes, together with some interpretations regarding potential reasons behind the regime switching in sentiment. We also provide additional discussions on return predictability over longer horizons in the online appendix (Appendix A.1).

4.3.1. 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 11 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

Figure 4. Time Series of In-Sample Excess Market Return Forecasts Based on Combined Fundamental Predictor μ_t and Combined Nonfundamental Predictor m_t 

Notes. 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 (nonfundamental 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 nonfundamental predictor m_t as regressors. μ_t is constructed from the seven macroeconomic categories described in Jurado et al. (2015). m_t is extracted from the six nonfundamental variables, including three time series momentum proxies, one anchoring variable, and two moving average indicators.

coefficients restriction, the out-of-sample R^2 s (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 11 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, whereas 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 with the unconstrained case) during the low-sentiment regime but fail to do so during the high-sentiment regime.

Table 4. Out-of-Sample Forecasting Results Using Variables From Campbell and Thompson (2008)

| | 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 |

Notes. 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.

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 nonfundamental 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

4.3.2. The Effect of the Oil Shock Period. This section 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 nonfundamental 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 Panel C of Table 3 (though less significant), showing that both fundamental and nonfundamental predictors still have forecasting power after 1975 (conditioning on sentiment).

Next, we rerun 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, whereas the nonfundamental 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 with Panel C of Table 3. Because the oil shock occurs within our low-sentiment periods, the results for the high-sentiment regime are less affected.

4.3.3. 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 nonfundamental variables are affected by

Table 5. Further Discussions

| Panel | | Whole | High | Low | Whole | High | Low | Whole | High | Low |
|-------|-----------|-------------------|-----------------|-------------------|------------------|-------------------|------------------|-------------------|-------------------|-------------------|
| A | μ_t | 0.43* [1.87] | 0.42 [1.18] | 0.61** [2.42] | | | | 0.45** [2.13] | 0.68 [1.53] | 0.63** [2.29] |
| | m_t | | | | 0.11 [0.42] | 0.86*** [2.79] | −0.28 [−0.91] | 0.16 [0.57] | 1.04*** [2.58] | −0.31 [−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*** [2.86] | 0.54 [1.60] | 0.57*** [3.19] | | | | 0.54*** [3.30] | 0.62* [1.92] | 0.58*** [3.29] |
| | m_t | | | | 0.28* [1.31] | 0.91*** [3.31] | 0.02 [0.07] | 0.34* [1.45] | 0.97*** [3.40] | 0.05 [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*** [2.94] | 0.28 [0.63] | 0.62*** [3.77] | | | | 0.54** [2.49] | 0.11 [0.27] | 0.68*** [3.46] |
| | m_t | | | | 0.06 [0.29] | 0.80** [2.06] | −0.13 [−0.65] | −0.05 [−0.19] | 0.77** [1.78] | −0.28 [−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*** [3.47] | 0.47* [1.71] | 0.94*** [3.39] | | | | 0.72*** [3.95] | 0.53** [2.29] | 0.94*** [3.49] |
| | m_t | | | | 0.36** [1.77] | 0.62** [2.10] | 0.12 [0.46] | 0.38** [1.68] | 0.66** [2.08] | 0.10 [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*** [3.47] | 0.55 [1.52] | 0.84*** [3.85] | | | | 0.72*** [3.95] | 0.68* [1.87] | 0.83*** [3.91] |
| | m_t | | | | 0.36** [1.77] | 0.70*** [2.65] | 0.21 [0.78] | 0.38** [1.68] | 0.81*** [2.66] | 0.16 [0.53] |
| | R^2 (%) | 2.51 | 1.57 | 3.56 | 0.65 | 2.50 | 0.22 | 3.23 | 4.85 | 3.69 |

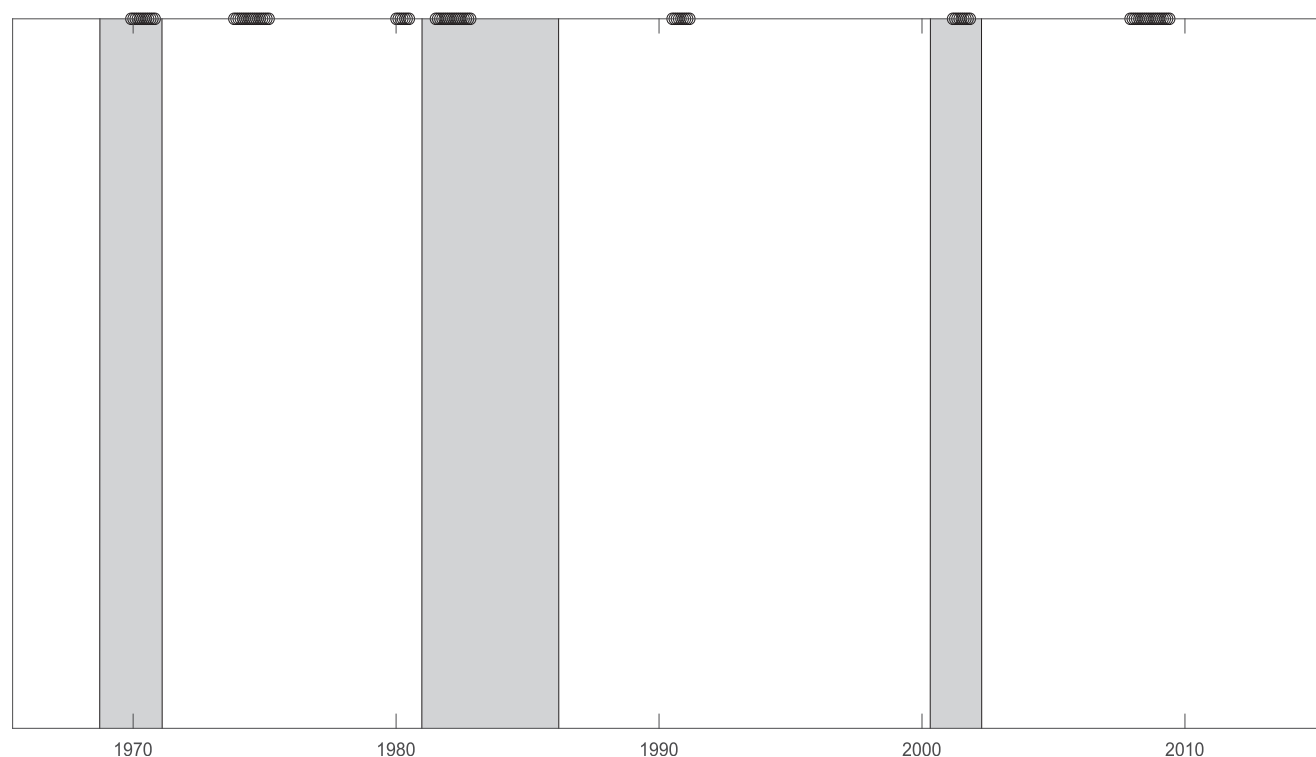
Notes. This table displays in-sample regression results under several different cases based on the combined fundamental predictor μ_t and combined nonfundamental predictor m_t over the whole sample, the high-sentiment and the low-sentiment regimes, respectively. Panel A reports results of in-sample predictive regressions for the period January 1976 to December 2005, 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 seven macroeconomic categories described in Jurado et al. (2015), and the combined nonfundamental predictor m_t is extracted from six individual nonfundamental 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^2 s in percentage points are reported in each panel.

*, ** and *** indicate significance based on bootstrapped p -values at the 10%, 5%, and 1% levels, respectively.

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*, whereas 90 months are identified as *REC* (see Figure 5). For comparison, we also plot the high-sentiment months estimated by the regime switching approach as the shaded areas in Figure 5. Our sentiment regimes do not comove substantially with the business cycles: the correlation between the NBER recession dummy and the high-sentiment dummy is only 0.23.

We rerun 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 nonfundamental variable m_t is significant in the

Figure 5. Times Series of Business Cycle and Investor Sentiment Regimes



Notes. 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 circles represent the NBER recession dummy. The sample period spans from July 1965 to December 2010.

high-sentiment months but insignificant over all expansion periods and low-sentiment months.

4.3.4. 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 underreact to such bad news. This underreaction 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 underreaction. Later, when the bad news is absorbed and the underreaction 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 index and not the NYSE/AMEX total market

Table 6. Anchoring Variables Constructed Based on Alternative Indices

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

Notes. 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^2 s in percentage points. The sample period spans from July 1965 to December 2010.

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 underreaction 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.

4.3.5. Nonparametric Approach to Classify Sentiment Regimes. In this section, we study alternative sentiment regimes based on a nonparametric 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 nonparametric naive median cut or a specific nonparametric 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 nonfundamental predictors (in high regime). This indicates that the results of this study are not likely due to overfitting 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 nonfundamental variable m_t in regime H . The reason seems straightforward: the median definition classifies 50% of the sample as high-regime 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 nonfundamental 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.

4.3.6. Alternative Variables Determining Regimes. There may be a concern that alternative variables, such as capital or funding constraints (such as credit and TED spreads), FEARS, tail risk concern, consumption surplus ratio, and aggregate disagreement, could also affect the time-varying return predictability. In this section, 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 July 1965 to December 2010. When CRDSPRD is used to determine the regimes, the results are reported in Panel A of Table 7.²⁶ The fundamental variable significantly forecasts returns in both regimes, whereas the nonfundamental 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 nonfundamental predictor and market

Table 7. Determining Regimes Using Alternative Variables

| Panel | | Whole | High | Low | Whole | High | Low | Whole | High | Low |
|---|-----------|-------------------|-------------------|-------------------|------------------|-------------------|-----------------|-------------------|-------------------|-------------------|
| A: Credit spread (funding constraints) | μ_t | 0.71*** [3.47] | 0.79*** [3.69] | 0.54** [1.75] | | | | 0.72*** [3.95] | 0.84*** [4.26] | 0.49** [1.98] |
| | m_t | | | | 0.36** [1.76] | 0.28 [0.81] | 0.47* [1.31] | 0.38** [1.68] | 0.39 [1.02] | 0.41 [1.17] |
| | R^2 (%) | 2.51 | 2.58 | 1.87 | 0.65 | 0.32 | 1.44 | 3.23 | 3.19 | 2.96 |
| B: TED (funding constraints) | μ_t | 0.21 [0.89] | 0.41 [1.33] | 0.01 [0.03] | | | | 0.32 [1.31] | 0.48* [1.55] | 0.14 [0.54] |
| | m_t | | | | 0.31 [0.97] | 0.30 [0.54] | 0.29 [0.97] | 0.40* [1.13] | 0.38 [0.65] | 0.34 [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 [0.66] | −0.85 [−1.71] | 1.69** [3.33] | | | | 1.05* [1.97] | 0.25 [0.41] | 2.09** [3.33] |
| | m_t | | | | 0.74** [1.32] | 1.55* [2.30] | 0.22 [0.34] | 1.22** [2.01] | 1.71* [1.96] | 1.03** [2.06] |
| | R^2 (%) | 0.56 | 2.71 | 15.90 | 3.51 | 9.02 | 0.27 | 7.58 | 9.16 | 20.92 |
| D: EQRIX (tail risk concern) | μ_t | 0.09 [0.24] | −0.50 [−1.05] | 0.55 [1.46] | | | | 0.64 [1.49] | 0.08 [0.22] | 0.96* [2.01] |
| | m_t | | | | 0.67** [1.93] | 1.12*** [3.94] | 0.59* [1.18] | 0.94*** [2.34] | 1.16** [3.22] | 0.99** [1.71] |
| | R^2 (%) | 0.03 | 1.72 | 0.95 | 2.28 | 8.77 | 1.09 | 3.43 | 8.80 | 3.48 |
| E: Consumption surplus ratio | μ_t | 0.71*** [3.47] | 0.63** [2.32] | 0.61*** [2.94] | | | | 0.72*** [3.95] | 0.61** [2.26] | 0.76*** [3.60] |
| | m_t | | | | 0.36** [1.76] | 0.19 [0.67] | 0.43 [1.13] | 0.38** [1.68] | 0.10 [0.36] | 0.61 [1.49] |
| | R^2 (%) | 2.51 | 1.93 | 1.96 | 0.65 | 0.18 | 0.95 | 3.23 | 1.99 | 3.79 |
| F: Disagreement | μ_t | 0.33 [1.43] | 0.53 [1.38] | −0.03 [−0.15] | | | | 0.45* [1.91] | 0.96** [2.79] | −0.04 [−0.15] |
| | m_t | | | | 0.36* [1.24] | 0.56* [1.32] | 0.01 [0.02] | 0.46** [1.43] | 0.99** [2.03] | 0.01 [0.03] |
| | R^2 (%) | 0.46 | 1.09 | 0.01 | 0.61 | 1.23 | 0.00 | 1.39 | 4.17 | 0.01 |

Notes. This table displays regression results of the combined fundamental predictor μ_t and combined nonfundamental 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, GRIX (tail risk concern), the consumption surplus ratio, and disagreement in Panels A, B, C, D, E, and F, respectively. The credit spread over July 1965–December 2010 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 January 1986 to December 2010; the FEARS index is constructed as per Da et al. (2015) and covers July 2004–December 2010; the EQRIX over January 1996–December 2010 based on Gao et al. (2018) and Gao et al. (2019) is from Zhaogang Song’s web page; the consumption surplus ratio defined by Campbell and Cochrane (1999) runs from July 1965–December 2010; 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 December 1981 to December 2010. μ_t is constructed from the seven macroeconomic categories described in Jurado et al. (2015). m_t is extracted from the six individual nonfundamental 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^2 s in percentage points are reported in each panel.

*, ** and *** indicate significance based on bootstrapped p -values at the 10%, 5%, and 1% levels, respectively.

returns is unlikely to be strengthened much. Indeed, we find that the nonfundamental 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 nonfundamental 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 January 1986 due to data availability. The results are reported in Panel B of Table 7. 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 nonfundamental 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 (nonfundamental behavioral-based) predictors and market returns is unlikely to be weakened (strengthened).

In addition, we use the FEARS index constructed in Da et al. (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 7. 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 nonfundamental predictors (in high regime). This is not surprising because 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.

Moreover, tail risk is related to but can be distinct from the fear measure. The tail risk could be one type of important fundamental risk (Kelly and Jiang 2014). A tail risk concern (Gao et al. 2018, Gao et al. 2019) may drive "sentiment-like" fears (Baron and Xiong 2017), which may be considered as a nonfundamental variable related to but different from the Baker and Wurgler sentiment measure. We determine the regimes by the level of the tail risk concern

(starting from January 1996, a shorter sample period compared with the Baker and Wurgler sentiment index).²⁹ The high (low) regime in Panel D of Table 7 refers to low (high) tail risk concern periods. The result shares a similar pattern of the paradigm shifts in return forecasting to that of the FEARS index, though a bit weaker.

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 E of Table 7. The fundamental variable significantly forecasts returns in both regimes, whereas the nonfundamental variable does not forecast returns 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 nonfundamental 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 (nonfundamental 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 F of Table 7. When the regimes are determined by the level of the aggregate disagreement, both the fundamental and nonfundamental 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 nonfundamental 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 nonfundamental predictors (in high regime). Cen et al. (2013) and Cen et al. (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 nonfundamental predictors (high regime) as we observe across high/low sentiment regimes. The only exceptions are the FEARS and tail risk concern indices that have rather short sample period compared with the Baker and Wurgler sentiment index.

4.3.7. 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 et al. (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.³⁰

5. 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.³¹

There is a risky asset with a positive net supply. The final payoff D of the risky asset is normally distributed $D \sim N(\mu_D, \sigma_D^2)$. Before observing any signals, investors have prior beliefs about the final payoff D of the risky asset, $D \sim N(\mu_{i,D}, \sigma_{i,D}^2)$ for $i = R, I$. 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 , that is, $\mu_{R,D} = \mu_D$. 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 $e^H \sim U(\underline{e}^H, \bar{e}^H)$, where the minimum and maximum

values \underline{e}^H and \bar{e}^H satisfy $0 < \underline{e}^H < \bar{e}^H$. During the low-sentiment regime, sentiment follows $e^L \sim U(\underline{e}^L, \bar{e}^L)$ with $\underline{e}^L < \bar{e}^L < 0$. The exogenous sentiment changes irrational investors’ prior belief about the mean value of D , $\mu_{I,D} = \mu_D(1 + e^k)$ for $k = H, L$. 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.³²

At each date $0 < t < T$, investors observe a public signal s_t and believe $s_t = D + \varepsilon_t$, where D , e^k , and $\varepsilon_t \sim N(0, \sigma_{\varepsilon,t}^2)$ are mutually independent. In order to show the momentum effect, we consider $T = 2$ for simplicity.³³ Due to the difference in priors, investors hold different posterior beliefs about the distribution of D at time 1,

$$\begin{aligned} E_{R,1}[D] &= \beta s_1 + (1 - \beta)\mu_D, \\ E_{I,1}[D] &= \beta s_1 + (1 - \beta)\mu_D(1 + e^k), \\ \beta &= \frac{1/\sigma_{\varepsilon,1}^2}{1/\sigma_D^2 + 1/\sigma_{\varepsilon,1}^2}. \end{aligned} \quad (21)$$

We normalize the time discount rate to zero. Type- i investors are willing to pay $P_t^i = E_{i,t}[D]$ at time t for a unit of the asset, and price at time t is given by $P_t = \max_{i=R,I}\{P_t^i\}$. Now we study return dynamics during high- and low-sentiment regimes.

5.1. 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

$$\begin{aligned} P_0 &= P_0^R = \mu_D, & P_1 &= P_1^R = \beta s_1 + (1 - \beta)\mu_D, \\ P_2 &= D. \end{aligned} \quad (22)$$

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

$$\begin{aligned} P_1 - P_0 &= \beta s_1 - \beta \mu_D = \beta(D - \mu_D) + \beta \varepsilon_1, \\ P_2 - P_1 &= D - [\beta s_1 + (1 - \beta)\mu_D] = (1 - \beta)(D - \mu_D) - \beta \varepsilon_1. \end{aligned}$$

Under the rational (or objective) belief,

$$\text{cov}_{R,0}[P_2 - P_1, P_1 - P_0] = \beta(1 - \beta)\sigma_D^2 - \beta^2\sigma_{\varepsilon,1}^2 = 0, \quad (23)$$

where the last equality is due to (21). In this case, there are no autocorrelations in price changes because asset prices respond to new information immediately and correctly.

5.2. 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 behavioral bias:

$$\begin{aligned} P_0 &= P_0^I = \mu_D(1 + e^H), \\ P_1 &= P_1^I = \beta s_1 + (1 - \beta)\mu_D(1 + e^H), \\ P_2 &= D. \end{aligned} \quad (24)$$

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

$$\begin{aligned} P_1 - P_0 &= \beta(D - \mu_D) + \beta\epsilon_1 - \beta\mu_De^H, P_2 - P_1 \\ &= (1 - \beta)(D - \mu_D) - \beta\epsilon_1 - (1 - \beta)\mu_De^H. \end{aligned}$$

In this case, prices exhibit momentum:

$$\begin{aligned} cov_{R,0}[P_2 - P_1, P_1 - P_0] &= \beta(1 - \beta)\mu_D^2\sigma_{e^H}^2 \\ &= \frac{1}{12}\beta(1 - \beta)\mu_D^2(\bar{e}^H - \underline{e}^H)^2 \\ &> 0. \end{aligned} \quad (25)$$

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.³⁴

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 downward 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.³⁵ 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 addi-

tional implications besides the paradigm shifts in returns forecasting (see Online Appendix A.2).

6. 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, because their connection with aggregate market return can be weakened during high sentiment periods. In contrast, nonfundamental variables predict the market return well only when sentiment is high but not when it is low, because 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 nonfundamental variable as debated in recent studies.

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Endnotes

¹De Long et al. (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 et al. (1998), Daniel et al. (1998), and Hong and Stein (1999), among others.

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

⁴ Carlson et al. (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 et al. 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.

⁷ In Section 5, 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.

⁸ This strand of literature relies on behavioral and psychological explanations by combining two prominent concepts, investor sentiment and short-selling constraints. Particularly, Antoniou et al. (2013) argue that the cognitive dissonance caused by news that contradicts investor sentiment gives rise to underreaction, which is strengthened mainly during high-sentiment periods due to short-selling constraints, raising the profits from cross-sectional momentum. There are other studies, including the idiosyncratic volatility puzzle (Stambaugh et al. 2015) and hedge fund investment (Smith et al. 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 nonfundamental type variable) and market equity premium is more significant when sentiment is positive.

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.

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).

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.

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/>.

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

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).

¹⁹ The negative forecasting power of F_2 is consistent with Santos and Veronesi (2006) showing that labor 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 with past consumption—can negatively forecast future stock market returns.

²⁰ Sentiment itself can be considered as a nonfundamental variable. By combining the sentiment variable with the six nonfundamental variables in Table 3 and comparing with the results in Panel C of Table 3 for the combination variable of the six nonfundamental variables, we find (the results are not reported here) that the new combined nonfundamental 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).

²² Although the price-scaled variables are normally considered as fundamental variables, they may also be partially sentiment-driven because 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.

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 nonfundamental 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.

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).

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 observations) compared with 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.

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 July 1965 to December 2010, whereas the sample period used here is January 1986 to December 2010. This difference exists for two of the following three alternative measures because their sample periods are also different from July 1965 to December 2010.

²⁸ We download the data over July 2004 to December 2010 from Zhi Da's web page <https://www3.nd.edu/zda/>.

²⁹ The data are from Zhaogang Song's web page <https://sites.google.com/a/cornell.edu/zgs/>. Among the multiple tail risk concern measures in Gao et al. (2019), we use the EQRIX tail risk concern measure because it is corresponding to the equity market.

³⁰ The alternation of investors' aggregate expectations in overoptimistic and overpessimistic states is also found in laboratory experiments, for example, Hommes et al. (2005).

³¹ Risk neutral investors are also considered by Harrison and Kreps (1978), Hong and Stein (2003), and Scheinkman and Xiong (2003). Bai et al. (2006) consider risk averse investors in a one-period model; however, in multiperiod environments, the optimal demands cannot be explicitly solved from the first order conditions due to the nonlinear expectations caused by the short-sale constraints.

³² 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, for example, Barberis et al. (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.

³³ Our model can be easily extended to more than two periods.

³⁴ 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 $\sigma_{\epsilon^H} = 0$, we have $\text{cov}_{R,0}[P_2 - P_1, P_1 - P_0] = 0$. 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.

³⁵ 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.

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