Investor Sentiment Aligned: A Powerful Predictor of Stock Returns

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First Version: May 2013

Current Version: February 2014

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Abstract

The widely used Baker and Wurgler (2006) sentiment index is likely to understate the predictive power on the aggregate stock market although their index, the first principal component of six individual sentiment proxies, captures well the cross-sectional variation of stock returns. In this paper, we propose a new sentiment index from the same six proxies to explain the time-series variation of stock returns. In so doing, our aligned sentiment index has greater power in predicting the aggregate stock market than the Baker and Wurgler (2006) index: it increases the R^2s by more than five times both in-sample and out-of-sample, and outperforms any of the well recognized macroeconomic variables. This predictability is both statistically and economically significant. Moreover, our new index improves substantially the forecasting power for the cross-sectional stock returns formed on industry, size, value, and momentum. Economically, we show that the driving force of the predictive power of investor sentiment stems from investors' biased belief about future cash flow.

JEL classifications: C53, G11, G12, G17

Keywords: Investor Sentiment, Asset Pricing, Return Predictability, Cash Flow

1. Introduction

At least as early as Keynes (1936), researchers have analyzed whether investor sentiment can affect asset prices due to the well-known psychological fact that people with high (low) sentiment tend to make overly optimistic (pessimistic) judgments and choices. Empirically, a major challenge for testing the importance of investor sentiment is that it is not directly observable. In their influential study, Baker and Wurgler (2006) construct a "top-down" investor sentiment index (BW index hereafter) and find that high investor sentiment strongly predicts lower returns for those stocks that are speculative and hard to arbitrage. Stambaugh, Yu, and Yuan (2012) show that investor sentiment is a significant negative predictor for the short legs of long-short investment strategies. Baker, Wurgler, and Yuan (2012) provide further international evidence for the forecasting power of investor sentiment.[1]

This paper studies how the cross-sectional effects of investor sentiment extend to the aggregate stock market, although Baker and Wurgler (2007) note that the predictive ability of their index on the aggregate stock market forecasting is modest and statistically insignificant but do not develop this point. Our question is important in threefold. First, investor sentiment is widely used as an alternative explanation to stock market events such as the Back Monday crash of October 1987, the Internet bubble of the 1990s, and the 2008 financial crashes. Second, BW index is supposed to predict the aggregate market by design since it "focuses on the measurement of reduced-form, aggregate sentiment and traces its effects to market returns and individual stocks" (Baker and Wurgler, 2007). Third, De Long, Shleifer, Summers, and Waldmann (1990), among others, show that investor sentiment can drive the market price to deviate from its fundamental value and lead to mispricing in the presence of limits to arbitrage, even when informed traders recognize the opportunity. Samuelson (1998) argues that the stock market may be "micro efficient" but "macro inefficient", suggesting that sentiment would be more powerful in affecting the price level of the aggregate market than in affecting the relative prices of invidvidual stocks on average.

Baker and Wurgler (2006) use the first principal component of six underlying sentiment proxies as their measure of aggregate investor sentiment. Econometrically, the first principal component is a combination of these six proxies that captures their maximum common variation. Since all the proxies may have approximation errors to the true but unobservable investor sentiment, and these errors are parts of their variations, the first principal component can potentially contain a

[1]There are a number of other applications. For example, Yu and Yuan (2011) show that investor sentiment affects mean-variance tradeoff, Baker and Wurgler (2012) demonstrate that investor sentiment explains the bond risk premium, and Yu (2012) finds that investor sentiment helps to understand the forward premium.

substantial amount of common approximation errors that are not relevant for forecasting returns. Not surprisingly, Baker and Wurgler (2007) show that the first principal predicts significantly the *cross-sectional* variation of stock returns but presents limited forecasting power in capturing the *time-series* variation of aggregate stock market returns.

To address this important issue of measuring aggregate investor sentiment, in this paper, we exploit the information of Baker and Wurgler's six sentiment proxies in an efficient manner to obtain a new investor sentiment index for the purpose of explaining the expected return on the aggregate stock market.[2] Our idea is to align the estimation of investment sentiment with the purpose of forecasting aggregate stock market returns by extracting the most relevant common time-series sentiment component from the underlying proxies. In other words, economically, we separate out information in the proxies that is relevant to the expected stock returns from errors or noises. Statistically, the partial least squares (PLS) method pioneered by Wold (1966, 1975) and extended by Kelly and Pruitt (2012, 2013) does exactly this job. We call our new index extracted in this way the *aligned* investor sentiment index.

Empirically, we find that the aligned sentiment index can predict the aggregate stock market remarkably well. The monthly in- and out-of-sample R^2s are 1.70% and 1.23%, more than five and eight times larger than 0.30% and 0.15%, the counterparts of BW index. Sincea monthly R^2 of 0.5% can signal economically significant return predictability (Campbell and Thompson, 2008), our aligned investor sentiment index is a powerful predictor of the aggregate market. Our empirical evidence is consistent with Tetlock (2007) and Garía (2013) that investor sentiment matters to the aggregate stock market although they use different proxies and focus on daily horizon.

It is of interest to explore how well the aligned investor sentiment index performs relative to alternative predictors, such as the short-term interest rate (Fama and Schwert, 1977; Breen, Glosten, and Jagannathan, 1989; Ang and Bekaert, 2007), the dividend yield (Fama and French, 1988; Campbell and Yogo, 2006; Ang and Bekaert, 2007), the earnings-price ratio (Campbell and Shiller, 1988), term spreads (Campbell, 1987; Fama and French, 1988), the book-to-market ratio (Kothari and Shanken, 1997; Pontiff and Schall, 1998), inflation (Fama and Schwert, 1977; Campbell and Vuolteenaho, 2004), corporate issuing activity (Baker and Wurgler, 2000), the consumption-wealth ratio (Lettau and Ludvigson, 2001), stock volatility (French, Schwert, and Stambaugh, 1987; Guo, 2006), and asset accrual (Hirshleifer, Hou, and Teoh, 2009). Goyal and Welch (2008) provide an extensive analysis on 14 of the most prominent predictors. The in-sample R^2s of those rec-

[2]The same method may apply to explaining the expected return on any other asset.

ognized macroeconomic variables vary from 0.01% to 1.23% (only two of them exceeding 1%), and all are below 1.70% of the aligned investor sentiment. In terms of the out-of-sample R^2, none of them have positive values. When any of these predictors is augmented, the predictive ability of the aligned investor sentiment is still significant and the in-sample R^2 ranges from 1.71% to 2.70%. In addition, the predictability of investor sentiment is of economic significance in terms of a mean-variance investor's certainty equivalent return (CER) gains.

Cross-sectionally, we compare how the aligned investor sentiment index performs relative to BW index. When stocks are sorted by industry, BW index has an impressive in-sample R^2 of 1.10% in explaining the time-varying returns on Technology, but the aligned investor sentiment index raises it to 1.92%. When stocks are sorted by size, value, and momentum, the aligned investor sentiment index always increases the predictive power, and doubles the R^2s on average. Hence, the aligned investor sentiment index is useful cross-sectionally as well.

We also explore the economic driving force of the predictive power of the aligned investor sentiment. We ask whether the predictability comes from time variations in cash flow or discount rate. We find that the aligned investor sentiment index that forecasts the market is a powerful predictor for future aggregate dividend growth (a standard cash flow proxy), but not for future dividend price ratio (a proxy of discount rate), supporting that the cash flow channel is the source for predictability. In addition, the ability of investor sentiment to forecast the cross-section of stock returns is strongly correlated with its ability to forecast the cross-section of future cash flows as well. Our findings are hence consistent with Baker and Wurgler (2007) that the lower aggregate stock returns following high investor sentiment seems to represent investors' overly optimistic belief about future cash flows that can not be justified by economic fundamentals.

The rest of the paper is organized as follows. Section 2 discusses the construction of the aligned investor sentiment index. Sections 3 and 4 provide the summary statistics of the data and the empirical results, respectively. Section 5 explores the sources of predictability, and Section 6 concludes.

2. Econometric Methodology

2.1 Estimation of S_t^{PLS}

We assume that one-period ahead expected log excess stock return to be explained by investor sentiment is

$$E_t(R_{t+1}) = \alpha + \beta S_t, \tag{1}$$

where S_t is the true but unobservable investor sentiment that matters for forecasting asset returns. Realized stock return then is equal to its conditional expectations plus an unpredictable shock,

$$\begin{aligned} R_{t+1} &= E_t(R_{t+1}) + \varepsilon_{t+1} \\ &= \alpha + \beta S_t + \varepsilon_{t+1}, \end{aligned} \tag{2}$$

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

Let $x_t = (x_{1,t}, ..., x_{N,t})'$ denotes an $N \times 1$ vector of individual investor sentiment proxies at period t ($t = 1, ..., T$). In Baker and Wurgler (2006), x_t is the close-end fund discount rate, share turnover, number of IPOs, first-day returns of IPOs, dividend premium, and the equity share in new issues. We assume that $x_{i,t}$ ($i = 1, ..., N$) has a factor structure,

$$x_{i,t} = \eta_{i,0} + \eta_{i,1} S_t + \eta_{i,2} E_t + e_{i,t}, \qquad \text{for } i = 1, ..., N, \tag{3}$$

where S_t is the investor sentiment that matters for forecasting asset returns, $\eta_{i,1}$ is the factor loading that summarizes the sensitivity of sentiment proxy $x_{i,t}$ to movements in S_t, E_t is the common approximation error component of all the proxies that is irrelevant to returns, and $e_{i,t}$ is the idiosyncratic noise associated with measure i only. The key idea here is to impose a factor structure on the proxies to efficiently estimate S_t, the collective contribution to the true yet unobservable investor sentiment, and at the same time, to eliminate E_t, their common approximation error, and $e_{i,t}$ from the estimation process.

In Baker and Wurgler (2006), investor sentiment is estimated as the first principle component (PC) of the cross-section of $x_{i,t}$s. By its econometric design, the PC is a linear combination of $x_{i,t}$s that explains the largest fraction of the total variations in $x_{i,t}$s, and hence is unable to separate S_t from E_t. In fact, the larger the variance the E_t, the more important role will it play in the PC. Then, it is possible that the PC may fail to generate significant forecasts for future stock return, even when stock return is indeed strongly predictable by the true investor sentiment S_t. This failure indicates the need for an improved econometric method that *aligns* investor sentiment estimation toward forecasting future stock return.

To overcome this econometric difficulty, following Wold (1966, 1975), and especially Kelly and Pruitt (2012, 2013), we apply the partial least squares (PLS) method to effectively extract S_t and filter out the irrelevant component E_t, while the PC method cannot be guaranteed to do so. The key idea is that PLS extracts the investor sentiment, S_t, from the cross-section according to its covariance with future stock return and chooses a linear combination of sentiment proxies that is optimal for forecasting. In doing so, PLS can be implemented by the following two steps of OLS regressions. In the first-step, for each individual investor sentiment proxy x_i, we run a time-series regression of $x_{i,t-1}$ on a constant and realized stock return R_t,

$$x_{i,t-1} = \pi_{i,0} + \pi_i R_t + u_{i,t-1}, \qquad \text{for } i = 1, ..., N. \tag{4}$$

The loading π_i captures the sensitivity of each sentiment proxy to the investor sentiment driving the future stock return as shown in (2). According to (2) and (3), each sentiment proxy is only a linear function of the expected component of future stock return and is uncorrelated with its unpredictable future shocks. Therefore, the coefficient π_i in the first-stage time-series regression (4) describes how each sentiment proxy depends on the true investor sentiment.

In the second-step, for each time period t, we run a cross-sectional regression of $x_{i,t}$ on the corresponding loading $\hat{\pi}_i$ estimated in first-stage regression (4),

$$x_{i,t} = c_t + S_t^{PLS} \hat{\pi}_i + v_{i,t}, \qquad \text{for } t = 1, ..., T. \tag{5}$$

where S_t^{PLS}, the regression coefficient in (5), is the estimated investor sentiment (the aligned sentiment index hereafter). That is, in (5), the first-stage loadings become the independent variables, and the aligned investor sentiment S_t^{PLS} is the coefficients to be estimated.

Intuitively, PLS exploits the factor nature of the joint system (2) and (3) to infer the relevant aligned sentiment factor S_t^{PLS}. If the true factor loading π_i was known, we could consistently estimate the S_t^{PLS} by simply running cross-section regressions of $x_{i,t}$ with π_i period-by-period. Since π_i is unknown, the first-stage regression coefficients provide a preliminary estimation of how $x_{i,t}$ depends on S_t^{PLS}. In other words, PLS uses future stock return to discipline the dimension reduction to extract S_t relevant for forecasting and discards common and idiosyncratic components such as E_t and $e_{i,t}$ that are irrelevant for forecasting.

Mathematically, the $T \times 1$ vector of aligned investor sentiment index $S^{PLS} = (S_1^{PLS}, ..., S_T^{PLS})'$ can be expressed as a one-step linear combination of $x_{i,t}$,

$$S^{PLS} = XJ_N X' J_T R (R' J_T X J_N X' J_T R)^{-1} R' J_T R, \tag{6}$$

where X denotes the $T \times N$ matrix of individual investor sentiment measures, $X = (x_1', ..., x_T')'$, and R denotes the $T \times 1$ vector of stock returns as $R = (R_2, ..., R_{T+1})'$. The matrices J_T and J_N, $J_T = I_T - \frac{1}{T}\iota_T \iota_T'$ and $J_T = I_N - \frac{1}{N}\iota_N \iota_N'$, enter because each regression is run with a constant. I_T is the T-dimensional identity matrix and ι_T is a T-vector of ones. The weight on each individual measure $x_{i,t}$ in S_t^{PLS} is based on its covariance with the stock return capturing the intertemporal relationship between aligned investor sentiment and expected stock returns as shown in (2).

2.2 Comparison of S^{BW} and S^{PLS}

This subsection discuss the analytical weights on individual sentiment proxies for the two sentiment indexes S^{BW} and S^{PLS}. We shows why these two sentiment indexes will put different weights on individual sentiment proxies.

As in (3), suppose there are two individual sentiment proxies, x_1 and x_2, that have the following factor structure

$$\begin{aligned} x_1 &= S+E+\varepsilon_1, \\ x_2 &= \eta_1 S+\eta_2 E+\varepsilon_2, \end{aligned}$$

where S is the true but unobservable investor sentiment, E is the common noise, and ε_i is the idiosyncratic noise. Without loss of generality, we assume these variables are independent with each other and have means zero and variances σ_S^2, σ_E^2 and σ_ε^2, where the idiosyncratic noises ε_1 and ε_2 have the same variation. More specifically, the covariance matrix of x_1 and x_2 is

$$\Sigma = \begin{pmatrix} \sigma_S^2+\sigma_E^2+\sigma_\varepsilon^2 & \eta_1\sigma_S^2+\eta_2\sigma_E^2 \\ \eta_1\sigma_S^2+\eta_2\sigma_E^2 & \eta_1^2\sigma_S^2+\eta_2^2\sigma_E^2+\sigma_\varepsilon^2 \end{pmatrix}. \tag{7}$$

Denote $\sigma_1^2=\sigma_S^2+\sigma_E^2+\sigma_\varepsilon^2$ and $\sigma_2^2=\eta_1^2\sigma_S^2+\eta_2^2\sigma_E^2+\sigma_\varepsilon^2$. Suppose $\sigma_1^2 \geq \sigma_2^2$. With simple algebra, we can find the weight in BW index is the eigenvector corresponding to the larger eigenvalue of Σ as

$$w^{BW} \propto \begin{pmatrix} \frac{\sigma_1^2-\sigma_2^2}{2}+\frac{1}{2}\sqrt{(\sigma_1^2-\sigma_2^2)^2+4(\eta_1\sigma_S^2+\eta_2\sigma_E^2)^2} \\ \eta_1\sigma_S^2+\eta_2\sigma_E^2 \end{pmatrix} \tag{8}$$

where $\propto$ indicates that the weight can be scaled by any positive real number. If η_2 in (8) is not equal to zero, BW index cannot exclude the common noise component in the individual sentiment proxies. In this case, even x_2 is a pure noise, $\eta_1=0$, it still will enters BW index. At the extreme cast, if x_1 and x_2 have equal variances, $\sigma_1^2=\sigma_2^2$, they have equal weights in BW index.

From (8), the sign of individual proxies in BW index depends on both η_1 and η_2. Economically, the sign of x_2 is the same as η_1. However, if the common noise term has an opposite sign and $\eta_2\sigma_E^2$ is relatively large, the weight of x_2 in BW index may have the same sign as η_2. For example, tn the index of sentiment changes, Baker and Wurgler (2007) notice that the sign of the equity share in new issue, one of sentiment proxies, has opposite sign as theory suggests, and "regard its unexpected sign as a chance event made possible by the fact that its changes at high frequencies are largely unrelated to sentiment."

Since we assume the mean of x_i is zero, the weight with PLS in (6) reduce to

$$w^{PLS} = X'J_T R(R'J_T XX'J_T R)^{-1} R'J_T R, \tag{9}$$

where $(R'J_T XX'J_T R)^{-1} R'J_T R$ is the adjusted scalar for the weight estimate $X'J_T R$. That is, we can rewrite w^{PLS} as

$$w^{PLS} \propto \begin{pmatrix} cov(x_{1t}, R_{t+1}) \\ cov(x_{2t}, R_{t+1}) \end{pmatrix} = \begin{pmatrix} cov(S_t, R_{t+1}) \\ \eta_1 cov(S_t, R_{t+1}) \end{pmatrix} \propto \begin{pmatrix} 1 \\ \eta_1 \end{pmatrix}. \tag{10}$$

Apparently, the weight with PLS incorporates only the information related to future stock returns and filters out the common noise component.

To construct the aggregate sentiment index, Baker and Wurgler (2006, 2007) make an implicit assumption that there is no common noise error among individual sentiment proxies, $\sigma_E^2 = 0$. When this assumption is satisfied, the weight of BW index is

$$w^{BW} \propto \begin{pmatrix} \sigma_S^2 \\ \eta_1 \sigma_S^2 \end{pmatrix} \propto \begin{pmatrix} 1 \\ \eta_1 \end{pmatrix}, \tag{11}$$

where the idiosyncratic variation in individual proxies is ironed out and the relative weights in (11) are equal to that in (10). That is, the PC approach is the same as the PLS approach.

3. Data and Summary Statistics

The excess aggregate stock market return is the continuously compounded log return on the S&P 500 index (including dividends) minus the risk-free rate. The six individual investor sentiment measures are

- *Close-end fund discount rate*, CEFD: value-weighted average difference between the net asset values of closed-end stock mutual fund shares and their market prices;
- *Share turnover*, TURN: log of the raw turnover ratio detrended by the past 5-year average, where raw turnover ratio is the ratio of reported share volume to average shares listed from the NYSE Fact Book;
- *Number of IPOs*, NIPO: monthly number of initial public offerings;
- *First-day returns of IPOs*, RIPO: monthly average first-day returns of initial public offerings;
- *Dividend premium*, PDND: log difference of the value-weighted average market-to-book ratios of dividend payers and nonpayers; and

- *Equity share in new issues*, EQTI: gross monthly equity issuance divided by gross monthly equity plus debt issuance.

The data are available from Jeffrey Wurgler's website who provides updated data for Baker and Wurgler (2006).[3] The data span from July 1965 through December 2010 (546 months), and have been widely used in a number of studies such as Baker and Wurgler (2006, 2007, 2012), Yu and Yuan (2011), Baker, Wurgler, and Yuan (2012), Stambaugh, Yu, and Yuan (2012), Yu (2012), and others. Since the data for the latest months are not available yet, our study here is limited to December 2010.

As discussed in Section 2, the aligned investor sentiment index S^{PLS} estimated by the PLS method for forecasting stock market return is a linear combination of the six individual measures,

$$S^{PLS} = -0.22\,CEFD + 0.16\,TURN - 0.04\,NIPO + 0.63\,RIPO + 0.07\,PDND + 0.53\,EQTI, \quad (12)$$

where each underlying individual measure is standardized, regressed on the growth of industrial production, the growth of durable consumption, the growth of nondurable consumption, the growth of service consumption, the growth of employment, and a dummy variable for NBER-dated recessions to remove the effect of business cycle variation, and smoothed with six month moving average values to iron out idiosyncratic jumps in the individual sentiment measures. The share turnover, average first-day return of IPOs, and dividend premium are lagged 12 months relative to the other three measures to incorporate the fact that some variables take longer to reveal the same sentiment. Following Baker and Wurgler (2006), S^{PLS} is standardized to have zero mean and unit variance over the full sample period.

Four of the six sentiment proxies (CEFD, TURN, RIPO, and EQTI) in S^{PLS} have the same signs as those in the Baker and Wurgler's measure of investor sentiment, S^{BW}. It is interesting to notice that, among the six proxies, RIPO and EQTI are the two most important underlying components in S^{PLS}, with the highest absolute coefficients. Instead, they are as equally important as the other proxies in BW index, S^{BW}. While the weights for NIPO and PDND in S^{PLS} have opposite signs to those in the Baker and Wurgler's index, their values are nearly zero and statistically negligible. We thus regard them as chance events.

Panel D of Table 2 reports the predictive ability of individual sentiment proxies on the aggregate market. Consistent with the findings in (12), the regression coefficients on CEFD, TURN, RIPO, and EQTI are consistent with the theoretical predictions when forecasting the aggregate

[3]The web address is: http://http://people.stern.nyu.edu/jwurgler/.

stock market returns. Again, the signs of NIPO and PDND are contradicting with the theoretical predictions, but their predictability is small with R^2s of 0.01% to 0.02%, suggesting that both of them are dominated by random noises. In addition, RIPO and EQTI present the highest power in forecasting stock market returns, consistent with their relatively higher weights in (12) of the S^{PLS} index. Therefore, we conclude that the estimated S^{PLS} is largely consistent with our theoretical promise that the weight of each proxy in S^{PLS} reflects its exposure to the aligned investor sentiment and its relevance in driving expected stock return.

[Insert Figure 1 about here]

Though the indices S^{PLS} and S^{BW} are constructed differently, they are highly correlated with each other with a positive correlation of 0.74. Consistent with the high correlation, Figure 1 shows that S^{PLS} appears to capture almost the same anecdotal accounts of fluctuations in sentiment with S^{BW}. The investor sentiment was low after the 1961 crash of growth stocks. It subsequently rose to a peak in the 1968 and 1969 electronics bubble. Sentiment fell again to a trough during the 1973 to 1974 stock market crash. But it picked up and reached a peak in the biotech bubble of the early 1980s. In the late 1980s, sentiment dropped but rose again in the early 1990s. It again reached a peak during the Internet bubble in the late 1990s. Sentiment dropped to a trough during the 2008 to 2009 subprime crisis but rose in the 2010.

While S^{PLS} and S^{BW} are highly correlated, they are different in many important aspects. S^{PLS} appears to lead S^{BW} in many cases, and S^{PLS} looks more volatile than S^{BW}. These findings suggest that S^{PLS} may better capture the short-term variations in investor sentiment aligned with future stock return compared to S^{BW} since the stock market is volatile.

We also consider 14 monthly economic return predictors from Goyal and Welch (2008), which are representative of the literature.[4] The 14 economic variables are the log dividend-price ratio (DP), log dividend yield (DY), log earnings-price ratio (EP), log dividend payout ratio (DE), Stock return variance (SVAR), book-to-market ratio (BM), net equity expansion (NTIS), Treasury bill rate (TBL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), default yield spread (DFY), default return spread (DFR), and inflation rate (INFL). More information on the economic predictors is provided in the Appendix.

[Insert Table 1 about here]

[4]The economic variables are available from Amit Goyal's website, http://www.hec.unil.ch/agoyal/.

Table 1 reports the summary statistics. The monthly log excess market return has a mean of 0.31% and a standard deviation of 4.46%, producing a monthly Sharpe ratio of 0.07. The sentiment indexes S^{PLS} and S^{BW} and many economic variables such as valuation ratios, nominal interest rates, and interest rate spreads are quite persistent. In summary, all summary statistics are generally consistent with the literature.

4. Empirical Results

4.1 Forecasting Aggregate Stock Market

In this section, we use the standard univariate predictive regression framework to analyze the predictive power of investor sentiment for excess return on the aggregate stock market

$$R^m_{t+1} = \alpha + \beta S^k_t + \varepsilon_{t+1}, \qquad k = PLS, BW, EW \tag{13}$$

where R^m_{t+1} is the monthly log return on the S&P 500 index in excess of the risk-free rate from period t to $t+1$. S^{PLS}_t is the aligned investor sentiment index at period t in (12), S^{BW}_t is the Baker and Wurgler (2006) investor sentiment index. For comparison, we also calculate a naive investor sentiment index, S^{EW}_t, that places equal weights on the standardized six individual sentiment proxies in Baker and Wurgler (2006).

The null hypothesis is that investor sentiment has no predictive ability, $\beta = 0$, and in this case, (13) reduces to the constant expected return model ($R^m_{t+1} = \alpha + \varepsilon_{t+1}$). Because economic theory suggests the sign of β, Inoue and Kilian (2004) recommend a one-sided alternative hypothesis to increase the power of in-sample tests of predictability. We then test $H_0 : \beta = 0$ against $H_A : \beta < 0$.

The well-known Stambaugh (1999) small-sample bias may inflate the t-statistic and distort test size when the predictor is highly persistent and correlated with market return. In addition, there is potentially a spurious regression concern when the predictor is highly persistent (Ferson, Sarkissian, Simin, 2003; Lewellen, 2004). Since S^{PLS} is an estimated factor based on PLS and full-sample data, this procedure may introduce another small-sample bias which can inflate the t-statistic for $\hat{\beta}$, as suggested by Kelly and Pruitt (2012, 2013).[5] Table 1 indicates that S^{PLS} displays positive skewness and excess kurtosis, which might raise concerns regarding the validity of statistical inference based on standard asymptotic arguments.

[5] Kelly and Pruitt (2012, 2013) show that there is no look-ahead bias in the PLS procedure and the small-sample bias will vanish as sample length T becomes large.

While our sample length is reasonably long ($T = 546$ months), we nonetheless take these econometric concerns seriously. We address these issues by computing the empirical p-values using a wild bootstrap procedure that accounts for the persistence in predictors, correlations between excess market return and predictor innovations, estimated PLS predictors, and general forms of return distribution. The Appendix details the wild bootstrap procedure.[6]

[Insert Table 2 about here]

As a benchmark, Panel A of Table 2 reports the in-sample estimation results for Baker and Wurgler (2006) investor sentiment S^{BW} in (13) to forecast log excess aggregate stock market return over the sample period 1965:07−2010:12.[7] S^{BW} is a negative return predictor and high sentiment is associated with lower expected market return in the next month. However, S^{BW} only generates a small White (1980) heteroskedasticity-consistent t-statistic of -1.21 and R^2 of 0.30%. Thus, the forecasting power of S^{BW} is insignificant, confirming the findings of Baker and Wurgler (2007).

Panel B of Table 2 reports the in-sample forecasting performance for the equally-weighted naive investor sentiment index S^{EW}. The equal-weighted index is analogous to a naive combination forecast which places equal weight on each individual sentiment measure and does not require the estimation of combining weights. As demonstrated by Timmermann (2006) and Rapach, Strauss, and Zhou (2010), this simple aggregation method frequently performs surprisingly well, since it is typically difficult to precisely estimate weights in data environments with substantial model uncertainty, structural break, and parameter instability. Consistent with our premise, S^{EW} generates an R^2 of 0.38%, about 25 percent higher than the corresponding R^2 for S^{BW} (0.30%), with marginally statistical significance at the 10% level.

According to Panel C of Table 2, the aligned investor sentiment S^{PLS} performs the best in (13). S^{PLS} is also a negative return predictor for excess aggregate stock market return, with an R^2 as high as 1.70%. Because of the large unpredictable component inherent in monthly stock market return, a monthly R^2 statistic near 0.5% can generate significant economic value (Kandel and Stambaugh, 1996; Xu, 2004; Campbell and Thompson, 2008). Thus, the 1.70% R^2 of S^{PLS} indicates economically sizable stock market predictability. In addition, according to Panel D, S^{PLS} sharply beats all of six individual sentiment proxies in forecasting the aggregate market returns.

[6] Kelly and Pruitt (2012) analyze the asymptotic properties of parameter estimates for predictive regressions with estimated PLS factors. Amihud and Hurvich (2004), Lewellen (2004), Campbell and Yogo (2006), and Amihud, Hurvich, and Wang (2009) develop predictive regression tests that explicitly account for the Stambaugh small-sample bias. Inferences based on these procedures are qualitatively similar to those based on the bootstrap procedure.

[7] We find similar results for simple raw excess return on the S&P 500 Index.

Moreover, S^{PLS} is statistically significant at the 1% level based on the wild bootstrap p-value, with a large t-statistic of -3.03.

The magnitude of the slope coefficient on S^{PLS} is -0.58, suggesting that a one-standard-deviation increase in S^{PLS} is associated with a -0.58% decrease in expected excess market return for the next month. Recall that the average monthly excess market return during our sample period is 0.31%, thus (13) implies that the expected equity premium based on S^{PLS} varies by about two times larger than its average level, signalling strong economic significance (Cochrane, 2011).

In summary, the aligned investor sentiment S^{PLS} exhibits statistically and economically significant in-sample predictability for monthly aggregate stock market return, while Baker and Wurgler (2006) investor sentiment index S^{BW} fails to do so. In addition, the R^2 of S^{PLS} is about five times greater than the R^2 of S^{BW}, indicating a huge improvement in stock return forecasting performance. This finding is consistent with our econometric set-up in Section 2 that S^{PLS} can enhance the forecasting performance of S^{BW} by only selecting the relevant investor sentiment component useful for return forecasting. Hence, previous studies based on S^{BW} potentially understate the investor sentiment's forecasting power for stock market returns.

[Insert Table 3 about here]

We further compare the relative information content in S^{PLS}, S^{BW}, and the panel of individual investor sentiment measures using the forecast encompassing test of Harvey, Leybourne, and Newbold (1998). Harvey, Leybourne, and Newbold (1998) develop a statistic for testing the null hypothesis that a given forecast contains all of the relevant information found in a competing forecast (i.e., the given forecast encompasses the competitor) against the alternative that the competing forecast contains relevant information beyond that in the given forecast.

Table 3 reports p-values for the Harvey, Leybourne, and Newbold (1998) statistic over the sample period 1965:07–2010:12. First, none of the individual investor sentiment measures of Baker and Wurgler (2006) encompass all of the remaining individual measures, indicating potential gains from combining individual measures into a common index to incorporate additional information. Second, S^{BW} fails to encompass two of the six individual measures, thus S^{BW} does not include all the relevant forecasting information in the cross-section of individual measures. Third, S^{PLS}, however, encompasses all of the individual investor sentiment measures as well as S^{BW} at the conventional significant levels. In summary, the forecast encompassing tests suggest that S^{PLS} incorporates all the relevant forecasting information in the panel of individual investor sentiment measures, while S^{BW} fails to do so, which helps to understand the improvement of forecasting performance corresponding to S^{PLS}.

4.2 Comparison with Alternative Predictors

In this section, we compare the forecasting power of aligned investor sentiment index S^{PLS} with a large number of alternative return predictors documented in the literature, and investigate whether the forecasting power of S^{PLS} is driven by omitted economic variables related to business cycle fundamentals.

We first compare the forecasting power of S^{PLS} with a large number of alternative return predictors that have been shown to predict the aggregate stock market (Campbell and Thompson, 2008; Cochrane, 2008, 2011; Goyal and Welch, 2008). In particular, we focus on the 14 economic variables recently reviewed by Goyal and Welch (2008), which are known to forecast monthly market return, and are typically related to business cycle conditions.[8]

To compare S^{PLS} with alternative predictors, we transform these alternative predictors to market return forecasts using the univariate predictive regressions, by replacing S_t^k in (13) with Z_t^k

$$R_{t+1}^m = \alpha + \psi Z_t^k + \varepsilon_{t+1}, \qquad k = 1, ..., 14, \tag{14}$$

where Z_t^k is one of the 14 economic predictors in Goyal and Welch (2008).

[Insert Table 4 about here]

Panel A of Table 4 reports the estimation results for (14) over the period 1965:07−2010:12. Three of the 14 economic predictors exhibit significant predictive ability for excess aggregate stock market return at the 5% or better levels. They are stock return variance (SVAR), long-term government bond return (LTR), and term spread (TMS), with R^2 ranging from 0.61% to 1.23%. In this sense, S^{PLS}, whose R^2 is 1.70%, has greater forecasting power for monthly aggregate stock market return comparing to all of the 14 economic predictors.

We then investigate whether the forecasting power of S^{PLS} remains robust after controlling for economic predictors. To analyze the incremental forecasting power of S^{PLS}, we conduct a set of bivariate predictive regressions based on S_t^{PLS} and Z_t^k

$$R_{t+1}^m = \alpha + \beta S_t^{PLS} + \psi Z_t^k + \varepsilon_{t+1}, \qquad k = 1, ..., 14. \tag{15}$$

[8] we have also compared with economic policy uncertainty variables, proposed recently by Baker, Bloom and Davis (2103), and find that the aligned investment sentiment outperforms them substantially because their predictive power is very limited.

We are interested in the regression slope coefficient β of S_t^{PLS}, and test $H_0 : \beta = 0$ against $H_A : \beta < 0$ based on the wild bootstrapped p-values.

Panel B of Table 4 shows that the estimates of the slope coefficient β in (15) are negative and large, in line with the results in the predictive regression (13) reported in Table 2. Most importantly, β remains statistically significant at the conventional levels when paired against the economic predictors one-by-one. All of R^2s in (15) that combines information in S^{PLS} together with economic predictors are substantially larger than the corresponding R^2 in (14) based on the economic predictors alone reported in Panel A. These results demonstrate that S^{PLS} contains sizable complementary forecasting information beyond what is contained in the economic predictors.[9]

4.3 Out-of-sample Forecasts

Although the in-sample analysis provides more efficient parameter estimates and thus more precise return forecasts by utilizing all available data, Goyal and Welch (2008), among others, argue that out-of-sample tests seem to be a more relevant standard for assessing genuine return predictability in real time, which implicitly examine the stability of the data-generating process and guard against in-sample over-fitting. In addition, out-of-sample tests are much less affected by the small-sample size distortions such as the Stambaugh bias (Busetti and Marcucci, 2012).

In Table 5, we investigate the out-of-sample forecasting ability of investor sentiment and 14 economic variables for aggregate stock market. We generate out-of-sample forecasts based on recursive predictive regressions, in which the aligned investor sentiment index, the Baker and Wurgler (2006) investor sentiment index, and predictive regression slopes are estimated recursively by using information available up to the period of forecast formation, t, to avoid the use of future data not available at the time of the forecast to the investor.

Specifically, the out-of-sample market return forecast at period $t+1$ based on investor sentiment in (13) and information available through period t is generated by

$$\hat{R}^m_{t+1} = \hat{\alpha}_t + \hat{\beta}_t S^k_{1:t;t}, \qquad k = PLS, BW, \tag{16}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates from regressing $\{R^m_{s+1}\}_{s=1}^{t-1}$ on a constant and $\{S^k_{1:t;s}\}_{s=1}^{t-1}$ ($k =$ PLS, BW). Like their in-sample analogues, $S^{PLS}_{1:t;t}$ is the out-of-sample aligned investor sentiment index extracted now recursively, and $S^{BW}_{1:t;t}$ is the out-of-sample Baker and Wurgler (2006) investor sentiment index computed recursively too.

[9]This finding does not apply to S^{BW} whose results are unreported for brevity but available upon request.

We then generate the out-of-sample forecasts based on one of the common 14 alternative economic variables analyzed by Goyal and Welch (2008) based on the standard predictive regression,

$$\hat{R}^m_{t+1} = \hat{\alpha}_t + \hat{\psi}_t Z^k_t, \qquad k = 1, ..., 14, \tag{17}$$

where $\hat{\alpha}_t$ and $\hat{\psi}_t$ are the OLS estimates from regressing $\{R^m_{s+1}\}_{s=1}^{t-1}$ on a constant and $\{Z^k_s\}_{s=1}^{t-1}$ ($k = 1, ..., 14$). Lastly, to analyze the incremental forecasting power of investor sentiment, we generate out-of-sample forecasts based on the out-of-sample aligned investor sentiment index and one of the 14 economic variables, as in (15)

$$\hat{R}^m_{t+1} = \hat{\alpha}_t + \hat{\beta}_t S^{PLS}_{1:t;t} + \hat{\psi}_t Z^k_t, \qquad k = 1, ..., 14, \tag{18}$$

where $\hat{\alpha}_t$, $\hat{\beta}_t$, and $\hat{\psi}_t$ are the OLS estimates from regressing $\{R^m_{s+1}\}_{s=1}^{t-1}$ on a constant, $\{S^{PLS}_{1:t;s}\}_{s=1}^{t-1}$, and $\{Z^k_s\}_{s=1}^{t-1}$.

We divide the total sample of length T into m initial estimation sub-sample and q out-of-sample evaluation sub-sample, where $T = m + q$, and get q out-of-sample forecasts: $\{\hat{R}^m_{t+1}\}_{t=m}^{T-1}$. In Table 5, we use 1965:07 to 1984:12 as the initial estimation period so that the forecast evaluation period spans 1985:01 to 2010:12. The length of the initial in-sample estimation period balances having enough observations for precisely estimating the initial parameters with the desire for a relatively long out-of-sample period for forecast evaluation.[10]

We use the widely used Campbell and Thompson (2008) R^2_{OS} statistic and Clark and West (2007) *MSFE-adjusted* statistic to evaluate the out-of-sample forecasts. The R^2_{OS} statistic measures the proportional reduction in mean squared forecast error (MSFE) for the predictive regression forecast relative to the historical average benchmark,

$$R^2_{OS} = 1 - \frac{\sum_{t=m}^{T-1}(R^m_{t+1} - \hat{R}^m_{t+1})^2}{\sum_{t=m}^{T-1}(R^m_{t+1} - \bar{R}^m_{t+1})^2}, \tag{19}$$

where $\bar{R}^m_{t+1}$ denotes the historical average benchmark corresponding to the constant expected return model ($R^m_{t+1} = \alpha + \varepsilon_{t+1}$),

$$\bar{R}^m_{t+1} = \frac{1}{t}\sum_{s=1}^{t} R^m_s. \tag{20}$$

Goyal and Welch (2008) show that the historical average is a very stringent out-of-sample benchmark, and individual economic variables typically fail to outperform the historical average. The

[10]Hansen and Timmermann (2012) and Inoue and Rossi (2012) show that out-of-sample tests of predictive ability have better size properties when the forecast evaluation period is a relatively large proportion of the available sample, as in our case.

R^2_{OS} statistic lies in the range $(-\infty, 1]$; when $R^2_{OS} > 0$, the predictive regression forecast $\hat{R}^m_{t+1}$ outperforms the historical average $\bar{R}^m_{t+1}$ in term of MSFE.

The *MSFE-adjusted* statistic tests the null hypothesis that the historical average MSFE is less than or equal to the predictive regression forecast MSFE against the one-sided (upper-tail) alternative hypothesis that the historical average MSFE is greater than the predictive regression forecast MSFE, corresponding to H_0: $R^2_{OS} \leq 0$ against $H_A : R^2_{OS} > 0$. Clark and West (2007) develop the *MSFE-adjusted* statistic by modifying the familiar Diebold and Mariano (1995) and West (1996) statistic so that it has a standard normal asymptotic distribution when comparing forecasts from the nested models.[11]

[Insert Table 5 about here]

According to Panel B of Table 5, none of the 14 economic variables generate positive R^2_{OS} over the 1985:01–2010:12 evaluation period. Thus, all the 14 economic variables fail to outperform the historical average benchmark in terms of MSFE, consistent with the findings of Goyal and Welch (2008) that economic variables display limited out-of-sample predictive ability. It is interesting to note that five out of 14 economic variables generate positive *MSFE-adjusted* statistics, despite their statistical insignificance and negative R^2_{OS}, which is possible when comparing nested model forecasts (Clark and McCracken, 2001; Clark and West, 2007; McCracken, 2007).[12]

In Panel A of Table 5, S^{BW} generates positive R^2_{OS} statistic (0.15%), thus S^{BW} delivers a lower MSFE than the historical average. However, the out-of-sample predictability of S^{BW} is statistically insignificant based on the *MSFE-adjusted* statistic. Thus, S^{BW} has little out-of-sample predictive ability for the aggregate stock market, confirming our previous in-sample findings in Table 2.

In contrast, S^{PLS} presents much stronger out-of-sample predictive ability for market return in Panel A of Table 5. The R^2_{OS} of S^{PLS} is 1.23%, which is economically sizable and substantially exceeds all of the other R^2_{OS} in Table 5. The *MSFE-adjusted* statistic of S^{PLS} is 1.97, which indi-

[11] While the Diebold and Mariano (1995) and West (1996) statistic has a standard normal asymptotic distribution when comparing forecasts from non-nested models, Clark and McCracken (2001) and McCracken (2007) show that it has a non-standard distribution when comparing forecasts from nested models. The non-standard distribution can lead the Diebold and Mariano (1995) and West (1996) statistic to be severely undersized when comparing forecasts from nested models, thereby substantially reducing power.

[12] Intuitively, under the null hypothesis that the constant expected return model generates the data, the predictive regression model produces a noisier forecast than the historical average benchmark, because it estimates slope parameters with zero population values. We thus expect the benchmark model MSFE to be smaller than the predictive regression model MSFE under the null. The MSFE-adjusted statistic accounts for the negative expected difference between the historical average MSFE and predictive regression MSFE under the null, so that it can reject the null even if the R^2_{OS} statistic is negative.

cates that the MSFE of S^{PLS} is significantly smaller than that of the historical average at the 5% significant level.

Panel C of Table 5 further shows that adding information in S^{PLS} in conjunction with economic variables can substantially improve the forecasting performance of all of the forecasts based on economic variables alone. 10 of the 14 forecasts generate positive R^2_{OS}s when combining S^{PLS} together with economic variables, ranging from 0.16% to 0.96%. And the MSFEs for 7 combining forecasts are significantly less than the historical average MSFE according to the *MSFE-adjusted* statistics.

In summary, Table 5 shows that the aligned investor sentiment S^{PLS} displays strong out-of-sample forecasting power for the aggregate stock market. In addition, S^{PLS} substantially outperforms S^{BW} and all of the economic variables, consistent with our previous in-sample results in Tables 2 and 4.

4.4 Asset Allocation Implications

In this section, we measure the economic value of stock market forecasts based on aligned investor sentiment index S^{PLS} for a risk-averse investor. Following Kandel and Stambaugh (1996), Campbell and Thompson (2008) and Ferreira and Santa-Clara (2011), among others, we compute the certainty equivalent return (CER) gain and Sharpe Ratio for the portfolio of a mean-variance investor who optimally allocates across equities and risk-free bills using the out-of-sample predictive regression forecasts.

At the end of period t, the investor optimally allocates

$$w_t = \frac{1}{\gamma}\frac{\hat{R}^m_{t+1}}{\hat{\sigma}^2_{t+1}} \tag{21}$$

of the portfolio to equities during period $t+1$, where γ is the risk aversion coefficient, $\hat{R}^m_{t+1}$ is the out-of-sample forecast of the simple excess market return, and $\hat{\sigma}^2_{t+1}$ is the forecast of its variance. The investor then allocates $1-w_t$ of the portfolio to risk-free bills, and the $t+1$ realized portfolio return is

$$R^p_{t+1} = w_t R^m_{t+1} + R^f_{t+1}, \tag{22}$$

where R^f_{t+1} is the gross risk-free return. Following Campbell and Thompson (2008), we assume that the investor uses a five-year moving window of past monthly returns to estimate the variance of excess market return and constrain w_t to lie between 0 and 1.5 to exclude short sales and at most

50% leverage. To examine the effect of risk aversion, we consider portfolio rules based on risk aversion coefficients γ of 1, 3 and 5, respectively.

The CER of the portfolio is

$$CER_p = \hat{\mu}_p - 0.5\gamma\hat{\sigma}_p^2, \tag{23}$$

where $\hat{\mu}_n$ and $\hat{\sigma}_n^2$ are the sample mean and variance, respectively, for the investor's portfolio over the q forecasting evaluation periods. The CER can be interpreted as the risk-free return that an investor is willing to accept instead of adopting the given risky portfolio.

The CER gain is the difference between the CER for the investor who uses a predictive regression forecast of market return generated by (16) or (17) and the CER for an investor who uses the historical average forecast (20). We multiply this difference by 12 so that it can be interpreted as the annual portfolio management fee that an investor would be willing to pay to have access to the predictive regression forecast instead of the historical average forecast. In addition, we also calculate the monthly Sharpe ratio of the portfolio, which is the mean portfolio return in excess of the risk-free rate divided by the standard deviation of the excess portfolio return.

[Insert Table 6 about here]

Table 6 shows that only 4, 6, and 2 of the 14 economic variables have positive CER gains under risk aversion coefficient of 1, 3, and 5, respectively. The positive CER gains are often economically small, while many negative CER losses are large in magnitude. None of the economic variables generate consistently positive CER gains across different risk aversion coefficients. In summary, economic variables are of limited economic value for a risk averse investor, in accord with the negative R^2_{OS} statistics in Table 5.

When turning to investor sentiment, as a benchmark, S^{BW} performs as well as or better than most of the economic variables, with a CER gain range of -0.94% to 0.53% and a Sharpe ratio range of 0.09 to 0.11.

S^{PLS} stands out again in term of economic value. All of the CER gains for S^{PLS} are consistently positive and economically large, ranging from 2.32% to 4.43%. It means that an investor with a risk aversion coefficient of 1, 3, and 5, respectively, would be willing to pay annual portfolio management fee up to 4.34%, 4.09%, and 2.32%, to have access to the predictive regression forecast based on S^{PLS} instead of the historical average forecast. In addition, the Sharpe ratios of portfolios formed on S^{PLS} range from 0.15 to 0.19, which more than double the Sharpe ratio for a buy-and-hold strategy of 0.07 in Table 1.

Overall, Table 6 demonstrates that the aligned investor sentiment S^{PLS} can generate sizable economic value for the investor comparing to S^{BW} and the economic variables.

4.5 Forecasting Characteristics Portfolios

Investor sentiment has differential effects on the cross-section of stock returns. In particular, stocks that are speculative, difficult to value, hard to arbitrage, and in the short leg are likely to be more sensitive to investor sentiment (Baker and Wurgler, 2006, 2007; Stambaugh, Yu, and Yuan, 2012; Antoniou, Doukas, and Subrahmanyam, 2013).

In this section, we investigate the forecasting power of aligned investor sentiment S^{PLS} for the cross-section of characteristics portfolios sorted on industry, size, book-to-market, and momentum using the univariate in-sample predictive regressions

$$R^j_{t+1} = \alpha_j + \beta_j S^{PLS}_t + \varepsilon^j_{t+1}, \tag{24}$$

where R^j_{t+1} is the monthly log excess returns for the 10 industry, 10 size, 10 book-to-market, and 10 momentum portfolios, respectively, with the null hypothesis $H_0 : \beta_j = 0$ against the alternative hypothesis $H_A : \beta_j < 0$ based on wild bootstrapped p-values. This exercise not only helps to strengthen our previous findings for aggregate stock market predictability but also helps to enhance our understanding for the economic sources of return predictability.[13]

[Insert Table 7 about here]

Panel A of Table 7 reports the estimation results for in-sample univariate predictive regressions for 10 industry portfolios with investor sentiment over the period 1965:07–2010:12.[14] Affirming our findings for the market portfolio in Table 2, S^{PLS} substantially enhances the return forecasting performance relative to S^{BW} across all industries, with the R^2s about two to ten times higher than the corresponding R^2s of S^{BW}.

In addition, almost all of the regression slope estimates for S^{PLS} and S^{BW} are negative, thus the negative predictability of investor sentiment for subsequent stock returns are pervasive across industry portfolios. The regression slope estimates and R^2 statistics vary significantly across industries, illustrating large cross-section difference in the exposures to investor sentiment. Specifically,

[13] See, for example, Ferson and Harvey (1991), Ferson and Korajczyk (1995), Baker and Wurgler (2006, 2007), Hong, Torous, and Valkanov (2007), Cohen and Frazzini (2008), Menzly and Ozbas (2010).

[14] Monthly value-weighted returns for portfolios sorted on industry, size, book-to-market ratio, and momentum are available from Kenneth French's data library.

Technology, Energy, and Telecom are the most predictable by investor sentiment, whereas Utility, Health, and Non-durable present the lowest predictability.

The remaining panels of Table 7 show that S^{PLS} sharply improves the forecasting performance relative to S^{BW} for the cross-sectional stock returns of size, book-to-market, and momentum portfolios as well. S^{PLS} significantly forecasts all of the 10 characteristic portfolios sorted on size, book-to-market, and past return, respectively, while S^{BW} only significantly forecasts 9, 5 and 5 corresponding characteristic portfolios. In addition, all the R^2s of S^{PLS} are much larger the corresponding R^2s of S^{BW}, for example, the R^2 of S^{PLS} for large cap portfolio is 1.65%, while the corresponding R^2 of S^{BW} is 0.26%.[15]

Moreover, consistent with the literature, there is a fairly large dispersion of regression slope estimates in the cross-section. Stocks that are small, distressed (high book-to-market ratio), with high growth opportunity (low book-to-market ratio), or past losers are more predictable by investor sentiment.

5. Economic Explanations

5.1 Cash Flow Predictability and Discount Rate Predictability

Stock prices are determined by both expected future cash flow and discount rate. The ability of investor sentiment to forecast aggregate stock market return hence may come from aggregate cash flow channel or discount rate channel (Baker and Wurgler, 2007). In this section, we investigate the predictability of aligned investor sentiment index S^{PLS} for future aggregate cash flow and discount rate, respectively. This exercise is important for understanding the economic forces driving the return predictability of investor sentiment.

Fama and French (1989) and Cochrane (2008, 2011), among others, argue that aggregate stock market predictability comes from the time variation in discount rate.[16] Under the discount rate channel, high S^{PLS} predicts lower future stock market return because it predicts lower discount rate driven by lower risk aversion or lower expected investment risk.

[15] The aligned investor sentiment S^{PLS} estimated earlier for explaining the aggregate stock market return is used throughout this paper, since the aggregate stock market return is our main focus. If it is estimated for explaining the characteristics portfolios, the results will be even stronger.

[16] The time variation in discount rate can be driven by rational reasons such as ICAPM and market volatility risk in Merton (1973, 1980), long run risk in Bansal and Yaron (2004), and disaster risk in Gabaix (2012), or behavioral reasons such as habit formation in Campbell and Cochrane (1999) and prospect theory in Barberis, Huang, and Santos (2001).

On the other hand, S^{PLS} may represent investors' biased belief about future cash flow not justified by economic fundamental (Baker and Wurgler, 2007). Since S^{PLS} is a negative predictor for future stock market return, the cash flow channel implies that the lower stock market return under high S^{PLS} reflects the downward correction of overpricing induced by overly optimistic cash flow forecasts under high investor sentiment, when true fundamental is revealed in the next period.[17]

We use aggregate dividend growth as our cash flow proxy, which is widely examined in the asset pricing literature (e.g., Campbell and Shiller, 1988; Fama and French, 2000; Menzly, Santos, and Veronesi, 2004; Lettau and Ludvigson, 2005; Cochrane, 2008, 2011; Binsbergen and Koijen, 2010; Koijen and Van Nieuwerburgh, 2011; Kelly and Pruitt, 2013; Garrett and Priestley, 2013). Since the time variation in aggregate dividend price ratio is primarily driven by discount rate (Cochrane, 2008, 2011), we then use aggregate dividend price ratio as our discount rate proxy.

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

$$R_{t+1} = k + DG_{t+1} - \rho D/P_{t+1} + D/P_t, \tag{25}$$

where R_{t+1} is the log aggregate stock market return from t to $t+1$, DG_{t+1} is the log aggregate dividend growth rate, D/P_{t+1} is the log aggregate dividend price ratio, and ρ is a positive log-linearization constant. (25) implies that if S_t^{PLS} helps to predict next period market return R_{t+1} beyond the information contained in D/P_t, it must predict either DG_{t+1} or D/P_{t+1} (or both). Since DG_{t+1} and D/P_{t+1} represent separately cash flow and discount rate in our setting, the forecasting power of S_t^{PLS} for DG_{t+1} and D/P_{t+1} would point to the cash flow predictability channel and discount rate predictability channel, respectively.[18]

[Insert Table 8 about here]

Panel A of Table 8 reports the estimation results for in-sample bivariate predictive regressions

[17] The overly optimistic cash flow forecasts relative to the rational expectation under high sentiment can be driven by various reasons, including overreaction to good cash flow news due to over-extrapolation and representativeness bias (Kahneman and Tversky, 1974), underreaction to bad cash flow news due to conservatism bias (Edwards, 1968; Barberis, Shleifer and Vishny, 1998) or cognitive dissonance (Festinger, 1957; Antoniou, Doukas, and Subrahmanyam, 2013), gradual information diffusion (Hong and Stein, 1999), and Bayesian learning (Timmermann, 1993, 1996; Lewellen and Shanken, 2002), among others.

[18] Campbell and Shiller (1988), Campbell and Ammer (1993), Campbell and Vuolteenaho (2004), Campbell, Polk, and Vuolteenaho (2010), and others use a VAR method to decompose stock return into cash flow news and discount rate news. However, Chen and Zhao (2009) show that the VAR news decomposition method is quite sensitive to the choice of state variables. In addition, Wen and Zhou (2013) argue that this approach is not suitable for examining the source of return predictability, since it implicitly assumes that all predictability is generated through time-varying discount rate channel. Nonetheless, we generate qualitatively similar results based on the VAR method.

over the 1965–2011 sample period

$$Y_{t+1} = \alpha + \beta S_t^{PLS} + \psi D/P_t + \upsilon_{t+1}, \qquad Y = DG, D/P, \tag{26}$$

where DG_{t+1} is the annual log dividend growth rate on the S&P 500 index from year t to $t+1$, D/P_{t+1} is the log dividend price ratio on the S&P 500 index at the end of year $t+1$, and S_t^{PLS} is the aligned investor sentiment index at the end of year t. Following the literature, we focus on annual data in order to avoid spurious predictability arising from within-year seasonality, and DG_{t+1} and D/P_{t+1} are constructed following Cochrane (2008, 2011) based on total market returns and market returns without dividends.

Lagged dividend price ratio D/P_t has strong forecasting power for future dividend price ratio D/P_{t+1} with slow mean reversion coefficient of 0.95, while its forecasting power for dividend growth DG_{t+1} is statistically insignificant, affirming the findings in Cochrane (2008, 2011) that dividend price ratio captures time variation in discount rate.

S^{PLS} displays distinct patterns for cash flow and discount rate predictability. According to Panel A of Table 8, the slope estimate of S^{PLS} for DG_{t+1} in predictive regression (26) is negative, with statistical significance at the 10% level based on the one-sided wild bootstrapped p-value. The predictive regression slope estimate of S^{PLS} for D/P_{t+1} however is virtually equal to zero and statistically insignificant.[19]

Based on the joint predictability perspective in (25), the significant negative predictability of S^{PLS} for DG_{t+1} and no predictability for D/P_{t+1} jointly indicate that S^{PLS} should present significantly negative predictive power for excess market return, which is in accord with the evidence of negative market return predictability of S^{PLS} in Tables 2 and 4. Moreover, Panel B of Table 8 shows that S^{BW} can not forecast both DG_{t+1} and D/P_{t+1}, which is also consistent with the evidence of insignificant market return predictability of S^{BW} in Panel B of in Table 2 and the joint predictability perspective.

In summary, the strong predictability of S^{PLS} for DG_{t+1} and weak predictability for D/P_{t+1} in Table 8 indicates that the negative return predictability of S^{PLS} for aggregate stock market is coming from the cash flow channel, different from the popular time-varying discount rate interpretation of market return predictability in the literature. Specifically, Table 8 shows that high sentiment predicts lower future aggregate cash flow. Our findings hence suggest that high sentiment causes the overvaluation of aggregate stock market because of the investor's overly optimistic belief about

[19]In an unreported table, we find that S^{PLS} cannot forecast future dividend-price ratio even when S^{PLS} is constructed by applying PLS to the six individual sentiment measures and dividend-price ratio.

future aggregate cash flow. When the low cash flow is revealed to the investor, the overvaluation will disappear and stock price will fall, leading to lower future aggregate stock return on average, consistent with the discussion in Baker and Wurgler (2007).

5.2 The Cross-Section of Cash Flow Channel

In order to further elucidate the economic source of the return predictability of investor sentiment, we conduct an additional cross-sectional robustness analysis on the cash flow channel at the firm level. Baker and Wurgler (2006, 2007) find that stock returns that are speculative and hard to arbitrage are more predictable by investor sentiment. Thus, if the return predictability of investor sentiment comes from the cash flow channel, investor sentiment would have stronger forecasting power for the cash flows of speculative and hard-to-arbitrage stocks as well. This exercise helps to understand the cash flow channel explanation of investor sentiment's return predictability discussed in Section 5.1 and Table 8.

Specifically, we conduct the cross-sectional test of the cash flow channel using the predictive regressions

$$DG_{t+1}^{j} = \alpha_j + \phi_j S_t^{PLS} + \vartheta_{t+1}^{j}, \tag{27}$$

where DG_{t+1}^{j} is annual log dividend growth rate from year t to $t+1$ for one of the characteristic portfolios examined in Table 7. We are interested with the predictive regression slope coefficient ϕ_j on S^{PLS} in (27), which measures the ability of investor sentiment to forecast cash flows in the cross-section.

In an unreported table, we find that S^{PLS} is a significant negative predictor of cash flows, DG_{t+1}^{j}, for most of the characteristic portfolios, consistent with our aggregate market evidence in Table 8. Most importantly, we find an interesting cross-sectional pattern of the cash flow predictability of investor sentiment: the cash flows of more speculative and hard-to-arbitrage stocks are much more predictable by investor sentiment. For example, the R^2 increases monotonically from 13.3% for large firms to 34.6% for small firms, which is usually regarded as more speculative and hard to arbitrage; and the regression coefficient ϕ_j decreases sharply from -5.1% for large firms to -14.5% for small firms. It implies that a one-standard-deviation increase in S^{PLS} associated with a -5.1% decrease in expected dividend growth for large firms and a -14.5% decrease for small firms for next year, respectively, and the cash flows of small firms are about three times more predictable than those of large firms.

We then use a cross-sectional regression framework to statistically test the cash flow channel, in the spirit of Hong, Torous, and Valkanov (2007), Hirshleifer, Hsu, and Li (2013), and Bakshi, Panayotov, and Skoulakis (2014). We ask whether the ability of investor sentiment to forecast stock returns is positively associated with its ability to forecast cash flows. If the hypothesis holds, firms that are most predictable by investor sentiment should have the highest cash flow predictability as well. We run the cross-section regression

$$\beta_j = a + g\phi_j + e_j, \tag{28}$$

where ϕ_j is from (27) which measures the ability of investor sentiment to forecast the cross-sectional cash flows, and β_j is from (24) which measures the ability of investor sentiment to forecast the cross-section of stock returns (annualized by multiplying 12). If the cash flow channel hypothesis holds, we expect a positive relationship between β_j and ϕ_j, that is, $g > 0$. Empirically, we do find that firms with higher return exposures to investor sentiment also have higher cash flow exposures to investor sentiment. For example, for the 10 size portfolios, the OLS estimate of g in (28) is 0.54, with a heteroskedasticity-consistent t-statistic of 9.48 and an R^2 of 80%, indicating significantly positive relationship between β_j and ϕ_j. Thus, small firms that are more predictable by S^{PLS} with larger negative β_j have significantly higher cash flow predictability by S^{PLS} with larger negative ϕ_j as well.

5.3 Market Volatility Risk

In this section, we examine whether market volatility risk can explain the stock return predictability of investor sentiment. Merton (1980) and French, Schwert, and Stambaugh (1987) show that lower stock market volatility implies lower market risk, leading to lower risk premium or discount rate for next period. It is thus possible that the predictability of S^{PLS} is due to the fact that S^{PLS} represents time variation in expected stock market volatility.

We estimate the following predictive regression model

$$LVOL_{t+1} = \alpha + \beta S_t^{PLS} + \psi LVOL_t + v_{t+1}, \tag{29}$$

where $LVOL_{t+1} \equiv \ln(\sqrt{SVAR_{t+1}})$ is log monthly aggregate stock market volatility at period $t+1$. The monthly aggregate stock market variance $SVAR_{t+1}$ is the sum of squared daily returns on the S&P 500 index at monthly frequency,

$$SVAR_{t+1} = \sum_{i=1}^{N_{t+1}} R_{i,t+1}^2, \tag{30}$$

where N_{t+1} is the number of trading days during period $t+1$, and $R_{i,t+1}$ is the daily excess return for the S&P 500 index on the ith trading day of period $t+1$ (e.g., French, Schwert, and Stambaugh, 1987; Schwert, 1989; Paye, 2012).[20]

We are interested in the slope coefficient β on S^{PLS} in (29). Given that S^{PLS} is negatively associated with future aggregate stock market return in Tables 2 and 4, the volatility risk-based argument implies that high S^{PLS} should predict lower aggregate stock market volatility and thus lower market risk, which in turn decreases the equity risk premium (discount rate). However, in an unreported table, we find that S^{PLS} indeed contains positive forecasting power for market volatility, with a $\beta = 0.028$ and a t-statistic of 2.10, inconsistent with the volatility risk-based hypothesis.

In summary, while we can not fully rule out the risk-based explanation, it seems unlikely that market volatility risk is driving the predictive power of S^{PLS} for stock market return.[21] To the extent that high investor sentiment proxies for more noise trading, our findings appear to provide further supports for the behavioral explanation of De Long, Shleifer, Summers, and Waldmann (1990) where high noise trading leads to excessive volatility.[22]

6. Conclusion

In this paper, we propose a new investor sentiment index aligned for explaining asset expected returns. With this new measure, we find that investor sentiment has much greater predictive power for the aggregate stock market than previously thought. In addition, it performs much better than any of the commonly used macroeconomic variables, and its predictability is both statistically and economically significant. Moreover, the new measure also improves substantially the forecasting power for the cross-section of stock returns formed on industry, size, value, and momentum.

[20] Stock market volatility is positively skewed and leptokurtic, which may distort statistical inferences in predictive regression. We hence focus on forecasting the log market volatility, following Andersen, Bollerslev, Diebold, and Ebens (2001) and Paye (2012). Stock market volatility is very persistent in dynamics, which may generate spuriou evidence of volatility predictability of investor sentiment, when investor sentiment is contemporaneously correlated with volatility. We thus include lagged volatility $LVOL_t$ as a control variable in (29) to examine the incremental forecasting power of investor sentiment for aggregate stock market volatility. Our results are robust to alternative measures such as measures based on absolute returns and measures that attempt to correct variation in expected market return.

[21] Aggregate cash flow is associated with aggregate consumption and the investor typically requires higher risk premium when the consumption growth is lower. Since high S^{PLS} predicts lower aggregate cash flow in Table 8, a rational risk-based theory will most likely require higher expected stock market return under high S^{PLS}, inconsistent with the evidence of lower stock market return following high S^{PLS}. Thus, it seems that cash flow risk or consumption risk can not explain the forecasting power of S^{PLS} for stock market return.

[22] Antweiler and Frank (2004) also find that higher sentiment, proxied by the number of messages posted and the bullishness of these messages posted on the Yahoo Finance and Raging Bull stock message boards, predicts higher future stock market volatility for a set of individual stocks.

Economically, we find that the return predictability of investor sentiment seems to comme from investor's biased belief about future cash flow channel rather than time-varying discount rate.

Overall, our empirical results suggest that investor sentiment is important not only cross-sectionally as established in the literature, but also important at the aggregate market level. The success of the aligned investor sentiment is due to the important proxies proposed by Baker and Wurgler (2006). While the principal components approach taken by Baker and Wurgler (2006) summarizes succinctly the information from the proxies, the partial least squares approach used in this paper exploits more efficiently the information in the proxies. Hence, the aligned investor sentiment can achieve substantial improvements in forecasting stock returns either at the aggregate level or cross-sectionally. Since investor sentiment has been widely used to examine a variety of financial issues, the aligned investor sentiment, as an improvement of the fundamental measure of Baker and Wurgler (2006), may yield a number of future applications.

Appendix

A.1 Detailed Description of Economic Variables

This section describes the 14 economic variables in Tables 1, 4, 5, and 6. The 14 economic variables are popular stock return predictors documented in the literature. They are monthly and described in more detail in Goyal and Welch (2008).[23]

- Dividend-price ratio (log), DP: log of a twelve-month moving sum of dividends paid on the S&P 500 index minus the log of stock prices (S&P 500 index).
- Dividend yield (log), DY: difference between the log of dividends and log of lagged prices.
- Earnings-price ratio (log), EP: difference between the log of earnings on the S&P 500 index and log of prices, where earnings are measured using a one-year moving sum.
- Dividend-payout ratio (log), DE: difference between the log of dividends and log of earnings on the S&P 500 index.
- Stock return variance, SVAR: sum of squared daily returns on the S&P 500 index.
- Book-to-market ratio, BM: ratio of book value to market value for the Dow Jones Industrial Average.
- Net equity expansion, NTIS: ratio of twelve-month moving sums of net issues by NYSE-listed stocks to total end-of-year market capitalization of NYSE stocks.
- Treasury bill rate, TBL: interest rate on a 3-month Treasury bill (secondary market).
- Long-term yield, LTY: long-term government bond yield.
- Long-term return, LTR: return on long-term government bonds.
- Term spread, TMS: difference between the long-term yield and Treasury bill rate.
- Default yield spread, DFY: difference between BAA- and AAA-rated corporate bond yields.
- Default return spread, DFR: difference between long-term corporate bond and long-term government bond returns.

[23] The data are available at Amit Goyal's website, http://www.hec.unil.ch/agoyal.

- Inflation, INFL: calculated from the CPI (all urban consumers); following Goyal and Welch (2008), inflation are lagged for two months relative to stock market return to account for the delay in CPI releases.

A.2 Bootstrap Procedures for Computing Empirical *p*-Values

This section describes the wild bootstrap procedures underlying the empirical p-values reported in Tables 2, 4, 7, and 8. The resampling scheme for the wild bootstrap is based on Cavaliere, Rahbek, and Taylor (2010), which is a multiequation extension of the time-series wild bootstrap.

First, we begin by describing the procedure that generates the wild bootstrapped p-values for the test statistics for the predictive regressions of excess aggregate stock market return reported in Tables 2 and 4. The wild bootstrap procedure simulates data under the null of no return predictability. Let

$$\hat{\varepsilon}_{t+1} = R^m_{t+1} - (\hat{\alpha} + \sum_{i=1}^{N} \hat{\beta}_i x_{i,t} + \sum_{i=1}^{M} \hat{\psi}_i Z_{i,t}), \tag{31}$$

where $\hat{\alpha}$, $\hat{\beta}_i$ $(i = 1,...,N)$, and $\hat{\psi}_i$ $(i = 1,...,M)$ are OLS parameter estimates for the general multiple predictive regression model that includes a constant, N standardized individual investor sentiment proxies of Baker and Wurgler (2006), and M economic variables as regressors.

Following convention, we assume that the predictors in (31) follow an AR(1) process:

$$x_{i,t+1} = \rho_{i,x,0} + \rho_{i,x,1} x_{i,t} + \varphi_{i,x,t+1}, \ \ i = 1,...,N, \tag{32}$$

$$Z_{i,t+1} = \rho_{i,Z,0} + \rho_{i,Z,1} Z_{i,t} + \varphi_{i,Z,t+1}, \ \ i = 1,...,M. \tag{33}$$

Define

$$\hat{\varphi}^c_{i,x,t+1} = x_{i,t+1} - \hat{\rho}^c_{i,x,0} - \hat{\rho}^c_{i,x,1} x_{i,t}, \ \ i = 1,...,N, \tag{34}$$

$$\hat{\varphi}^c_{i,Z,t+1} = Z_{i,t+1} - \hat{\rho}^c_{i,Z,0} - \hat{\rho}^c_{i,Z,1} Z_{i,t}, \ \ i = 1,...,M, \tag{35}$$

where

$$(\hat{\rho}^c_{i,x,0}, \ \hat{\rho}^c_{i,x,1}), \ \ i = 1,...,N, \tag{36}$$

and

$$(\hat{\rho}^c_{i,Z,0}, \ \hat{\rho}^c_{i,Z,1}), \ \ i = 1,...,M, \tag{37}$$

denote vectors of reduced-bias estimates of the AR(1) parameters in (32) and (33), respectively. The reduced-bias estimates of the AR parameters are computed by iterating on the Nicholls and

Pope (1988) expression for the analytical bias of the OLS estimates (e.g., Amihud, Hurvich, and Wang, 2009).

Based on these AR parameter estimates and fitted residuals, we build up a pseudo sample of observations for the excess aggregate stock market return, N individual investor sentiment proxies, and M macroeconomic variables under the null hypothesis of no return predictability:

$$\tilde{R}^m_{t+1} = \bar{R}^m + \hat{\varepsilon}_{t+1} w_{t+1}, \tag{38}$$

$$\tilde{x}_{i,t+1} = \hat{\rho}^c_{i,x,0} + \hat{\rho}^c_{i,x,1}\tilde{x}_{i,t} + \hat{\varphi}^c_{i,x,t+1} w_{t+1}, \;\; i = 1,...,N, \tag{39}$$

$$\tilde{Z}_{i,t+1} = \hat{\rho}^c_{i,Z,0} + \hat{\rho}^c_{i,Z,1}\tilde{Z}_{i,t} + \hat{\varphi}^c_{i,Z,t+1} w_{t+1}, \;\; i = 1,...,M, \tag{40}$$

where $\bar{R}^m$ is the sample mean of R^m_{t+1}, w_{t+1} is a draw from the standard normal distribution, $\tilde{x}_{i,0} = x_{i,0}$ $(i = 1,...,N)$, and $\tilde{Z}_{i,0} = Z_{i,0}$ $(i = 1,...,M)$. Observe that we multiply the fitted residuals $\hat{\varepsilon}_{t+1}$ in (38), each $\hat{\varphi}^c_{i,x,t+1}$ in (39), and each $\hat{\varphi}^c_{i,Z,t+1}$ in (40) by the same scalar, w_{t+1}, when generating the month-$(t+1)$ pseudo residuals, thereby making it a wild bootstrap. In addition to preserving the contemporaneous correlations in the data, this allows the wild bootstrap to capture the general forms of conditional heteroskedasticity. Employing reduced-bias parameter estimates in (39) and (40) helps to ensure that we adequately capture the persistence in the predictors.

Using the pseudo sample of observations for

$$\{(\tilde{R}^m_{t+1}, \tilde{x}_{1,t}, ..., \tilde{x}_{N,t}, \tilde{Z}_{1,t}, ..., \tilde{Z}_{M,t})\}_{t=0}^{T-1}, \tag{41}$$

we estimate the slope coefficients and the corresponding t-statistics for univariate predictive regressions based on each investor sentiment index in (13) or each macroeconomic variable in (14), and the bivariate predictive regressions based on aligned investor sentiment and each macroeconomic variable in (15). Note that we compute the aligned investor sentiment index, Baker and Wurgler (2006) investor sentiment index, and naive investor sentiment index in (13) and (15) using the pseudo sample of $\{\tilde{x}_{i,t}\}_{t=0}^{T-1}$ $(i = 1,...,N)$ and $\{\tilde{R}^m_{t+1}\}_{t=0}^{T-1}$, so that it accounts for the estimated regressors in the predictive regressions. We store the t-statistics for all of the predictive regressions. Repeating this process 2,000 times yields empirical distributions for each of the t-statistics. For a given t-statistic, the empirical p-value is the proportion of the bootstrapped t-statistics greater (less) than the t-statistic for the original sample.

Second, we modify the previous wild bootstrap procedure to simulate data for the predictive regressions on the C characteristics portfolios in Table 7 under the null of no predictability. Let

$$\hat{\varepsilon}^j_{t+1} = R^j_{t+1} - (\hat{\alpha}^j + \sum_{i=1}^{N} \hat{\beta}^j_i x_{i,t}), \;\; j = m, 1, ..., C, \tag{42}$$

where $\hat{\alpha}^j$ ($j = m, 1, ..., C$) and $\hat{\beta}_i^j$ ($i = 1, ..., N$, and $j = m, 1, ..., C$) are estimated by regressing excess market return ($j = m$) or each of the excess characteristics portfolio returns ($j = 1, ..., C$) on a constant and all of the N individual investor sentiment proxies. We continue to assume that $x_{i,t}$ follows an AR(1) process and use (32), (34), and (39). In accord with the null, we build up a pseudo sample of observations for excess returns on the market and characteristics portfolios

$$\tilde{R}_{t+1}^j = \bar{R}^j + \hat{\varepsilon}_{t+1}^j w_{t+1}, \quad j = m, 1, ..., C. \tag{43}$$

We use this process to simulate data for each portfolio j ($j = m, 1, ..., C$), and compute the aligned investor sentiment index and Baker and Wurgler (2006) investor sentiment index using the pseudo sample. We then use the pseudo sample to compute the slope coefficients and the corresponding t-statistics for univariate predictive regressions based on each investor sentiment index in Table 7. Repeating this process 2,000 times, the empirical p-value is the proportion of the bootstrapped t-statistics greater (less) than the t-statistic for the original sample.

Third, we change the previous wild bootstrap procedure to simulate data for the predictive regressions on the dividend growth or dividend price ratio in Table 8 under the null. Let

$$\hat{\upsilon}_{Y,t+1} = Y_{t+1} - (\hat{\alpha}_Y + \sum_{i=1}^{N} \hat{\beta}_{Y,i} x_{i,t} + \hat{\psi} D/P_t), \quad Y = DG, D/P. \tag{44}$$

Under the null, we allow for predictive power arising from lagged dividend price ratio, but not lagged investor sentiment measures. We continue to assume that $x_{i,t}$ follows an AR(1) process and use (32), (34), and (39). We simulate R_t^m using (31) and (38). In accord with the null, we build up a pseudo sample of observations for dividend growth and dividend price ratio

$$\tilde{Y}_{t+1} = \hat{\alpha}_Y + \hat{\psi} \widetilde{D/P}_t + \hat{\upsilon}_{Y,t+1} w_{t+1}, \quad Y = DG, D/P. \tag{45}$$

We use this process to simulate data for dividend growth and dividend price ratio, and compute the aligned investor sentiment index and Baker and Wurgler (2006) investor sentiment index using the pseudo sample. We then use the pseudo sample to compute the slope coefficients and the corresponding t-statistics for bivariate predictive regressions based on each investor sentiment index in Table 8. Repeating this process 2,000 times, the empirical p-value is the proportion of the bootstrapped t-statistics greater (less) than the t-statistic for the original sample.

Fourth, we alternate the previous wild bootstrap procedure to simulate data for the predictive regressions on the log aggregate stock market volatility in Section 5.3 under the null. Let

$$\hat{\nu}_{t+1} = LVOL_{t+1} - (\hat{\alpha} + \sum_{i=1}^{N} \hat{\beta}_i x_{i,t} + \hat{\psi} LVOL_t). \tag{46}$$

Under the null, we allow for market volatility predictability coming from lagged volatility, but not lagged investor sentiment measures. We continue to assume that $x_{i,t}$ follows an AR(1) process and use (32), (34), and (39). We simulate R_t^m using (42) and (43). In accord with the null, we generate a pseudo sample of observations for log market volatility

$$\widetilde{LVOL}_{t+1} = \hat{\alpha} + \hat{\psi}\widetilde{LVOL}_t + \hat{v}_{t+1}w_{t+1}. \tag{47}$$

We use this process to simulate data for log market volatility, and compute the aligned investor sentiment index and Baker and Wurgler (2006) investor sentiment index using the pseudo sample. We then use the pseudo sample to compute the slope coefficients and the corresponding t-statistics for bivariate predictive regressions based on investor sentiment index. Repeating this process 2,000 times, the empirical p-value is the proportion of the bootstrapped t-statistics greater (less) than the t-statistic for the original sample.

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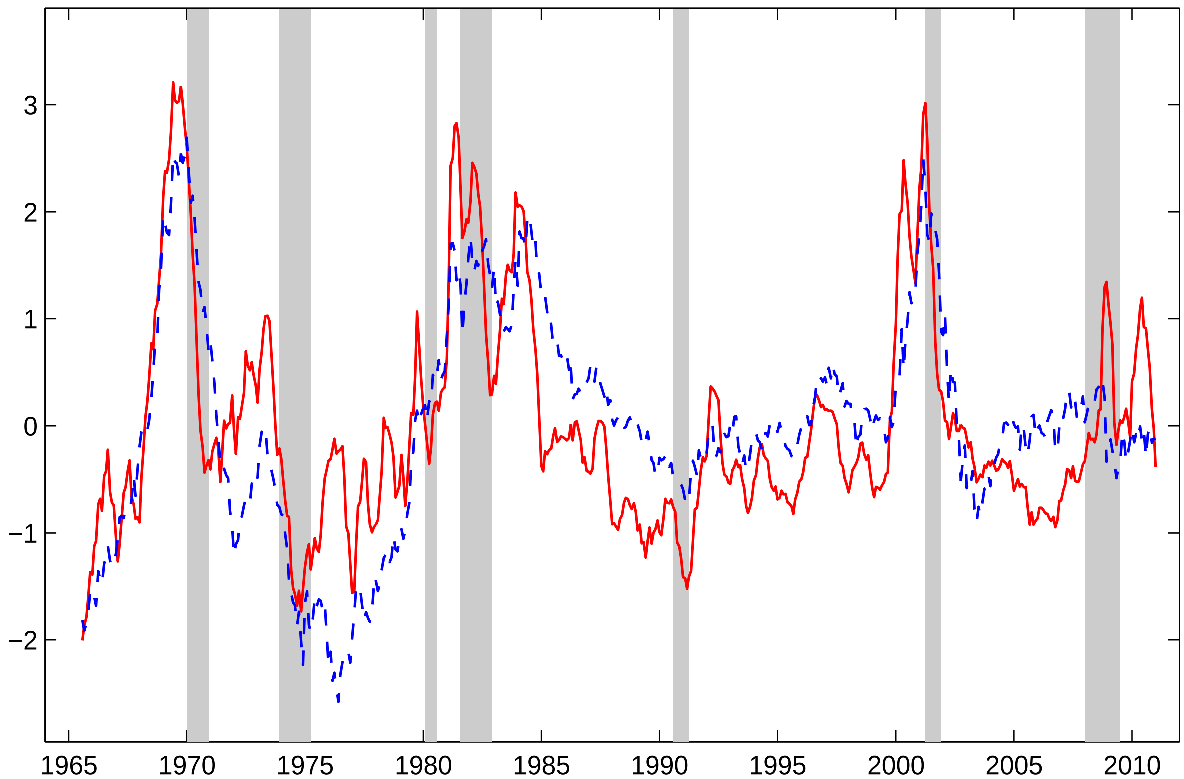

Figure 1. The Investor Sentiment Index, 1965:07−2010:12. The solid line depicts the aligned investor sentiment index S^{PLS} extracted from the Baker and Wurgler's six individual investor sentiment proxies by applying the partial least squares method. The dashed line depicts the Baker and Wurgler (2006) investor sentiment index S^{BW} as the first principle component of the six investor sentiment measures. The six individual investor sentiment measures are available from Jeffrey Wurgler's website: the close-end fund discount rate, share turnover, number of IPOs, average first-day returns of IPOs, dividend premium, and equity share in new issues. Each underlying individual investor sentiment measure is standardized, smoothed with six month moving average, and regressed on the growth of industrial production, the growth of durable consumption, the growth of nondurable consumption, the growth of service consumption, the growth of employment, and a dummy variable for NBER-dated recessions to remove the effect of macroeconomic conditions. The share turnover, average first-day return of IPOs, and dividend premium are lagged 12 months relative to the other three measures. The estimated investor sentiment indexes are standardized to have zero mean and unit variance. The vertical bars correspond to NBER-dated recessions.

Table 1
Summary Statistics

This table reports summary statistics for the log excess aggregate stock market return defined as the log return on the S&P 500 index in excess of the risk-free rate (in percentage, R^m), risk-free rate (in percentage, R^f), aligned investor sentiment index (S^{PLS}) extracted by partial least squares, Baker and Wurgler (2006) investor sentiment index (S^{BW}), and 14 economic variables from Amit Goyal's website: the log dividend-price ratio (DP), log dividend yield (DY), log earnings-price ratio (EP), log dividend payout ratio (DE), Stock return variance (in percentage, SVAR), book-to-market ratio (BM), net equity expansion (NTIS), Treasury bill rate (annual in percentage, TBL), long-term bond yield (annual in percentage, LTY), long-term bond return (in percentage, LTR), term spread (annual in percentage, TMS), default yield spread (annual in percentage, DFY), default return spread (in percentage, DFR), inflation rate (in percentage, INFL). For each variable, the time-series average (Mean), standard deviation (Std. Dev.), skewness (Skew.), kurtosis (Kurt.), minimum (Min.), maximum (Max.), and first-order autocorrelation ($\rho(1)$) are reported. The monthly Sharpe ratio (SR) is the mean log excess market return divided by its standard deviation. The sample period is over 1965:07−2010:12.

	Mean	Std. Dev.	Skew.	Kurt.	Min.	Max.	$\rho(1)$	SR
R^m (%)	0.31	4.46	-0.67	5.41	-24.84	14.87	0.06	0.07
R^f (%)	0.46	0.25	0.72	4.33	0.00	1.36	0.98	
S^{PLS}	0.00	1.00	1.19	4.10	-2.01	3.21	0.96	
S^{BW}	0.00	1.00	0.10	3.19	-2.58	2.69	0.98	
DP	-3.56	0.42	-0.37	2.24	-4.52	-2.75	0.99	
DY	-3.56	0.42	-0.38	2.26	-4.53	-2.75	0.99	
EP	-2.82	0.47	-0.77	5.26	-4.84	-1.90	0.99	
DE	-0.74	0.32	3.08	18.97	-1.22	1.38	0.98	
SVAR (%)	0.23	0.45	9.48	115.62	0.01	6.55	0.49	
BM	0.52	0.28	0.57	2.25	0.12	1.21	0.99	
NTIS	0.01	0.02	-0.84	3.78	-0.06	0.05	0.98	
TBL (%)	5.49	2.95	0.72	4.33	0.03	16.30	0.98	
LTY (%)	7.29	2.40	0.89	3.34	3.03	14.82	0.99	
LTR (%)	0.65	3.06	0.40	5.55	-11.24	15.23	0.03	
TMS (%)	1.79	1.55	-0.33	2.63	-3.65	4.55	0.95	
DFY (%)	1.07	0.47	1.70	6.71	0.32	3.38	0.96	
DFR (%)	0.01	1.46	-0.29	10.02	-9.75	7.37	-0.06	
INFL (%)	0.36	0.35	-0.20	7.20	-1.92	1.79	0.61	

Table 2
Forecasting Aggregate Stock Market with Investor Sentiment
This table reports in-sample estimation results for the univariate predictive regression models based on lagged investor sentiment

$$R_{t+1} = \alpha + \beta S_t + \varepsilon_{t+1}$$

where R_{t+1} denotes the monthly log excess return (in percentage) on the S&P 500 index from t to $t+1$. The sentiment predictor denotes the Baker and Wurgler (2006) investor sentiment index S_t^{BW} as the first principle component of six individual investor sentiment proxies (Panel A), the naive investor sentiment index S_t^{EW} with equal absolute weight on each of the six proxies (Panel B), the aligned investor sentiment index S_t^{PLS} extracted by applying the partial least squares to the six proxies (Panel C), and one of the six investor sentiment proxies (Panel D): the close-end fund discount rate (CEFD), share turnover (TURN), number of IPOs (NIPO), first-day returns of IPOs (RIPO), dividend premium (PDND), equity share in new issues (EQTI). All of the three investor sentiment indexes and six individual proxies are standardized to have zero mean and unit variance, and are orthogonal to macroeconomic variables to remove the effect of business cycle conditions. We report the regression slope coefficients, heteroskedasticity-consistent t-statistics, as well as R^2 statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on one-sided wild bootstrapped p-values. The sample period is over 1965:07−2010:12.

	β (%)	t-stat	R^2 (%)
Panel A: BW Investor Sentiment Index			
S^{BW}	-0.24	-1.21	0.30
Panel B: Naive Investor Sentiment Index			
S^{EW}	-0.27*	-1.39	0.38
Panel C: Aligned Investor Sentiment Index			
S^{PLS}	-0.58***	-3.04	1.70
Panel D: Individual Investor Sentiment Proxies			
CEFD	0.16	0.89	0.14
TURN	-0.13	-0.69	0.08
NIPO	0.04	0.18	0.01
RIPO	-0.47**	-2.35	1.16
PDND	-0.05	-0.27	0.02
EQTI	-0.40**	-2.26	0.80

Table 3
Forecast Encompassing Tests

This table reports p-values for the Harvey, Leybourne, and Newbold (1998) statistic. The statistic corresponds to a one-sided (upper-tail) test of the null hypothesis that the predictive regression log excess market return forecast based on one of the predictors given in the first column encompasses the forecast based on one of the predictors given in the first row, against the alternative hypothesis that the forecast given in the first column does not encompass the forecast given in the first row. The predictors include the Baker and Wurgler (2006) investor sentiment index S^{BW}, aligned investor sentiment index S^{PLS}, and six individual investor sentiment measures of Baker and Wurgler (2006): the close-end fund discount rate (CEFD), share turnover (TURN), number of IPOs (NIPO), first-day returns of IPOs (RIPO), dividend premium (PDND), equity share in new issues (EQTI). The sample period is over 1965:07−2010:12.

	CEFD	TURN	NIPO	RIPO	PDND	EQTI	S^{BW}	S^{PLS}
CEFD		0.35	0.50	0.01	0.44	0.02	0.12	0.01
TURN	0.45		0.50	0.01	0.45	0.02	0.12	0.01
NIPO	0.39	0.32		0.01	0.43	0.02	0.12	0.01
RIPO	0.51	0.52	0.50		0.47	0.06	0.48	0.07
PDND	0.40	0.34	0.49	0.01		0.02	0.12	0.01
EQTI	0.47	0.50	0.50	0.08	0.49		0.38	0.06
S^{BW}	0.55	0.53	0.51	0.03	0.43	0.03		0.02
S^{PLS}	0.54	0.52	0.50	0.40	0.46	0.19	0.64	

Table 4
Alternative Return Predictors
Panel A reports in-sample estimation results for the univariate predictive regression models based on one of the alternative return predictors

$$R^m_{t+1} = \alpha + \psi Z^k_t + \varepsilon_{t+1}, \qquad k = 1, ..., 14,$$

where R^m_{t+1} is the monthly log excess aggregate stock market return (in percentage), and Z^k_t is one of the 14 economic variables from Goyal and Welch (2008) given in the first column. Panel B reports in-sample estimation results for the bivariate predictive regression models based on aligned investor sentiment index S^{PLS}_t and Z^k_t,

$$R^m_{t+1} = \alpha + \beta S^{PLS}_t + \psi Z^k_t + \varepsilon_{t+1}, \qquad k = 1, ..., 14.$$

We report the regression slope coefficients, heteroskedasticity-consistent t-statistics, as well as R^2 statistics. To save space, we do not report the intercept in the regressions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on one-sided wild bootstrapped p-values. The sample period is over 1965:07−2010:12. The data are described in the Appendix.

	Panel A: Univariate Predictive Regressions			Panel B: Bivariate Predictive Regressions				
	ψ (%)	t-stat	R^2 (%)	β (%)	t-stat	ψ (%)	t-stat	R^2 (%)
DP	0.47	0.99	0.20	-0.59***	-3.02	0.49	1.02	1.91
DY	0.54	1.13	0.26	-0.58**	-3.01	0.53	1.14	1.96
EP	0.21	0.43	0.05	-0.58**	-3.03	0.19	0.38	1.74
DE	0.36	0.50	0.07	-0.59**	-3.06	0.44	0.61	1.80
SVAR	-1.09**	-2.29	1.23	-0.55**	-2.82	-0.99**	-2.00	2.70
BM	0.15	0.20	0.01	-0.59**	-2.95	0.38	0.49	1.76
NTIS	-3.70	-0.33	0.03	-0.59**	-2.90	-1.16	-0.10	1.71
TBL	-0.07	-0.94	0.19	-0.57**	-2.62	-0.01	-0.15	1.71
LTY	0.00	0.05	0.00	-0.62**	-2.90	0.06	0.66	1.80
LTR	0.15**	2.22	1.07	-0.57**	-2.97	0.15**	2.21	2.72
TMS	0.23**	1.83	0.61	-0.54**	-2.73	0.18*	1.39	2.06
DFY	0.46	0.90	0.23	-0.68***	-3.36	0.81**	1.59	2.38
DFR	0.18	0.89	0.36	-0.58**	-3.01	0.18	0.88	2.05
INFL	0.18	0.27	0.02	-0.58**	-3.02	0.23	0.34	1.73

Table 5
Out-of-sample Forecasting Results

The out-of-sample forecasts for aggregate stock market return in Panel A are generated by univariate recursive predictive regressions based on the out-of-sample aligned investor sentiment index S^{PLS} or out-of-sample Baker and Wurgler (2006) investor sentiment index S^{BW}. The out-of-sample market return forecasts in Panel B are generated by univariate recursive predictive regressions based on one of the 14 economic variables from Goyal and Welch (2008) given in the fourth column. The out-of-sample market return forecasts in Panel C are generated by bivariate recursive predictive regressions based on S^{PLS} and one of the 14 economic variables. All of the S^{PLS}, S^{BW}, and predictive regression slopes in out-of-sample forecasts are estimated recursively using the data available through period of forecast formation t. R^2_{OS} is the Campbell and Thompson (2008) out-of-sample R^2 statistic (in percentage), which measures the reduction in mean squared forecast error (MSFE) for the competing predictive regression forecast relative to the historical average benchmark forecast. *MSFE-adjusted* is the Clark and West (2007) statistic for testing the null hypothesis that the historical average forecast MSFE is less than or equal to the competing predictive regression forecast MSFE against the one-sided (upper-tail) alternative hypothesis that the historical average forecast MSFE is greater than the competing predictive regression forecast MSFE. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The out-of-sample evaluation period is over 1985:01–2010:12.

	R^2_{OS} (%)	*MSFE-adjusted*		R^2_{OS} (%)	*MSFE-adjusted*
Panel A: Investor Sentiment					
S^{PLS}	1.23**	1.97			
S^{BW}	0.15	0.96			
Panel B: Economic Variables			Panel C: S^{PLS} and Economic Variables		
DP	-1.25	-0.71	S^{PLS} + DP	-0.16	0.81
DY	-1.24	-0.56	S^{PLS} + DY	0.44	0.97
EP	-0.78	-0.48	S^{PLS} + EP	-0.22	0.76
DE	-1.50	-0.68	S^{PLS} + DE	-0.07	0.94
SVAR	-1.56	0.14	S^{PLS} + SVAR	0.16	0.82
BM	-1.06	-1.66	S^{PLS} + BM	0.31**	1.66
NTIS	-1.28	0.52	S^{PLS} + NTIS	0.80*	1.49
TBL	-0.51	-0.16	S^{PLS} + TBL	0.90*	1.36
LTY	-0.22	-1.37	S^{PLS} + LTY	0.68**	1.63
LTR	-0.60	0.57	S^{PLS} + LTR	0.42*	1.40
TMS	-0.85	0.41	S^{PLS} + TMS	-1.15	0.56
DFY	-1.91	-1.45	S^{PLS} + DFY	0.96	1.26
DFR	-0.28	0.04	S^{PLS} + DFR	0.85**	1.74
INFL	-0.43	-0.27	S^{PLS} + INFL	0.45**	1.89

Table 6
Asset Allocation Results

Panels A and B report the portfolio performance measures for a mean-variance investor with a risk aversion coefficient (γ) of 1, 3 and 5, respectively, who allocates monthly between equities and risk-free bills using the out-of-sample predictive regression forecast for excess market return based on one of the return predictors given in the first column. Δ is the annualized certainty equivalent return gain (in percentage) for an investor who uses the predictive regression forecast instead of the historical average benchmark forecast. The weight on stocks in the investors portfolio is restricted to lie between 0 and 1.5. The monthly Sharpe ratio (SR) is the mean portfolio return based on the predictive regression forecast in excess of the risk-free rate divided by the standard deviation of the excess portfolio return. The out-of-sample aligned investor sentiment index S^{PLS} and out-of-sample Baker and Wurgler (2006) investor sentiment index S^{BW} are estimated recursively using the data available through period of forecast formation t. The out-of-sample evaluation period is over 1985:01–2010:12.

	Panel A: $\gamma = 1$		Panel B: $\gamma = 3$		Panel C: $\gamma = 5$	
	Δ (%)	SR	Δ (%)	SR	Δ (%)	SR
Investor Sentiment						
S^{PLS}	4.34	0.19	4.09	0.17	2.32	0.15
S^{BW}	-0.94	0.11	0.53	0.10	0.36	0.09
Economic Variables						
DP	-4.84	0.06	-3.59	0.01	-1.74	0.02
DY	-5.05	0.06	-3.13	0.01	-1.43	0.01
EP	-1.64	0.11	0.73	0.10	0.84	0.10
DE	-1.59	0.10	-1.23	0.07	-0.88	0.06
SVAR	-1.20	0.11	0.07	0.09	-0.08	0.07
BM	-3.40	0.08	-1.47	0.06	-1.22	0.05
NTIS	0.22	0.12	0.11	0.10	-0.63	0.10
TBL	0.15	0.12	0.09	0.10	-1.08	0.08
LTY	-0.72	0.11	-0.12	0.09	-0.26	0.07
LTR	-2.25	0.10	-0.53	0.08	-0.48	0.08
TMS	1.20	0.14	0.40	0.11	-1.53	0.09
DFY	-3.72	0.07	-2.39	0.03	-3.31	0.02
DFR	-0.22	0.12	0.84	0.11	0.68	0.10
INFL	0.17	0.12	-0.32	0.09	-0.90	0.08

Table 7
Forecasting Characteristics Portfolios with Investor Sentiment

This table reports in-sample estimation results for predictive regression models based on the lagged investor sentiment

$$R^j_{t+1} = \alpha_j + \beta_j S^k_t + \varepsilon^j_{t+1}, \qquad k = PLS, BW,$$

where R^j_{t+1} is the monthly log excess returns (in percentage) for the 10 industry, 10 size, 10 book-to-market, and 10 momentum portfolios, respectively. S^{PLS}_t is the aligned investor sentiment index at period t, and S^{BW}_t is the Baker and Wurgler (2006) investor sentiment index at period t. We report the slope coefficients, heteroskedasticity-consistent t-statistics, as well as R^2 statistics. To save space, we do not report the intercept in the regressions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on one-sided wild bootstrapped p-values. Portfolio returns are value-weighted and available from Kenneth French's data library. The sample period is over 1965:07–2010:12.

	S^{PLS}_t (%)	t-stat	R^2 (%)	S^{BW}_t (%)	t-stat	R^2 (%)
Panel A: Industry Portfolios						
Non-durable	-0.38	-1.91	0.74	-0.02	-0.08	0.00
Durable	-0.46	-1.82	0.52	-0.13	-0.54	0.04
Manufacture	-0.66**	-3.15	1.70	-0.27	-1.17	0.27
Energy	-0.67**	-2.59	1.47	-0.44**	-1.84	0.64
Technology	-0.95**	-2.90	1.92	-0.72**	-2.22	1.10
Telecom	-0.56**	-2.76	1.35	-0.27*	-1.40	0.33
Shop	-0.43	-1.87	0.64	0.05	0.19	0.01
Health	-0.35	-1.49	0.48	-0.01	-0.03	0.00
Utility	-0.28	-1.52	0.46	-0.11	-0.60	0.07
Other	-0.69**	-2.77	1.55	-0.32	-1.28	0.33
Panel B: Size Portfolios						
Small	-1.06***	-3.47	2.54	-0.82***	-2.80	1.52
2	-0.90**	-3.01	1.88	-0.66***	-2.32	1.00
3	-0.89***	-3.29	2.00	-0.57**	-2.07	0.82
4	-0.89***	-3.52	2.16	-0.59***	-2.24	0.95
5	-0.85***	-3.44	2.12	-0.54**	-2.10	0.84
6	-0.82***	-3.50	2.22	-0.50**	-2.04	0.85
7	-0.76***	-3.27	1.97	-0.44**	-1.84	0.68
8	-0.63**	-2.79	1.46	-0.36*	-1.52	0.47
9	-0.64**	-3.09	1.75	-0.29*	-1.38	0.37
Large	-0.56**	-2.89	1.65	-0.22	-1.11	0.26

Table 7 (Continued)

	S_t^{PLS} (%)	t-stat	R^2 (%)	S_t^{BW} (%)	t-stat	R^2 (%)
Panel C: Book-to-market Portfolios						
Growth	-0.75**	-2.93	1.97	-0.37*	-1.46	0.49
2	-0.58**	-2.82	1.42	-0.21	-0.98	0.19
3	-0.64***	-3.27	1.78	-0.26	-1.27	0.30
4	-0.57**	-2.74	1.34	-0.28	-1.29	0.32
5	-0.53**	-2.91	1.32	-0.26	-1.33	0.31
6	-0.57**	-2.94	1.51	-0.34**	-1.66	0.53
7	-0.59***	-3.05	1.67	-0.33*	-1.57	0.52
8	-0.54**	-2.74	1.32	-0.31*	-1.51	0.44
9	-0.52**	-2.68	1.13	-0.29	-1.36	0.35
Value	-0.62**	-2.78	1.08	-0.39*	-1.54	0.43
Panel D: Momentum Portfolios						
Loser	-1.14***	-3.07	1.92	-0.84**	-2.34	1.06
2	-0.66*	-2.15	1.05	-0.32	-1.09	0.26
3	-0.58*	-2.43	1.12	-0.20	-0.83	0.13
4	-0.53*	-2.41	1.13	-0.20	-0.91	0.17
5	-0.48*	-2.42	1.08	-0.18	-0.89	0.15
6	-0.68***	-3.37	2.10	-0.33*	-1.56	0.50
7	-0.54**	-2.76	1.40	-0.23	-1.16	0.26
8	-0.67***	-3.69	2.11	-0.30*	-1.53	0.43
9	-0.72***	-3.57	2.07	-0.43**	-2.04	0.72
Winner	-1.00***	-3.56	2.43	-0.67***	-2.52	1.10

Table 8
Forecasting Dividend Growth and Dividend Price Ratio with Investor Sentiment
This table reports in-sample estimation results for the bivariate predictive regressions

$$Y_{t+1} = \alpha + \beta S_t^k + \psi D/P_t + \upsilon_{t+1}, \qquad Y = DG, D/P, \qquad k = PLS, BW,$$

where DG_{t+1} is the annual log dividend growth rate on the S&P 500 index from year t to $t+1$ (in percentage), D/P_{t+1} is the log dividend price ratio on the S&P 500 index at the end of year $t+1$, S_t^{PLS} is the aligned investor sentiment index at the end of year t, and S_t^{BW} is the Baker and Wurgler (2006) investor sentiment index at the end of year t. DG_{t+1} and D/P_{t+1} are constructed following Cochrane (2008, 2011). We report the regression slope coefficients, heteroskedasticity-consistent t-statistics, as well as R^2 statistics. To save space, we do not report the intercept in the regressions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on one-sided wild bootstrapped p-values. The sample period is over 1965–2011.

	β	t-stat	ψ	t-stat	R^2 (%)
Panel A: Aligned Investor Sentiment, S^{PLS}					
DG (%)	-3.46*	-2.35	3.55	0.73	10.3
D/P	-0.00	-0.09	0.95***	19.33	89.8
Panel B: Baker and Wurgler (2006) Investor Sentiment, S^{BW}					
DG (%)	-2.02	-1.29	4.71	0.97	5.51
D/P	-0.01	-0.55	0.95***	19.56	89.9