

Investor Sentiment Aligned: A Powerful Predictor of Stock Returns

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Abstract

In this paper, we propose a new sentiment index constructed with the purpose of predicting the aggregate stock market. In contrast with the widely used Baker and Wurgler (2006) sentiment index, our aligned index eliminates the common noise component of multiple sentiment proxies. Empirically, we find that our index has greater power in predicting the aggregate stock market than the Baker and Wurgler (2006) index: it increases the predictive R^2 s by more than five times both in-sample and out-of-sample, and outperforms any of the well recognized macroeconomic variables. The predictability is both statistically and economically significant. Moreover, our new index improves substantially the forecasting power too for the cross-sectional stock returns formed on industry, size, value, and momentum. Finally, consistent with Baker and Wurgler (2007), we show that the driving force of the predictive power of investor sentiment stems from investors' biased belief about future cash flows.

JEL classifications: C53, G11, G12, G17

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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 novel investor sentiment index (BW index hereafter) that aggregates the information from six proxies, and find that high investor sentiment strongly predicts low returns in the cross-section, such as 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 However, whether investor sentiment can predict the aggregate stock market is still an open question. For example, Baker and Wurgler (2007) note that the predictability on the market is statistically insignificant.

In this paper, we exploit the information of Baker and Wurgler's (2006) six sentiment proxies in a more efficient manner to obtain a new index for the purpose of explaining the expected return on the aggregate stock market.² In their pioneering study, Baker and Wurgler use the first principal component of the proxies as their measure of investor sentiment. Econometrically, the first principal component is the best combination of the six proxies that maximally represents the total variations of the six proxies. 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 substantial amount of common approximation errors that are not relevant for forecasting returns. Our idea is to align the investment sentiment measure with the purpose of explaining the returns by extracting the most relevant common component from the proxies. In other words, economically, we separate out information in the proxies that is relevant to the expected stock returns from the error or noise. 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 the new index extracted this way the *aligned* investor sentiment index, which does incorporate efficiently all the relevant forecasting information from the proxies as shown by forecast encompassing tests in our applications.

¹There are a number of other applications and related studies. The latest number of Google citations of Baker and Wurgler (2006) reaches 1266.

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

Empirically, we find that the aligned sentiment index can predict the aggregate stock market remarkably well. The monthly in- and out-of-sample R^2 s are 1.70% and 1.23%, more than five and eight times larger than 0.30% and 0.15%, the counterparts of BW index. Since a monthly out-of-sample R^2 of 0.5% can signal substantial economic value (Campbell and Thompson, 2008), our aligned investor sentiment index is not only statistically significant, but also economically significant in providing sizable utility gains or certainty equivalent returns for a mean-variance investor.

Our finding of strong market predictability of investor sentiment compliments in a unique way to early studies by Baker and Wurgler (2007) and many others who find investor sentiment plays an important role in explaining returns on the cross-section of stock returns. Since forecasting and understanding how the market risk premium varies over time is one of the central issues in financial research that has implications in both corporate finance and asset pricing (see, e.g., Spiegel, 2008 and Cochrane, 2011), our study suggests that investor sentiment is related to central problems in finance beyond its impact on certain segments of the market. De Long, Shleifer, Summers, and Waldmann (1990), among others, provide theoretical explanations why sentiment can cause asset price to deviate from its fundamental in the presence of limits of arbitrage even when informed traders recognize the opportunity. But almost all such theories deal with one risky asset in their analysis, that is, they effectively study the role of investor sentiment on the aggregate market. Hence, the empirical results of our paper can also be interpreted as perhaps the first strong empirical evidence supporting those theoretical models on investor sentiment.

It is of interest to compare 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), asset accrual (Hirshleifer, Hou, and Teoh, 2009), and economic policy uncertainty (Baker, Bloom, and Davis, 2013). In our study here, we consider the same 14 most prominent predictors examined earlier by Goyal and Welch (2008). The in-sample R^2 s of these well known macroeconomic variables vary from 0.01% to 1.23% (only two of them exceeding 1%), all of which are

below 1.70% of the aligned investor sentiment. In terms of the out-of-sample R^2 , none of macroeconomic variables has a positive R^2 , while the aligned investor sentiment has an R^2 of 1.23%. When each of these macroeconomic predictors is augmented in the predictive regression, the predictive ability of the aligned investor sentiment is still significant and the in-sample R^2 ranges from 1.71% to 2.72%.

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^2 s 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 flows or discount rates. We find that the aligned investor sentiment index forecasts significantly future aggregate dividend growth (a standard cash flow proxy), but does not forecast 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. Hence, our findings are consistent with Baker and Wurgler (2007) that the low aggregate stock return following high investor sentiment seems to represent investors' overly optimistic belief about future cash flows that cannot be justified by subsequent 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

In this section, we provide first the econometric method for constructing our new sentiment index following Wold (1966, 1975) and especially Kelly and Pruitt (2012, 2013). Then, we analytically compare it with BW index to understand their differences.

2.1 New index S_t^{PLS}

We assume that the one-period ahead expected log excess stock return explained by investor sentiment follows the standard linear relation,

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

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

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

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

Let $x_t = (x_{1,t}, \dots, x_{N,t})'$ denote an $N \times 1$ vector of individual investor sentiment proxies at period t ($t = 1, \dots, T$). 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 $x_{i,t}$ ($i = 1, \dots, N$) has a factor structure,

$$x_{i,t} = \eta_{i,0} + \eta_{i,1} S_t + \eta_{i,2} E_t + e_{i,t}, \quad \text{for } i = 1, \dots, N, \quad (3)$$

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 the above 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 of E_t , the more important role will it play in the PC (see the next subsection for some analytical insights). Then, it is possible that the PC may fail to generate significant forecasts for future stock returns, even when stock returns are 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 returns.

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 returns 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 ,

$$x_{i,t-1} = \pi_{i,0} + \pi_i R_t + u_{i,t-1}, \quad \text{for } i = 1, \dots, N. \quad (4)$$

The loading π_i captures the sensitivity of each sentiment proxy $x_{i,t-1}$ to investor sentiment S_{t-1} instrumented by future stock return R_t . Since the expected component of R_t is driven by S_{t-1} , sentiment proxies are related to the expected stock returns and are uncorrelated with the unpredictable return shocks, as shown in (2) and (3). Therefore, the coefficient π_i in the first-stage time-series regression (4) approximately 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 (4),

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

where S_t^{PLS} , the regression slope 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 regression slope 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 S_t^{PLS} by simply running cross-sectional regressions of $x_{i,t}$ on π_i period-by-period. Since π_i is unknown, however, the first-stage regression slopes provide a preliminary estimation of how $x_{i,t}$ depends on S_t^{PLS} . In other words, PLS uses time t stock returns 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 $S^{PLS} = (S_1^{PLS}, \dots, S_T^{PLS})'$ can be expressed as a one-step linear combination of $x_{i,t}$ s,

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

where X denotes the $T \times N$ matrix of individual investor sentiment measures, $X = (x'_1, \dots, x'_T)'$, and R denotes the $T \times 1$ vector of stock returns as $R = (R_2, \dots, R_{T+1})'$. The matrices J_T and J_N , $J_T = I_T - \frac{1}{T} \mathbf{1}_T \mathbf{1}'_T$ and $J_N = I_N - \frac{1}{N} \mathbf{1}_N \mathbf{1}'_N$, enter the formula because each regression is run with a constant. I_T is a T -dimensional identity matrix and $\mathbf{1}_T$ 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 to capture the intertemporal relationship between the aligned investor sentiment and the expected stock return.

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

To obtain analytical insights on the difference between S^{BW} with S^{PLS} , we consider a simple case of (3), in which there are only two individual sentiment proxies, x_1 and x_2 , that have the following factor structure

$$x_1 = S + E + e_1, \quad (7)$$

$$x_2 = \eta_1 S + \eta_2 E + e_2, \quad (8)$$

where S is the true but unobservable investor sentiment, E is the common noise, and e_i ($i = 1, 2$) are the idiosyncratic noises. η_1 and η_2 are the sensitivity parameters of x_2 to the investor sentiment and common noise. Without loss of generality, we assume further that these variables are independent of each other and have means zero and variances σ_S^2 , σ_E^2 and σ_e^2 , where the idiosyncratic noises e_1 and e_2 have the same variance. Then the covariance matrix of x_1 and x_2 is

$$\Sigma = \begin{pmatrix} \sigma_S^2 + \sigma_E^2 + \sigma_e^2 & \eta_1 \sigma_S^2 + \eta_2 \sigma_E^2 \\ \eta_1 \sigma_S^2 + \eta_2 \sigma_E^2 & \eta_1^2 \sigma_S^2 + \eta_2^2 \sigma_E^2 + \sigma_e^2 \end{pmatrix}. \quad (9)$$

With some algebra, we can solve the weights of BW index on those proxies, which are the eigenvector corresponding to the larger eigenvalue of Σ , as

$$w^{BW} \propto \left(\frac{(1-\eta_1^2)\sigma_S^2 + (1-\eta_2^2)\sigma_E^2}{2} + \sqrt{\left[\frac{(1-\eta_1^2)\sigma_S^2 + (1-\eta_2^2)\sigma_E^2}{2} \right]^2 + (\eta_1 \sigma_S^2 + \eta_2 \sigma_E^2)^2} \right) \quad (10)$$

where \propto is the proportion operator, indicating that the weights can be scaled by any positive real number. As long as $\eta_2 \neq 0$ in (10), BW index will have the common noise component in the weights. The greater the value of σ_E^2 , the greater its influence on w^{BW} . Hence, the noise component can drastically alter the index. Indeed, if σ_E^2 approaches infinity, the weights converge to $(1, \eta_2)$. Hence, when σ_E^2 is large enough, the population BW index will be driven largely by the noise, so will its sample estimate, the widely used BW index.

On the other hand, based on the theoretical results of Wold (1966, 1975), and especially Kelly and Pruitt (2012, 2013), the new index S^{PLS} will eliminate the noise asymptotically and converge to S . Hence, S^{PLS} should outperform S^{BW} in the presence of a common noise component.

3. Data

The excess aggregate stock market return is computed as the continuously compounded log return on the S&P 500 index (including dividends) minus the risk-free rate. The six individual investor sentiment proxies of Baker and Wurgler (2006) 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 on these measures are available from Jeffrey Wurgler's website who provides the updated data.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 confined to December 2010.

Using the procedures in Section 2, we can obtain the aligned investor sentiment index S^{PLS} from the six individual sentiment proxies,

$$S^{PLS} = -0.22 CEFD + 0.16 TURN - 0.04 NIPO + 0.63 RIPO + 0.07 PDND + 0.53 EQTI, \quad (11)$$

³The web page is <http://people.stern.nyu.edu/jwurgler/>.

where, following Baker and Wurgler (2006), each underlying individual measure is further 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. Four of the six sentiment proxies (CEFD, TURN, RIPO, and EQTI) in S^{PLS} have the same signs as those in BW index. However, it is interesting to note that, among the six proxies, RIPO and EQTI are the two most important underlying components in S^{PLS} , as they have the highest absolute coefficients. In contrast, they are just as important as the other proxies in BW index. While the weights for NIPO and PDND in S^{PLS} have opposite signs to those in BW index, their values are nearly zero and statistically insignificant.

[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} . 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 2010.

While S^{PLS} and S^{BW} are highly correlated, they are different in two important aspects. S^{PLS} appears to lead S^{BW} in many cases, and 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 returns compared to S^{BW} since the stock market is volatile.

We also consider the same 14 monthly economic variables used by Goyal and Welch (2008), which are representative of macroeconomic predictors in the literature.⁴ These 14 economic variables are the log dividend-price ratio (DP), log dividend yield (DY), log earnings-price ratio (EP),

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

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 details on these economic predictors are provided in the Appendix.

[Insert Table 1 about here]

Table 1 reports the summary statistics of the data. The monthly market excess return has a mean of 0.31% and a standard deviation of 4.46%, implying a monthly Sharpe ratio of 0.07. While the stock return has little autocorrelation, most of other variables are quite persistent. The summary statistics are generally consistent with the literature.

4. Empirical Results

In this section, we provide a number of empirical results. Section 4.1 examines the market predictability of various sentiment indices. Section 4.2 compare the aligned investor sentiment index with macroeconomic predictors. Section 4.3 is about out-of-sample predictability and section 4.4 is on asset allocation. Section 4.5 investigates the predictability of characteristics portfolios.

4.1 Forecasting the Market

Consider the standard predictive regression model,

$$R_{t+1}^m = \alpha + \beta S_t^k + \varepsilon_{t+1}, \quad k = PLS, BW, EW \quad (12)$$

where R_{t+1}^m is the monthly return on the S&P 500 index in excess of the risk-free rate, S_t^{PLS} is the aligned investor sentiment index, S_t^{BW} is BW index. For comparison, we also consider a naive investor sentiment index, S_t^{EW} , that places equal weights on the six individual sentiment proxies of Baker and Wurgler (2006). The null hypothesis of interest is that investor sentiment has no predictive ability, $\beta = 0$. In this case, (12) reduces to the constant expected return model, $R_{t+1}^m = \alpha + \varepsilon_{t+1}$. Because finance theory suggests a negative sign of β , we test $H_0 : \beta = 0$ against $H_A : \beta < 0$, which is closer to theory than the common alternative of $\beta \neq 0$. Econometrically, Inoue and Kilian (2004) suggest the use of a one-sided alternative hypothesis which usually increases the power of the test.

Econometrically, there are two other major issues for the predictive regression model. First, the well-known Stambaugh (1999) small-sample bias can inflate the t -statistic and distort test size

when the predictor is highly persistent and correlated with the market return. Second, there is potentially a spurious regression concern when the predictor is highly persistent (Ferson, Sarkissian, Simin, 2003; Lewellen, 2004). To guard against these issues, we base our inference on the empirical p -values using a wild bootstrap procedure that accounts for the persistence in predictors, correlations between the market return and predictor innovations, and general forms of return distribution. The Appendix details the wild bootstrap procedure.⁵

[Insert Table 2 about here]

Table 2 reports the results in the predictive regression. Panel A provides the estimation and testing results for BW index, S^{BW} , over the sample period of 1965:07–2010:12.⁶ Consistent with theory, S^{BW} is a negative return predictor: high sentiment is associated with low expected market return in the next month with a regression slope, β , of -0.24 . However, S^{BW} only generates a small White (1980) heteroskedasticity-consistent t -statistic of -1.21 and an R^2 of only 0.30%. Hence, the market forecasting power of S^{BW} is insignificant, confirming the earlier finding of Baker and Wurgler (2007).

Panel B of Table 2 reports the in-sample performance for the equally-weighted naive investor sentiment index, S^{EW} . Interestingly, this simple index, which requires no estimation of combining weights at all, performs as well as S^{BW} . The regression slope β is equal to -0.27 , slightly more negative than -0.24 . The t -statistic is slightly larger in absolute value, with marginally statistical significance at the 10% level. The R^2 is slightly greater too. Econometrically, Timmermann (2006) and Rapach, Strauss, and Zhou (2010), among others, show that naive combination of forecasts typically performs well due to model uncertainty, structural break, and parameter instability. Our result here seems to be consistent with their findings.

Panel C of Table 2 shows that the aligned investor sentiment, S^{PLS} , performs the best among the three indices. S^{PLS} is also a negative return predictor for the market return, with a regression slope of -0.58 that is statistically significant at the 1% level based on the wild bootstrap p -value. The magnitude of the beta suggests that a 1% 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 only 0.31%, thus (12) implies that the expected equity premium

⁵Kelly 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.

⁶We find similar results for simple raw excess return on the S&P 500 Index.

based on S^{PLS} varies by about two times larger than its average level, signalling strong economic impact (Cochrane, 2011).

As expected, S^{PLS} has an R^2 as high as 1.70%. Given that the large unpredictable component inherent in monthly stock market return, a monthly R^2 statistic of 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. This point will be further analyzed later.

For comparison, Panel D of Table 2 reports the predictive ability of the 6 individual sentiment proxies on the market. The slopes of CEFD, TURN, RIPO, and EQTI are consistent with the theoretical predictions, but the signs of NIPO and PDND are not. However, the predictability of the latter two is very weak with R^2 s of 0.01% and 0.02%, suggesting that both of them are dominated by random noises. Of all the proxies, RIPO and EQTI present higher power in forecasting the market returns, consistent with their relatively higher weights in forming the S^{PLS} index. Overall, S^{PLS} beats sharply all the proxies, suggesting the importance of using an index to aggregate all information among proxies rather than relying on a single proxy.⁷

In summary, the aligned investor sentiment S^{PLS} exhibits statistically and economically significant in-sample predictability for monthly aggregate stock market return, while BW index S^{BW} cannot. In addition, the R^2 of S^{PLS} is about five times greater than that of S^{BW} , indicating that our index is a substantial improvement over the seminal BW index. This finding is consistent with our early econometric objective of enhancing the forecasting performance by eliminating the common noise component of the proxies.

[Insert Table 3 about here]

To further assess the relative information content in S^{PLS} , S^{BW} , and the 6 proxies, we conduct the forecast encompassing test of Harvey, Leybourne, and Newbold (1998). Harvey, Leybourne, and Newbold (1998) develop a statistic for testing the null hypothesis whether 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.

⁷In untabulated results, we also consider a “kitchen sink” model that includes all the six individual sentiment proxies into a multiple predictive regression model. The in- and out-of-sample R^2 s are 3.02% and -0.22% , respectively. This finding is consistent with Goyal and Welch (2010) and Rapach, Strauss, and Zhou (2010) that while the kitchen sink model may has good in-sample forecasting power, it has very poor out-of-sample performance due to data-generating process uncertainty and parameter instability.

Table 3 reports p -values of the test. We summarize the results with three observations. First, none of the individual investor sentiment measures of Baker and Wurgler (2006) encompasses all of the remaining individual measures, indicating potential gains from combining individual measures into a common index to make use of additional information. Second, S^{BW} fails to encompass two of the six individual measures, implying that S^{BW} does not make full use of all the relevant information in individual measures. Third, as expected, S^{PLS} encompasses all of the individual investor sentiment measures as well as S^{BW} at the conventional significant level. Therefore, the forecast encompassing test suggests that S^{PLS} is an efficient index that incorporates all the relevant forecasting information, which helps to understand why it has superior forecasting performance as reported in Table 2.

4.2 Comparison with Economic Predictors

In this subsection, we compare the forecasting power of aligned investor sentiment index S^{PLS} with macroeconomic economic predictors and examine whether the forecasting power of S^{PLS} is driven by omitted economic variables related to business cycle fundamentals.

First, we consider predictive regressions on a single economic variable,

$$R_{t+1}^m = \alpha + \psi Z_t^k + \varepsilon_{t+1}, \quad k = 1, \dots, 14, \quad (13)$$

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 (13) over the period of 1965:07–2010:12. Out of the 14 economic predictors, only three, stock return variance (SVAR), long-term government bond return (LTR), and term spread (TMS), exhibit significant predictive ability for the market at the 5% or better significance levels. In contrast, S^{PLS} has an R^2 of 1.70%. Hence, S^{PLS} outperforms the 14 economic predictors in forecasting the market.

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

$$R_{t+1}^m = \alpha + \beta S_t^{PLS} + \psi Z_t^k + \varepsilon_{t+1}, \quad k = 1, \dots, 14. \quad (14)$$

We are interested in the regression slope 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 β in (14) are negative and large, in line with the results in the predictive regression (12) reported in Table 2. More importantly, β remains statistically significant when compared with the economic predictors. All of the R^2 s in (14) are substantially larger than those in (13) based on the economic predictors alone. These results demonstrate that S^{PLS} contains sizable complementary forecasting information beyond what is contained in the economic predictors.⁸

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 more relevant for assessing genuine return predictability in real time and avoid the in-sample over-fitting issue. In addition, out-of-sample tests are much less affected by the small-sample size distortions such as the Stambaugh bias (Buseti and Marcucci, 2012). Hence, it is of interest to investigate the out-of-sample performance of investor sentiment and the 14 economic variables.

The key requirement for out-of-sample forecasts at time t is that we can only use information available up to t , and nothing beyond t . Following many studies, we run the out-of-sample analysis by estimating the predictive regression model recursively,

$$\hat{R}_{t+1}^m = \hat{\alpha}_t + \hat{\beta}_t S_{1:t;t}^k, \quad k = PLS, BW, \quad (15)$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates from regressing $\{R_{s+1}^m\}_{s=1}^{t-1}$ on a constant and $\{S_{1:t;s}^k\}_{s=1}^{t-1}$ ($k = PLS, BW$). Like their in-sample analogues, $S_{1:t;t}^{PLS}$ is the out-of-sample aligned investor sentiment index extracted recursively, and $S_{1:t;t}^{BW}$ is the out-of-sample Baker and Wurgler (2006) investor sentiment index computed recursively too. m is a fixed number chosen for initial estimation, so that the future expected return can be estimated at time $t = m + 1, m + 2, \dots, T$. Hence, there are q out-of-sample evaluation periods. That is, we have q out-of-sample forecasts: $\{\hat{R}_{t+1}^m\}_{t=m}^{T-1}$.

For the 14 economic variables, we run similar predictive regression recursively,

$$\hat{R}_{t+1}^m = \hat{\alpha}_t + \hat{\psi}_t Z_t^k, \quad k = 1, \dots, 14, \quad (16)$$

where $\hat{\alpha}_t$ and $\hat{\psi}_t$ are the OLS estimates from regressing $\{R_{s+1}^m\}_{s=1}^{t-1}$ on a constant and $\{Z_s^k\}_{s=1}^{t-1}$ ($k = 1, \dots, 14$). We also do the same in the bivariate model,

$$\hat{R}_{t+1}^m = \hat{\alpha}_t + \hat{\beta}_t S_{1:t;t}^{PLS} + \hat{\psi}_t Z_t^k, \quad k = 1, \dots, 14, \quad (17)$$

⁸This result does not apply to S^{BW} and is not reported for brevity (but available upon request).

where $\hat{\alpha}_t$, $\hat{\beta}_t$, and $\hat{\psi}_t$ are the OLS estimates from regressing $\{R_{s+1}^m\}_{s=1}^{t-1}$ on a constant, $\{S_{1:t;s}^{PLS}\}_{s=1}^{t-1}$, and $\{Z_s^k\}_{s=1}^{t-1}$.

More specifically, we use the data over 1965:07 to 1984:12 as the initial estimation period so that the forecast evaluation period spans over 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.⁹

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

$$R_{OS}^2 = 1 - \frac{\sum_{t=m}^{T-1} (R_{t+1}^m - \hat{R}_{t+1}^m)^2}{\sum_{t=m}^{T-1} (R_{t+1}^m - \bar{R}_{t+1}^m)^2}, \quad (18)$$

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

$$\bar{R}_{t+1}^m = \frac{1}{t} \sum_{s=1}^t R_s^m. \quad (19)$$

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 R_{OS}^2 statistic lies in the range $(-\infty, 1]$; when $R_{OS}^2 > 0$, the predictive regression forecast \hat{R}_{t+1}^m outperforms the historical average \bar{R}_{t+1}^m 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 $H_0: R_{OS}^2 \leq 0$ against $H_A: R_{OS}^2 > 0$. 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 an asymptotically standard normal distribution when comparing forecasts from the nested models.

[Insert Table 5 about here]

In Panel A of Table 5, S^{BW} generates a positive R_{OS}^2 statistic (0.15%), and thus delivers a lower MSFE than the historical average. However, this outperformance is not statistically significant

⁹Hansen 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.

according to the *MSFE-adjusted* statistic. Thus, S^{BW} has weak out-of-sample predictive ability for the aggregate stock market, confirming our previous in-sample results (Table 2). In contrast, S^{PLS} exhibits much stronger out-of-sample predictive ability for the market return. Its R_{OS}^2 is 1.23%, exceeding all of the other R_{OS}^2 s substantially in Table 5. The *MSFE-adjusted* statistic of S^{PLS} is 1.97, which indicates that its MSFE is significantly smaller than that of the historical average at the 5% significant level.

Panel B of Table 5 shows that none of the 14 economic variables generates a positive R_{OS}^2 over the 1985:01–2010:12 evaluation period. Thus, they all fail to outperform the historical average benchmark, consistent with the findings of Goyal and Welch (2008) that economic variables display limited out-of-sample predictive power.¹⁰ It is interesting to note that five out of the 14 economic variables generate positive *MSFE-adjusted* statistics, despite their statistical insignificance and negative R_{OS}^2 s. This is possible when comparing nested model forecasts (Clark and McCracken, 2001; Clark and West, 2007; McCracken, 2007).¹¹

Panel C of Table 5 further shows that adding S^{PLS} into the predictive regression makes a huge difference. Now 10 of the 14 bivariate forecasts generate positive R_{OS}^2 s, ranging from 0.16% to 0.96%. In addition, the MSFEs for 7 of them 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 (Tables 2–4).

4.4 Asset Allocation Implications

Now we examine the economic value of stock market forecasts based on the aligned investor sentiment index S^{PLS} . 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 a mean-variance investor who optimally allocates across equities

¹⁰When the PLS approach is applied to the 14 economic variables, the extracted factor generates an in-sample R^2 of 1.51% and a poor out-of-sample R^2 of -1.50% , in accord with the performance of individual economic variables.

¹¹Intuitively, 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_{OS}^2 statistic is negative.

and the risk-free asset using the out-of-sample predictive regression forecasts.

At the end of period t , the investor optimally allocates

$$w_t = \frac{1}{\gamma} \frac{\hat{R}_{t+1}^m}{\hat{\sigma}_{t+1}^2} \quad (20)$$

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

$$R_{t+1}^p = w_t R_{t+1}^m + R_{t+1}^f, \quad (21)$$

where R_{t+1}^f 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 the market return and constrain w_t to lie between 0 and 1.5 to exclude short sales and to allow for at most 50% leverage. To examine the effect of risk aversion, we consider portfolio rules based on risk aversion coefficient of 1, 3 and 5, respectively.

The CER of the portfolio is

$$CER_p = \hat{\mu}_p - 0.5\gamma\hat{\sigma}_p^2, \quad (22)$$

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 gain is the difference between the CER for the investor who uses a predictive regression forecast of market return generated by (15) or (16) and the CER for an investor who uses the historical average forecast (19). 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 generates consistently positive CER gain across different risk aversion coefficients. In short, for the

macroeconomic variables, the economic value of predictability is limited for a risk averse investor, in accord with the negative R_{OS}^2 statistics in Table 5.

When turning to investor sentiment, S^{BW} performs as well as or better than most of the economic variables, with a CER gain ranging from -0.78% to 0.75% and a Sharpe ratio ranging from 0.09 to 0.11. The net-of-transactions-costs CER gains for S^{BW} range from -0.83% to 0.70%.

Of all the predictors, S^{PLS} stands out again in term of the economic value. The CER gains for S^{PLS} across the risk aversions are consistently positive and economically large, ranging from 2.34% to 4.39%. This says that an investor with a risk aversion coefficient of 1, 3, and 5 would be willing to pay an annual portfolio management fee up to 4.39%, 4.14%, and 2.34%, respectively, to have access to the predictive regression forecast based on S^{PLS} instead of using the historical average forecast. Moreover, the Sharpe ratios of portfolios formed based on S^{PLS} range from 0.15 to 0.19, which more than double the market Sharpe ratio, 0.07, with a buy-and-hold strategy (Table 1). The net-of-transactions-costs CER gains of the S^{PLS} portfolios range from 2.08% to 4.17%, well above those of S^{BW} and of all the economic variables, and are of economic significance.

Overall, Table 6 demonstrates that the aligned investor sentiment S^{PLS} can generate sizable economic value for a mean-variance investor, while S^{BW} and the economic variables cannot.

4.5 Forecasting Characteristics Portfolios

Investor sentiment has different impacts on different stocks. 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 subsection, we investigate how well the aligned investor sentiment S^{PLS} can forecast portfolios sorted on industry, size, book-to-market, and momentum. This study 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.¹²

Consider now the predictive regression,

$$R_{t+1}^j = \alpha_j + \beta_j S_t^{PLS} + \varepsilon_{t+1}^j, \quad (23)$$

where R_{t+1}^j 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

¹²See, 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).

hypothesis $H_A : \beta_j < 0$ based on wild bootstrapped p -values.

[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 of 1965:07–2010:12.¹³ 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^2 s about two to ten times higher than the corresponding R^2 s 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, 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^2 s of S^{PLS} are much larger than the corresponding R^2 s 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%.¹⁴

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.

¹³Monthly value-weighted returns for portfolios sorted on industry, size, book-to-market ratio, and momentum are available from Kenneth French's data library.

¹⁴The 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.

5. Economic Explanations

In this section, we explore first the source of predictability at both the market and portfolio levels. Then, we explore the relation of investor sentiment with volatility, accruals and consumer sentiment.

5.1 Cash Flow and Discount Rate Predictability

Valuation models suggest that stock prices are determined by both future expected cash flows and discount rates. From this perspective, the ability of investor sentiment to forecast aggregate stock market may come from either the cash flow channel or the discount rate channel or both (Baker and Wurgler, 2007). Hence, it is of interest to investigate this issue.

Fama and French (1989) and Cochrane (2008, 2011), among others, argue that aggregate stock market predictability comes from the time variation in discount rates. Under the discount rate channel, high S^{PLS} predicts low future return because it predicts low discount rates. On the other hand, S^{PLS} may represent investors' biased belief about future cash flows not justified by economic fundamentals (Baker and Wurgler, 2007). Since S^{PLS} is a negative predictor for future stock market return, the cash flow channel implies that the low stock market return following 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.¹⁵

To test whether the predictability of S^{PLS} is from either or both of the channels, proxies of the channels are needed. We use aggregate dividend growth as the cash flow proxy, which is widely examined and used in similar studies in the 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 rates (Cochrane, 2008, 2011), we use the aggregate dividend price ratio as our discount rate proxy.

The Campbell and Shiller (1988) log-linearization of stock return generates an approximate

¹⁵The 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.

identity, as argued in Cochrane (2008, 2011) and Campbell, Polk, and Vuolteenaho (2010),

$$R_{t+1} = k + DG_{t+1} - \rho D/P_{t+1} + D/P_t, \quad (24)$$

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. (24) implies that if S_t^{PLS} predicts 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 flows and discount rates 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.

[Insert Table 8 about here]

Therefore, our study focuses on the following bivariate predictive regressions,

$$Y_{t+1} = \alpha + \beta S_t^{PLS} + \psi D/P_t + v_{t+1}, \quad Y = DG, D/P, \quad (25)$$

where Y_{t+1} is either DG_{t+1} or D/P_{t+1} , of which DG_{t+1} is the annual log dividend growth rate on the S&P 500 index from year t to $t + 1$ and 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 v_{t+1} is the noise term. Following the similar studies in the literature, we use annual data in above regressions to avoid spurious predictability arising from within-year seasonality, and construct DG_{t+1} and D/P_{t+1} according to Cochrane (2008, 2011) based on total market returns and market returns without dividends. The sample period is from 1965 to 2011.

Panel A of Table 8 reports the results. S^{PLS} displays distinct patterns for cash flow and discount rate predictability. The slope estimate of S^{PLS} for DG_{t+1} in predictive regression (25) is -3.46 with statistical significance at the 10% level based on the one-sided wild bootstrapped p -value. The slope of S^{PLS} for D/P_{t+1} , however, is virtually equal to zero and statistically insignificant.¹⁶ From (24), 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.

Panel A also shows that the lagged dividend price ratio D/P_t has strong forecasting power for future dividend price ratio D/P_{t+1} with a slow mean reverting coefficient of 0.95, while its

¹⁶We obtain similar results when controlling the lagged dividend growth DG_t .

forecasting power for dividend growth DG_{t+1} is statistically insignificant. This result is consistent with Cochrane (2008, 2011) that the dividend price ratio captures the time variation in discount rates.

For comparison, Panel A of Table 8 reports the corresponding results of using BW index S^{BW} in replacing of S^{PLS} . The slopes of S^{BW} on either DG_{t+1} or D/P_{t+1} are not statistically significant. This is consistent with the early evidence of insignificant market return predictability of S^{BW} .

In summary, the strong predictability of S^{PLS} for DG_{t+1} and weak predictability for D/P_{t+1} in Table 8 indicate 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.¹⁷ Specifically, Table 8 shows that high sentiment predicts low future aggregate cash flows. Our findings hence suggest that high sentiment causes the overvaluation of aggregate stock market because of investors' overly optimistic belief about future aggregate cash flows. When low cash flows are revealed to investors gradually, the overvaluation will diminish and stock price will fall, leading to low 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 predictability of investor sentiment, we extend our analysis to cross-section at the portfolio 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 predictability of investor sentiment comes from the cash flow channel, it should have stronger forecasting power for the cash flows of speculative and hard-to-arbitrage stocks as well. This analysis complements the cash flow channel explanation of investor sentiment's return predictability discussed in Section 5.1.

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

$$DG_{t+1}^j = \alpha_j + \phi_j S_t^{PLS} + \vartheta_{t+1}^j, \quad (26)$$

where DG_{t+1}^j is annual log dividend growth rate for one of the characteristic portfolios examined in Table 7. We are interested in the predictive regression slope ϕ_j on S^{PLS} in (26), which measures

¹⁷Campbell and Ammer (1993), Chen and Zhao (2009), and Campbell, Polk, and Vuolteenaho (2010) argue that since the nominal cash flows of Government bonds are fixed, any Government bond return predictability should be driven by time-varying discount rates alone. Thus, Government bond provides a clean discount rate proxy without any modeling assumption and variable choice. In untabulated results, we find that S^{PLS} does not have any forecasting power for monthly log excess returns of Government bonds with maturities from less than 1 to 10 years.

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: the cash flows of more speculative and hard-to-arbitrage portfolios are much more predictable by investor sentiment. For example, the R^2 increases monotonically from 13.3% for large size portfolio to 34.6% for small size portfolio, which is usually regarded as more speculative and hard to arbitrage; and the regression coefficient ϕ_j decreases sharply from -5.1% for large size portfolio to -14.5% for small size portfolio. This pattern implies that a one-standard-deviation increase in S^{PLS} is associated with a -5.1% decrease in expected dividend growth for large size portfolio and a -14.5% decrease for small size portfolio next year, suggesting that the cash flows of small size portfolio are about three times more predictable than those of large size portfolio.

We then use a cross-sectional regression framework to statistically test the cash flow channel, in the spirit of Hong, Torous, and Valkanov (2007), 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 more predictable by investor sentiment should have higher cash flow predictability as well. We run the cross-section regression

$$\beta_j = a + g\phi_j + e_j, \quad (27)$$

where ϕ_j is from (26) that measures the ability of investor sentiment to forecast the cross-sectional cash flows, and β_j is from (23) measuring 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 (27) is 0.54 with a heteroskedasticity-consistent t -statistic of 9.48, 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 subsection, we examine whether the 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

$$LVOL_{t+1} = \alpha + \beta S_t^{PLS} + \psi LVOL_t + v_{t+1}, \quad (28)$$

where $LVOL_{t+1} = \log(\sqrt{SVAR_{t+1}})$ 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,

$$SVAR_{t+1} = \sum_{i=1}^{N_{t+1}} R_{i,t+1}^2, \quad (29)$$

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 i th trading day of period $t + 1$ (e.g., French, Schwert, and Stambaugh, 1987; Schwert, 1989; Paye, 2012).¹⁸

We are interested in the slope β on S^{PLS} in (28). 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 low aggregate stock market volatility and thus low market risk, which in turn decreases the equity risk premium (discount rate). However, in an unreported table, we find that S^{PLS} indeed displays 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 cannot fully rule out the risk-based explanation, it seems unlikely that market risk is driving the predictive power of S^{PLS} for stock market return. To the extent that high investor sentiment proxies for more noise trading, our findings appear to provide further support for the behavioral explanation of De Long, Shleifer, Summers, and Waldmann (1990) that high noise trading leads to excessive volatility.¹⁹

¹⁸Stock 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 spurious 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 (28) 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.

¹⁹Antweiler and Frank (2004) also find that higher sentiment, proxied by the number of messages posted and the bullishness messages posted on the Yahoo Finance and Raging Bull stock message boards, predicts higher future stock market volatility for a set of individual stocks.

5.4 Alternative Behavioral Interpretations

Many studies provide evidence that behavioral biases can generate misvaluation and return predictability. For example, Merton (1987), Hirshleifer and Teoh (2003), and Hirshleifer, Lim, and Teoh (2009), among others, show that investor attention is a limited cognitive resource, so prices do not fully and immediately reflect relevant public information. Hong and Stein (1999), Hong, Torous, and Valkanov (2007), Cohen and Frazzini (2008), Menzly and Ozbas (2010) and others show that fundamental information diffuses gradually in the stock market due to market frictions and bounded rationality. Thus, it is interesting to compare the aligned investor sentiment S^{PLS} with alternative return predictors that are related to behavioral bias.

We first compare S^{PLS} with aggregate accruals. Accruals have been widely interpreted as proxies for market misvaluation, or managers' efforts to manipulate earnings and stock prices to induce such misvaluation. Sloan (1996) show that accruals negatively predict future stock returns, which is caused by investors' fixation on reported earnings and their failure to understand the lower persistence of accruals relative to cash flows. In other words, investors are overly optimistic (pessimistic) about the prospects of firms with high (low) accruals. Hirshleifer, Hou, and Teoh (2009) extend the cross-sectional evidence to the time-series of aggregate stock market returns, and show that aggregate accruals positively predict future aggregate stock market returns at an annual frequency. However, in an unreported table, we find that aggregate accruals have limited forecasting power for the monthly stock market returns with an R^2 of only 0.23%. S^{PLS} hence has much greater forecasting power than accruals at the monthly horizon. Moreover, S^{PLS} remains significant when controlling for the accruals in the predictive regression, indicating that the predictability of S^{PLS} cannot be explained away by stock market misvaluation captured by accruals.

We then compare S^{PLS} with the consumer sentiment index published by the Thomson Reuters/University of Michigan. Different with S^{PLS} that is constructed by Baker and Wurgler's market-based sentiment proxies, the Michigan consumer sentiment index is based on a large number of survey responses to queries about households' current and expected financial conditions. Indeed, the Michigan consumer sentiment index is reported regularly in the media, along with commentary on its significance for the economy and financial market. The index has been used to predict household spending activity (e.g., Ludvigson, 2004) as well as small-stock premium as an investor sentiment proxy (e.g., Fisher and Statman, 2003; Lemmon and Portniaguina, 2006). In an unreported table, we confirm previous research and show that the Michigan consumer sentiment index fails to forecast significantly the future monthly aggregate stock market returns (the R^2 is 0.01%).

Therefore, S^{PLS} strongly outperforms the Michigan consumer sentiment index in forecasting the time-series of aggregate stock market returns.

Finally, we analyze the Conference Board consumer confidence index, another popular survey-based proxy of investor sentiment, and find its predictability is as weak as the University of Michigan consumer sentiment index.²⁰

6. Conclusion

In this paper, we propose a new investor sentiment index aligned for predicting the aggregate stock market. 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. Economically, we find that the return predictability of investor sentiment seems to come from investors' biased belief about future cash flows rather than discount rates.

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 the portfolio level. Since investor sentiment has been widely used to examine a variety of financial issues, the aligned investor sentiment, as a significant improvement of the fundamental measure of Baker and Wurgler (2006), may yield a number of future applications.

²⁰We have also examined the economic policy uncertainty index developed by Baker, Bloom and Davis (2013) and do not find any predictability either.

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).

- 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.

- 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

$$\hat{\varepsilon}_{t+1} = R_{t+1}^m - (\hat{\alpha} + \sum_{i=1}^N \hat{\beta}_i x_{i,t} + \sum_{i=1}^M \hat{\psi}_i Z_{i,t}), \quad (30)$$

where $\hat{\alpha}$, $\hat{\beta}_i$ ($i = 1, \dots, N$), and $\hat{\psi}_i$ ($i = 1, \dots, M$) 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 (30) follow an AR(1) process:

$$x_{i,t+1} = \rho_{i,x,0} + \rho_{i,x,1}x_{i,t} + \phi_{i,x,t+1}, \quad i = 1, \dots, N, \quad (31)$$

$$Z_{i,t+1} = \rho_{i,Z,0} + \rho_{i,Z,1}Z_{i,t} + \phi_{i,Z,t+1}, \quad i = 1, \dots, M. \quad (32)$$

Define

$$\hat{\phi}_{i,x,t+1}^c = x_{i,t+1} - \hat{\rho}_{i,x,0}^c - \hat{\rho}_{i,x,1}^c x_{i,t}, \quad i = 1, \dots, N, \quad (33)$$

$$\hat{\phi}_{i,Z,t+1}^c = Z_{i,t+1} - \hat{\rho}_{i,Z,0}^c - \hat{\rho}_{i,Z,1}^c Z_{i,t}, \quad i = 1, \dots, M, \quad (34)$$

where

$$(\hat{\rho}_{i,x,0}^c, \hat{\rho}_{i,x,1}^c), \quad i = 1, \dots, N, \quad (35)$$

and

$$(\hat{\rho}_{i,Z,0}^c, \hat{\rho}_{i,Z,1}^c), \quad i = 1, \dots, M, \quad (36)$$

denote vectors of reduced-bias estimates of the AR(1) parameters in (31) and (32), 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:

$$\tilde{R}_{t+1}^m = \bar{R}^m + \hat{\varepsilon}_{t+1} w_{t+1}, \quad (37)$$

$$\tilde{x}_{i,t+1} = \hat{\rho}_{i,x,0}^c + \hat{\rho}_{i,x,1}^c \tilde{x}_{i,t} + \hat{\phi}_{i,x,t+1}^c w_{t+1}, \quad i = 1, \dots, N, \quad (38)$$

$$\tilde{Z}_{i,t+1} = \hat{\rho}_{i,Z,0}^c + \hat{\rho}_{i,Z,1}^c \tilde{Z}_{i,t} + \hat{\phi}_{i,Z,t+1}^c w_{t+1}, \quad i = 1, \dots, M, \quad (39)$$

where \bar{R}^m is the sample mean of R_{t+1}^m , w_{t+1} is a draw from the standard normal distribution, $\tilde{x}_{i,0} = x_{i,0}$ ($i = 1, \dots, N$), and $\tilde{Z}_{i,0} = Z_{i,0}$ ($i = 1, \dots, M$). Observe that we multiply the fitted residuals $\hat{\varepsilon}_{t+1}$ in (37), each $\hat{\phi}_{i,x,t+1}^c$ in (38), and each $\hat{\phi}_{i,Z,t+1}^c$ in (39) 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 (38) and (39) helps to ensure that we adequately capture the persistence in the predictors.

Using the pseudo sample of observations for

$$\{(\tilde{R}_{t+1}^m, \tilde{x}_{1,t}, \dots, \tilde{x}_{N,t}, \tilde{Z}_{1,t}, \dots, \tilde{Z}_{M,t})\}_{t=0}^{T-1}, \quad (40)$$

we estimate the slopes and the corresponding t -statistics for univariate predictive regressions based on each investor sentiment index in (12) or each macroeconomic variable in (13), and the bivariate predictive regressions based on aligned investor sentiment and each macroeconomic variable in (14). Note that we compute the aligned investor sentiment index, Baker and Wurgler (2006) investor sentiment index, and naive investor sentiment index in (12) and (14) using the pseudo sample of $\{\tilde{x}_{i,t}\}_{t=0}^{T-1}$ ($i = 1, \dots, N$) and $\{\tilde{R}_{t+1}^m\}_{t=0}^{T-1}$, 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 characteristics portfolios including the 10 industry, 10 size, 10 book-to-market,

and 10 momentum portfolios in Table 7 under the null of no predictability. Let

$$\hat{\varepsilon}_{t+1}^j = R_{t+1}^j - (\hat{\alpha}^j + \sum_{i=1}^N \hat{\beta}_i^j x_{i,t}), \quad j = 1, \dots, K, \quad (41)$$

where $\hat{\alpha}^j$ and $\hat{\beta}_i^j$ ($i = 1, \dots, N$) are estimated by regressing excess returns of characteristics portfolio j 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 (31), (33), and (38). In accord with the null, we build up a pseudo sample of observations for excess returns on the characteristics portfolios

$$\tilde{R}_{t+1}^j = \bar{R}^j + \hat{\varepsilon}_{t+1}^j w_{t+1}, \quad i = 1, \dots, K. \quad (42)$$

We use this process to simulate data for each characteristics portfolio j ($j = 1, \dots, K$), 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 slopes and the corresponding t -statistics for 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

$$\hat{v}_{Y,t+1} = Y_{t+1} - (\hat{\alpha}_Y + \sum_{i=1}^N \hat{\beta}_{Y,i} x_{i,t} + \hat{\psi} D/P_t), \quad Y = DG, D/P. \quad (43)$$

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 (31), (33), and (38). We simulate R_t^m using (30) and (37). In accord with the null, we build up a pseudo sample of observations for dividend growth and dividend price ratio

$$\tilde{Y}_{t+1} = \hat{\alpha}_Y + \widetilde{\hat{\psi} D/P_t} + \hat{v}_{Y,t+1} w_{t+1}, \quad Y = DG, D/P. \quad (44)$$

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 slopes 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

$$\hat{v}_{t+1} = LVOL_{t+1} - (\hat{\alpha} + \sum_{i=1}^N \hat{\beta}_i x_{i,t} + \hat{\psi} LVOL_t). \quad (45)$$

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 (31), (33), and (38). We simulate R_t^m using (41) and (42). In accord with the null, we generate a pseudo sample of observations for log market volatility

$$\widetilde{LVOL}_{t+1} = \hat{\alpha} + \hat{\psi} \widetilde{LVOL}_t + \hat{v}_{t+1} w_{t+1}. \quad (46)$$

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 slopes 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.

References

- Amihud, Y., and C. M. Hurvich. 2004. Predictive regressions: A reduced-bias estimation method. *Journal of Financial and Quantitative Analysis* 39, 813–841.
- Amihud, Y., C. M. Hurvich, and Y. Wang. 2009. Multiple-predictor regressions: Hypothesis tests. *Review of Financial Studies* 22, 413–434.
- Andersen, T. G., T. Bollerslev, F. X. Diebold, and H. Ebens. 2001. The distribution of realized stock return volatility. *Journal of Financial Economics* 61, 43–76.
- Ang, A., and G. Bekaert. 2007. Return predictability: Is it there? *Review of Financial Studies* 20, 651–707.
- Antoniou, C., J. A. Doukas, and A. Subrahmanyam. 2013. Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quantitative Analysis* 48, 245–275.
- Antweiler, W., and M. Z. Frank. 2004. Is all that talk just noise? The information content of internet stock message boards. *Journal of Finance* 59, 1259–1294.
- Baker, S., N. Bloom, and S. Davis. 2013. Measuring economic policy uncertainty. Working paper, Stanford University.
- Baker, M., J. Wurgler. 2000. The equity share in new issues and aggregate stock returns. *Journal of Finance* 55, 2219–2257.
- Baker, M., and J. Wurgler. 2006. Investor sentiment and the cross-section of stock returns. *Journal of Finance* 61, 1645–1680.
- Baker, M., and J. Wurgler. 2007. Investor sentiment in the stock market. *Journal of Economic Perspectives* 21, 129–152.
- Baker, M., and J. Wurgler. 2012. Comovement and predictability relationships between bonds and the cross-section of stocks. *Review of Asset Pricing Studies* 2, 57–87.
- Baker, M., J. Wurgler, and Y. Yuan. 2012. Global, local, and contagious investor sentiment. *Journal of Financial Economics* 104, 272–287.
- Bakshi, G., G. Panayotov, and G. Skoulakis. 2013. In Search of Explanation for the Predictive Ability of the Baltic Dry Index for Global Stock Returns, Commodity Returns, and Global Economic Activity. Working paper, University of Maryland.
- Binsbergen, J. H. v., and R. S. Koijen. 2010. Predictive regressions: A present-value approach. *Journal of Finance* 65, 1439–1471.
- Breen, W., L. R. Glosten, and R. Jagannathan. 1989. Economic significance of predictable variations in stock index returns. *Journal of Finance* 64, 1177–1189.

- Busetti, F., and J. Marcucci. 2012. Comparing forecast accuracy: A Monte Carlo investigation. *International Journal of Forecasting* 29, 13–27.
- Campbell, J. Y. 1987. Stock returns and the term structure. *Journal of Financial Economics* 18, 373–399.
- Campbell, J. Y., and J. Ammer. 1993. What moves the stock and bond markets? A variance decomposition for long-term asset returns. *Journal of Finance* 48, 3–37.
- Campbell, J., C. Polk, and T. Vuolteenaho. 2010. Growth or glamour? Fundamentals and systematic risk in stock returns. *Review of Financial Studies* 23, 305–344.
- Campbell, J. Y., and R. J. Shiller. 1988. The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies* 1, 195–228.
- Campbell, J. Y., and S. B. Thompson. 2008. Predicting the equity premium out of sample: Can anything beat the historical average? *Review of Financial Studies* 21, 1509–1531.
- Campbell, J. Y., T. Vuolteenaho. 2004. Inflation illusion and stock prices. *American Economic Review* 94, 19–23.
- Campbell, J. Y., and M. Yogo. 2006. Efficient tests of stock return predictability. *Journal of Financial Economics* 81, 27–60.
- Cavaliere, G., A. Rahbek, and A.M. R. Taylor. 2010. Cointegration rank testing under conditional heteroskedasticity. *Econometric Theory* 26, 1719–1760.
- Chen, L., and X. Zhao. 2009. Return decomposition. *Review of Financial Studies* 22, 5213–5249.
- Clark, T. E., and K. D. West. 2007. Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics* 138, 291–311.
- Clark, T. E., and M. W. McCracken. 2001. Tests of equal forecast accuracy and encompassing for nested models. *Journal of Econometrics* 105, 85–110.
- Cochrane, J. H. 2008. The dog that did not bark: A defense of return predictability. *Review of Financial Studies* 21, 1533–1575.
- Cochrane, J. H. 2011. Presidential address: Discount rates. *Journal of Finance* 66, 1047–1108.
- Cohen, L., and A. Frazzini. 2008. Economic links and predictable returns. *Journal of Finance* 63, 1977–2011.
- De Long, J. B., A. Shleifer, L. H. Summers, and R. Waldmann. 1990. Noise trader risk in financial markets. *Journal of Political Economy* 98, 703–738.
- Diebold, F. X., and R. S. Mariano. 1995. Comparing predictive accuracy. *Journal of Business and Economic Statistics* 13, 253–263.

- Edwards, W. 1968. Conservatism in human information processing. In B. Kleinmütz (eds.), *Formal Representation of Human Judgment*. New York: John Wiley and Sons.
- Fama, E. F., and K. R. French. 1988. Dividend yields and expected stock returns. *Journal of Financial Economics* 22, 3–25.
- Fama, E. F., and K. R. French. 1989. Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics* 25, 23–49.
- Fama, E. F., and K. R. French. 2000. Forecasting profitability and earnings. *Journal of Business* 73, 161–175.
- Fama, E. F., G. W. Schwert. 1977. Asset returns and inflation. *Journal of Financial Economics* 5, 115–146.
- Ferreira, M. A., and P. Santa-Clara. 2011. Forecasting stock market returns: The sum of the parts is more than the whole. *Journal of Financial Economics* 100, 514–537.
- Ferson, W. E., and C. R. Harvey. 1991. The variation of economic risk premiums. *Journal of Political Economy* 99, 385–415.
- Ferson, W., and R. A. Korajczyk. 1995. Do arbitrage pricing models explain the predictability of stock returns? *Journal of Business* 68, 309–349.
- Ferson, W. E., S. Sarkissian, and T. T. Simin. 2003. Spurious regressions in financial economics? *Journal of Finance* 58, 1393–1413.
- Festinger, L. 1957. A theory of cognitive dissonance. Stanford, CA: Stanford University Press.
- Fisher, L. K., and M. Statman. 2003. Consumer confidence and stock returns. *Journal of Portfolio Management* 30, 115–127.
- French, K. R., G. W. Schwert, and R. F. Stambaugh. 1987. Expected stock returns and volatility. *Journal of Financial Economics* 19, 3–29.
- Garrett, I., and R. Priestley. 2012. Dividend growth, cash flow, and discount rate news. *Journal of Financial and Quantitative Analysis* 47, 1003–1028.
- Goyal, A., and I. Welch. 2008. A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies* 21, 1455–508.
- Guo, H. 2006. On the out-of-sample predictability of stock market returns. *Journal of Business* 79, 645–670.
- Hansen, P. R., and A. Timmermann. 2012. Choice of sample split in out-of-sample forecast evaluation. Working paper, University of California at San Diego.
- Harvey, D. I., S. J. Leybourne, and P. Newbold. 1998. Tests for forecast encompassing. *Journal of*

- Business and Economic Statistics* 16, 254–259.
- Hirshleifer, D., K. Hou, and S. H. Teoh. 2009. Accruals, cash flows, and aggregate stock returns. *Journal of Financial Economics* 91, 389–406.
- Hirshleifer, D., S. Lim, and S. H. Teoh. 2009. Driven to distraction: Extraneous events and underreaction to earnings news. *Journal of Finance* 63, 2287–2323.
- Hirshleifer, D., and S. H. Teoh. 2003. Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics* 36, 337–386.
- Hong, H., and J. C. Stein. 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance* 54, 2143–2184.
- Hong, H., W. Torous, and R. Valkanov. 2007. Do industries lead stock markets? *Journal of Financial Economics* 83, 367–396.
- Inoue, A., and L. Kilian. 2004. In-sample or out-of-sample tests of predictability: Which one should we use? *Econometric Reviews* 23, 371–402.
- Inoue, A., and B. Rossi. 2012. Out-of-sample forecast tests robust to the choice of window size. *Journal of Business and Economic Statistics* 30, 432–453.
- Kahneman, D., and A. Tversky. 1974. Judgment under uncertainty: Heuristics and biases. *Science* 185, 1124–1131.
- Kandel, S., and R. F. Stambaugh. 1996. On the predictability of stock returns: An asset allocation perspective. *Journal of Finance* 51, 385–424.
- Kelly, B., and S. Pruitt. 2012. The three-pass regression filter: A new approach to forecasting using many predictors. Working paper, University of Chicago.
- Kelly, B., and S. Pruitt. 2013. Market expectations in the cross-section of present values. *Journal of Finance* 68, 1721–1756.
- Keynes, J. M. 1936. *The General Theory of Employment, Interest and Money*. London: Macmillan.
- Koijen, R. S., and S. Van Nieuwerburgh. 2011. Predictability of returns and cash flows. *Annual Review of Financial Economics* 3, 467–491.
- Kothari, S. P., and J. Shanken. 1997. Book-to-market, dividend yield, and expected market returns: A time-series analysis. *Journal of Financial Economics* 44, 169–203.
- Lemmon, M., and E. Portniaguina. 2006. Consumer confidence and asset prices: Some empirical evidence. *Review of Financial Studies* 19, 1499–1529.
- Lettau, M., and S. Ludvigson. 2001. Resurrecting the (C)CAPM: A cross-sectional test when risk premia are time-varying. *Journal of Political Economy* 109, 1238–1287.

- Lettau, M., and S. C. Ludvigson. 2005. Expected returns and expected dividend growth. *Journal of Financial Economics* 76, 583–626.
- Lewellen, J. 2004. Predicting returns with financial ratios. *Journal of Financial Economics* 74, 209–235.
- Lewellen, J., and J. Shanken. 2002. Learning, asset-pricing tests, and market efficiency. *Journal of Finance* 57, 1113–1145.
- Ludvigson, S. C. 2004. Consumer confidence and consumer spending. *Journal of Economic Perspectives* 18, 29–50.
- McCracken, M. W. 2007. Asymptotics for out of sample tests of Granger causality. *Journal of Econometrics* 140, 719–752.
- Menzly, L., and O. Ozbas. 2010. Market segmentation and the cross-predictability of returns. *Journal of Finance* 65, 1555–1580.
- Menzly, L., T. Santos, and P. Veronesi. 2004. Understanding predictability. *Journal of Political Economy* 112, 1–47.
- Merton, R. C. 1980. On estimating the expected return on the market: An exploratory investigation. *Journal of Financial Economics* 8, 323–361.
- Nicholls, D. F., and A. L. Pope. 1988. Bias in the estimation of multiple autoregressions. *Australian Journal of Statistics* 30A, 296–309.
- Pástor, Ľ., and R. F. Stambaugh. 2009. Predictive systems: Living with imperfect predictors. *Journal of Finance* 64, 1583–1628.
- Paye, B. S. 2012. ‘Déjà vol’: Predictive regressions for aggregate stock market volatility using macroeconomic variables. *Journal of Financial Economics* 106, 527–546.
- Pontiff, J., and L. D. Schall. 1998. Book-to-market ratios as predictors of market returns. *Journal of Financial Economics* 49, 141–160.
- Rapach, D. E., J. K. Strauss, and G. Zhou. 2010. Out-of-sample equity premium prediction: Combination forecast and links to the real economy. *Review of Financial Studies* 23, 821–62.
- Schwert, G. W. 1989. Why does stock market volatility change over time? *Journal of Finance* 44, 1115–1153.
- Sloan, R. G. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71, 289–315.
- Stambaugh, R. F. 1999. Predictive regressions. *Journal of Financial Economics* 54, 375–421.
- Stambaugh, R. F., J. Yu, and Y. Yuan. 2012. The short of it: Investor sentiment and anomalies.

- Journal of Financial Economics* 104, 288–302.
- Timmermann, A. G. 1993. How learning in financial markets generates excess volatility and predictability in stock prices. *Quarterly Journal of Economics* 108, 1135–1145.
- Timmermann, A. 1996. Excess volatility and predictability of stock prices in autoregressive dividend models with learning. *Review of Economic Studies* 63, 523–557.
- Timmermann, A. 2006. Forecast combinations. In G. Elliott, C. W. J. Granger, and A. Timmermann (eds.), *Handbook of Economic Forecasting*, Volume 1. Amsterdam: Elsevier.
- West, K. D. 1996. Asymptotic inference about predictive ability. *Econometrica* 64, 1067–1084.
- White, H. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48, 817–838.
- Wold, H. 1966. Estimation of principal components and related models by iterative least squares. In P. R. Krishnaiah (eds.), *Multivariate Analysis*, 391–420. New York: Academic Press.
- Wold, H. 1975. Path models with latent variables: The NIPALS approach. In H. M. Blalock, A. Aganbegian, F. M. Borodkin, R. Boudon, and V. Cappecchi (eds.), *Quantitative Sociology: International Perspectives on Mathematical and Statistical Modeling*. New York: Academic Press.
- Xu, Y. 2004. Small levels of predictability and large economic gains. *Journal of Empirical Finance* 11, 247–75.
- Yu, J. 2013. A sentiment-based explanation of the forward premium puzzle. *Journal of Monetary Economics* 60, 474–491.
- Yu, J., and Y. Yuan. 2011. Investor sentiment and the mean-variance relation. *Journal of Financial Economics* 100, 367–381.

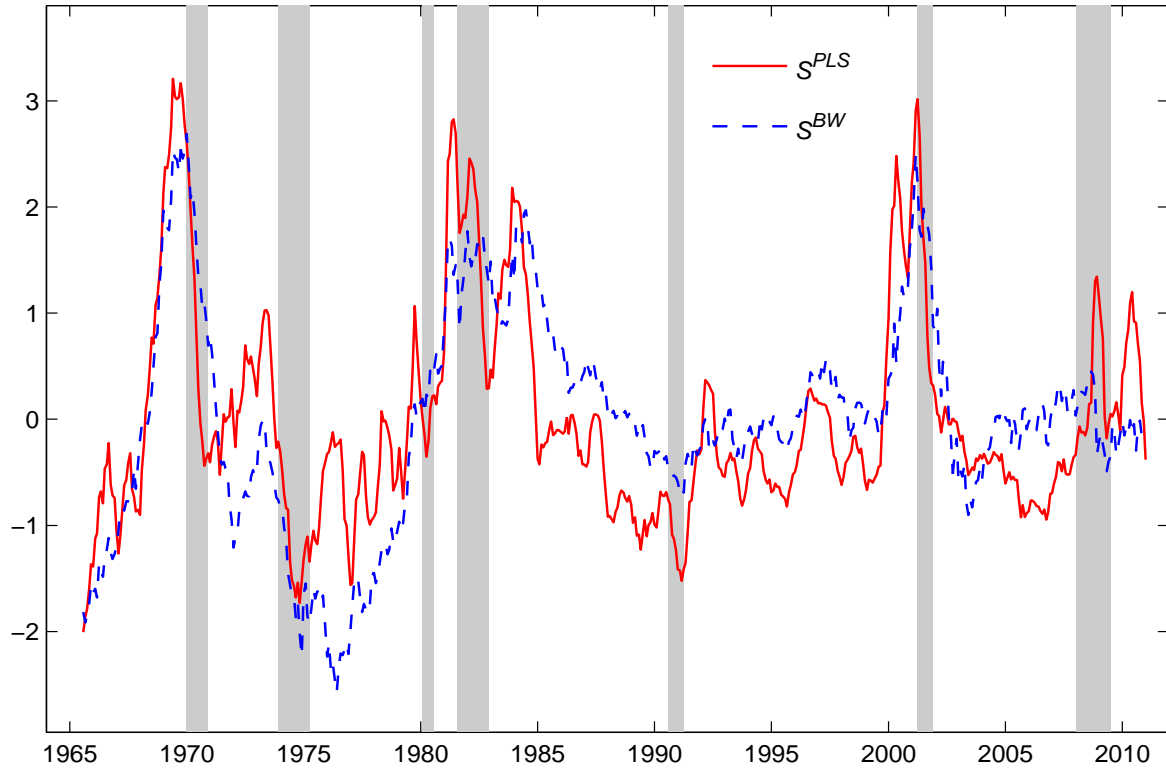


Figure 1. The Investor Sentiment Index, 1965:07–2010:12. The solid line depicts the aligned investor sentiment index S^{PLS} extracted from the Baker and Wurgler’s six individual investor sentiment proxies by applying the partial least squares method. The dashed line depicts the Baker and Wurgler (2006) 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 slopes, 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_t^{BW}	-0.24	-1.21	0.30
Panel B: Naive Investor Sentiment Index			
S_t^{EW}	-0.27*	-1.39	0.38
Panel C: Aligned Investor Sentiment Index			
S_t^{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
Comparison with Economic Return Predictors

Panel A reports in-sample estimation results for the univariate predictive regression models based on one of the alternative economic return predictors

$$R_{t+1}^m = \alpha + \psi Z_t^k + \varepsilon_{t+1}, \quad k = 1, \dots, 14,$$

where R_{t+1}^m is the monthly log excess aggregate stock market return (in percentage), and Z_t^k 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 both aligned investor sentiment index S_t^{PLS} and Z_t^k ,

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

We report the regression slopes, 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 first 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_{OS}^2 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_{OS}^2 (%)	<i>MSFE-adjusted</i>		R_{OS}^2 (%)	<i>MSFE-adjusted</i>
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 (CER) gain for an investor who uses the predictive regression forecast instead of the historical average benchmark forecast. The weight on stock in the investor's 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 last column of each panel report the annualized CER gain by assuming a transaction cost of 50 basis points per transaction. 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.

Predictor	Panel A: $\gamma = 1$			Panel B: $\gamma = 3$			Panel C: $\gamma = 5$		
	Δ (%)	SR	transaction	Δ (%)	SR	transaction	Δ (%)	SR	transaction
			cost (50bps)			cost (50bps)			cost (50bps)
			Δ (%)			Δ (%)			Δ (%)
Investor Sentiment									
S^{PLS}	4.39	0.19	4.17	4.14	0.17	3.82	2.34	0.15	2.08
S^{BW}	-0.78	0.11	-0.83	0.75	0.10	0.70	0.53	0.09	0.52
Economic Variables									
DP	-4.84	0.06	-4.95	-3.59	0.01	-3.77	-1.74	0.02	-1.83
DY	-5.05	0.06	-5.37	-3.13	0.01	-3.40	-1.43	0.01	-1.56
EP	-1.64	0.11	-1.76	0.73	0.10	0.61	0.84	0.10	0.79
DE	-1.59	0.10	-1.70	-1.23	0.07	-1.53	-0.88	0.06	-1.06
SVAR	-1.20	0.11	-2.02	0.07	0.09	-0.72	-0.08	0.07	-0.69
BM	-3.40	0.08	-3.43	-1.47	0.06	-1.52	-1.22	0.05	-1.29
NTIS	0.22	0.12	0.09	0.11	0.10	-0.23	-0.63	0.10	-0.98
TBL	0.15	0.12	0.14	0.09	0.10	-0.02	-1.08	0.08	-1.19
LTY	-0.72	0.11	-0.78	-0.12	0.09	-0.16	-0.26	0.07	-0.31
LTR	-2.25	0.10	-5.40	-0.53	0.08	-3.81	-0.48	0.08	-3.08
TMS	1.20	0.14	0.93	0.40	0.11	-0.04	-1.53	0.09	-1.97
DFY	-3.72	0.07	-4.01	-2.39	0.03	-2.66	-3.31	0.02	-3.49
DFR	-0.22	0.12	-1.63	0.84	0.11	-0.69	0.68	0.10	-0.44
INFL	0.17	0.12	-0.34	-0.32	0.09	-1.40	-0.90	0.08	-1.81

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

$$R_{t+1}^j = \alpha_j + \beta_j S_t^k + \varepsilon_{t+1}^j, \quad k = PLS, BW,$$

where R_{t+1}^j is the monthly log excess returns (in percentage) for the 10 industry, 10 size, 10 book-to-market, and 10 momentum portfolios, respectively. S_t^{PLS} is the aligned investor sentiment index at period t , and S_t^{BW} is the Baker and Wurgler (2006) investor sentiment index at period t . We report the slopes, 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_t^{PLS} (%)	t -stat	R^2 (%)	S_t^{BW} (%)	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

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

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 slopes, 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