Investor Sentiment Aligned: A Powerful Predictor of Stock Returns

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First Version: May, 2013  
Current Version: December, 2013

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Abstract

The widely used Baker and Wurgler (2006) sentiment index is likely to understate the predictive power of investor sentiment because their index is based on the first principal component of six sentiment proxies that may have a common noise component. In this paper, we propose a new sentiment index that is aligned for explaining stock expected returns by eliminating the noise component. We find that the aligned sentiment index has much greater power in predicting the aggregate stock market than the Baker and Wurgler (2006) index: it increases the $R^2$s by more than five times both in-sample and out-of-sample, and outperforms any of the well recognized macroeconomic variables. Its predictability is both statistically and economically significant. Moreover, the new index improves substantially the forecasting power for the cross-section of stock returns formed on industry, size, value, and momentum. Economically, the driving force of the predictive power of investor sentiment appears stemming from market underreaction to cash flow information.

JEL classifications: C53, G11, G12, G17

Keywords: Investor Sentiment, Asset Pricing, Return Predictability, Cash Flow, Discount Rate
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. 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. 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 an investor sentiment index estimated easily from data, and find that it has strong forecasting power for a large number of cross-sectional stock returns. Stambaugh, Yu, and Yuan (2012) find that investor sentiment predicts 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

In contrast, the significance of the predictability of investor sentiment on the aggregate stock market has not been empirically established yet. For instance, Baker and Wurgler (2007) find that the predictability of investor sentiment on the aggregate stock market is statistically insignificant and is much weaker than the case with cross-sectional studies. If the impacts of investor sentiment were restricted only to the cross-section, its role in finance could be limited. Therefore, the open question is whether or not investor sentiment is only relevant at the cross-section or matters to the aggregate stock market as well.

To address this important issue, in this paper, we exploit the information of Baker and Wurgler’s (2006) six sentiment proxies in an 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 invest-

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

²The same method may be applied for explaining the expected return on any other asset.
ment 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.

Empirically, we find that the aligned sentiment index can predict the aggregate stock market remarkably well. While the in-sample $R^2$ of Baker and Wurgler’s measure of investor sentiment is only 0.30%, the new aligned measure has an $R^2$ of 1.54%, more than 5 times higher than the former, and is both economically and statistically significant. Out-of-sample, Baker and Wurgler’s measure has a predictive power with an $R^2$ of 0.11%, but the new measure achieves a level of 1.26%, more than 10 times greater. This is again both economically and statistically significant. Hence, the aligned investor sentiment index is a powerful predictor of the aggregate market, although Baker and Wurgler’s measure is not. Our empirical evidence suggests for the first time that investor sentiment matters to the aggregate stock market.

Many predictors of the aggregate stock market have been identified by various studies. For example, Campbell and Shiller (1988), Fama and French (1988), Lewellen (2004), Campbell and Yogo (2006), Cochrane (2008), Lettau and Van Nieuwerburgh (2008), and Pástor and Stambaugh (2009), among others, find that the dividend-price ratio is a useful predictor, while Ang and Bekaert (2007), and Henkel, Martin, and Nadari (2011) provide the international evidence. Goyal and Welch (2008) provide an extensive analysis on 14 of the most prominent predictors. It is of interest to explore how well the aligned investor sentiment index performs relative to them. The in-sample $R^2$ s of those recognized macroeconomic variables vary from 0.01% to 1.23% (only two of them exceeding 1%), all are below 1.54% of the aligned investor sentiment. In terms of the out-of-sample $R^2$, none of them have positive values, confirming Goyal and Welch’s concern that these variables fail to predict the market out-of-sample. In contrast, the aligned investor sentiment has an out-of-sample $R^2$ value of 1.26%, indicating significant predictive power. In addition, the return predictability of investor sentiment is of economic significance in terms of a mean-variance investor’s certainty equivalent return (CER) gains.

Cross-sectionally, we compare how the aligned investor sentiment index performs relative to Baker and Wurgler’s original sentiment index. When stocks are sorted by industry, the Baker and Wurgler sentiment index has an impressive in-sample $R^2$ of 1.1% in explaining the time-varying
returns on Technology, but the aligned investor sentiment index raises it to 2.21%. 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 flow or discount rate. We find that the aligned investor sentiment index that forecasts the market is also a powerful predictor for future aggregate dividend growth (a standard cash flow proxy), but not for future dividend price ratio (a proxy of discount rate), supporting that the cash flow channel is the source for predictability. In addition, the ability of investor sentiment to forecast the cross-section of stock returns is strongly correlated with its ability to forecast the cross-section of future cash flows. Our findings are hence consistent with Baker and Wurgler (2007) that the predictability of investor sentiment seems to represent investors’ irrational belief about future cash flows that can not be justified by economic fundamentals.

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

### 2. Econometric Methodology

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

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

where $S_t$ is the true but unobservable investor sentiment that matters for forecasting asset returns, and we name it the **aligned** investor sentiment throughout this paper. Realized stock return then is equal to its conditional expectations plus an unpredictable shock,

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

where $\epsilon_{t+1}$ is unforecastable and unrelated to $S_t$.

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

\[
x_{i,t} = \eta_{i,0} + \eta_{i,1} S_t + \eta_{i,2} E_t + e_{i,t}, \quad \text{for } i = 1, \ldots, N,
\]

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

In Baker and Wurgler (2006), investor sentiment is estimated as the first principle component (PC) of the cross-section of \( x_{i,t} \)'s. By its econometric design, the PC is a linear combination of \( x_{i,t} \)'s that explains the largest fraction of the total variations in \( x_{i,t} \)'s, and hence is unable to separate \( S_t \) from \( E_t \). In fact, the larger the variance the \( E_t \), the more important role will it play in the PC. Then, it is possible that the PC may fail to generate significant forecasts for future stock return, even when stock return is indeed strongly predictable by the aligned investor sentiment \( S_t \). This failure indicates the need for an improved econometric method that aligns investor sentiment estimation toward forecasting future stock return.

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

\[
x_{i,t-1} = \pi_{i,0} + \pi_{i} R_t + u_{i,t-1}, \quad \text{for } i = 1, \ldots, N.
\]

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

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

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

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

Intuitively, PLS exploits the factor nature of the joint system (2) and (3) to infer the relevant aligned sentiment factor $S_i^{PLS}$. If the true factor loading $\pi_i$ was known, we could consistently estimate the $S_i^{PLS}$ by simply running cross-section regressions of $x_{i,t}$ with $\pi_i$ period-by-period. Since $\pi_i$ is unknown, the first-stage regression coefficients provide a preliminary estimation of how $x_{i,t}$ depends on $S_i^{PLS}$. In other words, PLS uses future stock return to discipline the dimension reduction to extract $S_i$ relevant for forecasting and discard common or 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 $S^{PLS} = (S_1^{PLS}, \ldots, S_T^{PLS})'$ can be expressed as a one-step linear combination of $x_{i,t}$,

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

where $X$ denotes the $T \times N$ matrix of individual investor sentiment measures, $X = (x_1', \ldots, x_T')'$, and $R$ denotes the $T \times 1$ vector of stock returns as $R = (R_2, \ldots, R_{T+1})'$. The matrix $J_T$, $J_T = I_T - \frac{1}{T} t_T t_T'$, enters because each regression is run with a constant, where $I_T$ is the $T$-dimensional identity matrix and $t_T$ is a $T$-vector of ones. The weight on each individual measure $x_{i,t}$ in $S_i^{PLS}$ is based on its covariance with the stock return $R_{t+1}$ that represents the latent relevant investor sentiment.

### 3. Data and Summary Statistics

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

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3Since the first-stage regression has an errors-in-variables issue, the second-stage estimate of aligned investor sentiment contains a multiplicative bias. However, because OLS regression is invariant to affine transformation, both the estimated aligned investor sentiment and the predictive forecasts in Section 4 are consistent.

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• **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.

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

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

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

$$S_{PLS} = -0.44CEFD - 0.16TURN - 0.32NIPO + 0.57RIPO - 0.26PDND + 0.62EQT,$$  \hspace{1cm} (7)

where each individual measure is standardized 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 business cycle variation. The share turnover, average first-day return of IPOs, and dividend premium are lagged 12 months relative to the other three measures to incorporate the fact that some variables take longer to reveal the same sentiment. Following Baker and Wurgler (2006), $S_{PLS}$ is standardized to have zero mean and unit variance over the full sample period. Interestingly, the signs of TURN and NIPO in $S_{PLS}$ are opposite to those in the Baker and

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4The web address is: http://people.stern.nyu.edu/jwurgler/.
Wurgler’s measure of investor sentiment, $S^{BW}$. The new signs indicate a hedging role played by them in minimizing the noise in the aligned index.

[Insert Figure 1 about here]

Though the indexes $S^{PLS}$ and $S^{BW}$ are constructed differently, we find that they are highly correlated with each other, with a positive correlation of 0.7. Consistent with the high correlation, Figure 1 shows that $S^{PLS}$ appears to capture almost the same anecdotal accounts of fluctuations in sentiment with $S^{BW}$. The investor sentiment was low after the 1961 crash of growth stocks. It subsequently rose to a peak in the 1968 and 1969 electronics bubble. Sentiment fell again to a trough during the 1973 to 1974 stock market crash. But it picked up and reached a peak in the biotech bubble of the early 1980s. In the late 1980s, sentiment dropped but rose again in the early 1990s. It again reached a peak during the Internet bubble in the late 1990s. Sentiment dropped to a trough during the 2008 to 2009 subprime crisis but rose in the 2010.

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

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

[Insert Table 1 about here]

Table 1 reports the summary statistics. All summary statistics are generally consistent with the literature. The monthly log excess market return has a mean of 0.31% and a standard deviation of 4.46%, producing a monthly Sharpe ratio of 0.07. The first-order autocorrelation of $S^{PLS}$ is only 0.73, much less persistent than the level of $S^{BW}$ and many economic variables such as valuation ratios, nominal interest rates, and interest rate spreads, which often exhibit near-unit-root

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5The economic variables are available from Amit Goyal’s website, http://www.hec.unil.ch/agoyal/.
4. Empirical Results

4.1 Forecasting Aggregate Stock Market

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

\[ R_{t+1}^m = \alpha + \beta S_t^k + \epsilon_{t+1}, \quad k = PLS, BW, EW \]  

where \( R_{t+1}^m \) is the monthly log return on the S&P 500 index in excess of the risk-free rate from period \( t \) to \( t + 1 \). \( S_t^{PLS} \) is the aligned investor sentiment index at period \( t \) in (7), \( S_t^{BW} \) is the Baker and Wurgler (2006) investor sentiment index. For comparison, we also calculate a naive investor sentiment index, \( S_t^{EW} \), that places equal weights on the standardized six proxies of Baker and Wurgler (2006).

The null hypothesis is that investor sentiment has no predictive ability, \( \beta = 0 \), and (8) reduces to the constant expected return model \( (R_{t+1}^m = \alpha + \epsilon_{t+1}) \). Because economic theory suggests the sign of \( \beta \), Inoue and Kilian (2004) recommend a one-sided alternative hypothesis to increase the power of in-sample tests of predictability. We then test \( H_0 : \beta = 0 \) against \( H_A : \beta < 0 \).

The well-known Stambaugh (1999) small-sample bias may inflate the \( t \)-statistic and distort test size when the predictor is highly persistent and correlated with market return. In addition, there is potentially a spurious regression concern when the predictor is highly persistent (Ferson, Sarkissian, Simin, 2003; Lewellen, 2004; Novy-Marx, 2013). Since \( S_t^{PLS} \) is an estimated factor based on PLS and full-sample data, this procedure may introduce another small-sample bias which can inflate the \( t \)-statistic for \( \hat{\beta} \), as suggested by Kelly and Pruitt (2012, 2013).\(^6\) Table 1 indicates that \( S_t^{PLS} \) displays positive skewness and excess kurtosis, which might raise concerns regarding the validity of statistical inference based on standard asymptotic arguments.

While \( S_t^{PLS} \) is much less persistent than many traditional economic predictors in the literature and our sample length is reasonably long, we nonetheless take these econometric concerns seriously. We address these issues by computing the empirical \( p \)-values using a wild bootstrap procedure that accounts for the persistence in predictors, correlations between excess market return and predictor innovations, estimated PLS predictors, and general forms of return distribution. The Internet

\(^6\)Kelly and Pruitt (2012, 2013) show that there is no look-ahead bias in the PLS procedure and the small-sample bias will vanish as sample length \( T \) becomes large.
Appendix details the wild bootstrap procedure.\textsuperscript{7}

As a benchmark, Panel B of Table 2 reports the in-sample estimation results for Baker and Wurgler (2006) investor sentiment $S_{BW}$ in (8) to forecast log excess aggregate stock market return over the sample period 1965:07–2010:12.\textsuperscript{8} $S_{BW}$ is a negative return predictor and high sentiment is associated with lower expected market return in the next month. However, $S_{BW}$ only generates a small White (1980) heteroskedasticity-consistent $t$-statistic of -1.21 and $R^2$ of 0.30%. Thus, the forecasting power of $S_{BW}$ is insignificant, confirming the findings of Baker and Wurgler (2007).

Panel C of Table 2 reports the in-sample forecasting performance for the naive investor sentiment index $S_{EW}$. The equally-weighted investor sentiment index is analogous to a naive combination forecast which places equal weight on each individual sentiment measure, which do not require the estimation of combining weights. As demonstrated by Timmermann (2006) and Rapach, Strauss, and Zhou (2010), this simple aggregation method frequently performs surprisingly well, since it is typically difficult to precisely estimate weights in data environments with substantial model uncertainty, structural break, and parameter instability. Consistent with our premise, $S_{EW}$ generates an $R^2$ of 0.41%, about 30 percent higher than the corresponding $R^2$ for $S_{BW}$ in Panel B (0.30%). In addition, $S_{EW}$ is marginally significant at the 10% level, with a heteroskedasticity-consistent $t$-statistic of -1.41.

According to Panel A of Table 2, the aligned investor sentiment $S_{PLS}$ performs the best in (8). $S_{PLS}$ is also a negative return predictor for excess aggregate stock market return, with an $R^2$ as high as 1.54%. Because of the large unpredictable component inherent in monthly stock market return, a monthly $R^2$ statistic near 0.5% can generate significant economic value (Kandel and Stambaugh, 1996; Xu, 2004; Campbell and Thompson, 2008). Thus, the 1.54% $R^2$ of $S_{PLS}$ indicates economically huge stock market predictability. Moreover, $S_{PLS}$ is statistically significant at the 5% level based on the wild bootstrap $p$-value, with a large $t$-statistic of -2.53.

The absolute magnitude of the slope coefficient on $S_{PLS}$ is 0.55, suggesting that a one-standard-deviation increase in $S_{PLS}$ is associated with a 0.55% decrease in expected excess market return for the next month. Recall that the average monthly excess market return during our sample period is

\textsuperscript{7}Kelly and Pruitt (2012) analyze the asymptotic properties of parameter estimates for predictive regressions with estimated PLS factors. Amihud and Hurvich (2004), Lewellen (2004), Campbell and Yogo (2006), and Amihud, Hurvich, and Wang (2009) develop predictive regression tests that explicitly account for the Stambaugh small-sample bias. Inferences based on these procedures are qualitatively similar to those based on the bootstrap procedure.

\textsuperscript{8}We find similar results for simple raw excess return on the S&P 500 Index.
0.31%, thus (8) implies that market return based on $S_{PLS}$ varies by about two times larger than the average equity risk premium, signalling strong economic significance (Cochrane, 2011).

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

[Insert Table 3 about here]

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

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

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

We first compare the forecasting power of $S_{PLS}$ with a large number of alternative return predictors that have been shown to predict the aggregate stock market (Campbell and Thompson, 2008; Cochrane, 2008, 2011; Goyal and Welch, 2008). In particular, we focus on the 14 economic variables recently reviewed by Goyal and Welch (2008), which are known to forecast monthly market return, and are typically related to business cycle conditions.\footnote{We have also compared with economic policy uncertainty variables, proposed recently by Baker, Bloom and Davis (2103), and find that the aligned investment sentiment outperforms them substantially because their predictive power is very limited.}

To compare $S_{PLS}$ with alternative predictors, we transform these alternative predictors to market return forecasts using the univariate predictive regressions, by replacing $S_t^k$ in (8) with $Z_t^k$:

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

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

Panel A of Table 4 reports the estimation results for (9) over the period 1965:07–2010:12. Three of the 14 economic predictors exhibit significant predictive ability for excess aggregate stock market return at the 5% or better levels. They are stock return variance (SVAR), long-term government bond return (LTR), and term spread (TMS), with $R^2$ ranging from 0.61% to 1.23%. In this sense, $S_{PLS}$, whose $R^2$ is 1.54%, has greater forecasting power for monthly aggregate stock market return comparing to all of the 14 economic predictors.

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

$$R_{t+1}^m = \alpha + \beta S_{t}^{PLS} + \psi Z_t^k + \epsilon_{t+1}, \quad k = 1, \ldots, 14.$$

We are interested in the regression slope coefficient $\beta$ of $S_t^{PLS}$, and test $H_0 : \beta = 0$ against $H_A : \beta < 0$ based on the wild bootstrapped $p$-values.
Panel B of Table 4 shows that the estimates of the slope coefficient $\beta$ in (10) are negative and large, in line with the results in the predictive regression (8) reported in Table 2. Most importantly, $\beta$ remains statistically significant at the conventional levels when paired against the economic predictors one-by-one. All of $R^2$s in (10) that combines information in $S^{PLS}$ together with economic predictors are much larger than the corresponding $R^2$ in (9) based on the economic predictors alone reported in Panel A. These results demonstrate that $S^{PLS}$ contains complementary forecasting information beyond what is contained in the economic predictors.\textsuperscript{10}

4.3 Out-of-sample Forecasts

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

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

Specifically, the out-of-sample market return forecast at period $t+1$ based on investor sentiment in (8) and information available through period $t$ is generated by

$$\hat{R}_{t+1}^m = \hat{\alpha}_t + \hat{\beta}_t S^k_{1:t}, \quad k = PLS, BW,$$

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

We then generate the out-of-sample forecasts based on one of the common 14 alternative eco-

\textsuperscript{10}This finding does not apply to $S^{BW}$ whose results are unreported for brevity but available upon request.
nomic variables analyzed by Goyal and Welch (2008) based on the standard predictive regression,

\[ \hat{R}_{m+1}^m = \hat{\alpha}_t + \hat{\psi}_t Z_t^k, \quad k = 1, \ldots, 14, \]  

(12)

where \( \hat{\alpha}_t \) and \( \hat{\psi}_t \) are the OLS estimates from regressing \( \{R_{m+1}\}_{t=1}^{T-1} \) on a constant and \( \{Z_t^k\}_{s=1}^{t-1} \) \( (k = 1, \ldots, 14) \). Lastly, to analyze the incremental forecasting power of investor sentiment, we generate out-of-sample forecasts based on the out-of-sample aligned investor sentiment index and one of the 14 economic variables, as in (10)

\[ \hat{R}_{m+1}^m = \hat{\alpha}_t + \hat{\beta}_t S_{PLS}^{t} + \hat{\psi}_t Z_t^k, \quad k = 1, \ldots, 14, \]  

(13)

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

We divide the total sample of length \( T \) into \( m \) initial estimation sub-sample and \( q \) out-of-sample evaluation sub-sample, where \( T = m + q \), and get \( q \) out-of-sample forecasts: \( \{\hat{R}_{m+1}^m\}_{t=m}^{T-1} \). In Table 5, we use 1965:07 to 1984:12 as the initial estimation period so that the forecast evaluation period spans 1985:01 to 2010:12. The length of the initial in-sample estimation period balances having enough observations for precisely estimating the initial parameters with the desire for a relatively long out-of-sample period for forecast evaluation.\(^{11}\)

We use the widely used Campbell and Thompson (2008) \( R_{OS}^2 \) statistic and Clark and West (2007) MSFE-adjusted statistic to evaluate the out-of-sample forecasts. 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,

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

(14)

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

\[ \bar{R}_{m+1}^m = \frac{1}{T-m} \sum_{t=m}^{T-1} R_{m+1}^m. \]  

(15)

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 \( \hat{R}_{m+1}^m \) outperforms the historical average \( \bar{R}_{m+1}^m \) in term of MSFE.

\(^{11}\)Hansen and Timmermann (2012) and Inoue and Rossi (2012) show that out-of-sample tests of predictive ability have better size properties when the forecast evaluation period is a relatively large proportion of the available sample, as in our case.
The *MSFE-adjusted* statistic tests the null hypothesis that the historical average MSFE is less than or equal to the predictive regression forecast MSFE against the one-sided (upper-tail) alternative hypothesis that the historical average MSFE is greater than the predictive regression forecast MSFE, corresponding to $H_0: R^2_{OS} \leq 0$ against $H_A: R^2_{OS} > 0$. Clark and West (2007) develop the *MSFE-adjusted* statistic by modifying the familiar Diebold and Mariano (1995) and West (1996) statistic so that it has a standard normal asymptotic distribution when comparing forecasts from the nested models.\(^\text{12}\)

[Insert Table 5 about here]

According to Panel B of Table 5, none of the 14 economic variables generate positive $R^2_{OS}$ over the 1985:01–2010:12 evaluation period. Thus, all the individual economic variables fail to outperform the historical average benchmark in terms of MSFE, consistent with the findings of Goyal and Welch (2008) that individual economic variables display limited out-of-sample predictive ability. It is interesting to note that the *MSFE-adjusted* statistic indicates that the MSFE of LTR is less than that of the historical average in 10% level, despite its negative $R^2_{OS}$, which is possible when comparing nested model forecasts (Clark and McCracken, 2001; Clark and West, 2007; McCracken, 2007).\(^\text{13}\)

In Panel A of Table 5, $S^{BW}$ generates positive $R^2_{OS}$ statistic (0.11%), thus $S^{BW}$ delivers a lower MSFE than the historical average. However, the out-of-sample predictability of $S^{BW}$ is statistically insignificant based on the *MSFE-adjusted* statistic. In summary, $S^{BW}$ has weak out-of-sample predictive ability for the aggregate stock market.

$S^{PLS}$ presents much stronger out-of-sample predictive ability for market return in Panel A of Table 5. The $R^2_{OS}$ of $S^{PLS}$ is 1.26%, which is economically sizable and substantially exceeds all of the other $R^2_{OS}$ in Table 5. The *MSFE-adjusted* statistic of $S^{PLS}$ indicates that the MSFE of $S^{PLS}$ is significantly smaller than that of the historical average at the conventional significant level.

\(^{12}\)While the Diebold and Mariano (1995) and West (1996) statistic has a standard normal asymptotic distribution when comparing forecasts from non-nested models, Clark and McCracken (2001) and McCracken (2007) show that it has a non-standard distribution when comparing forecasts from nested models. The non-standard distribution can lead the Diebold and Mariano (1995) and West (1996) statistic to be severely undersized when comparing forecasts from nested models, thereby substantially reducing power.

\(^{13}\)Intuitively, under the null hypothesis that the constant expected return model generates the data, the predictive regression model produces a noisier forecast than the historical average benchmark, because it estimates slope parameters with zero population values. We thus expect the benchmark model MSFE to be smaller than the predictive regression model MSFE under the null. The MSFE-adjusted statistic accounts for the negative expected difference between the historical average MSFE and predictive regression MSFE under the null, so that it can reject the null even if the $R^2_{OS}$ statistic is negative.
Panel C of Table 5 further shows that adding information in $S^{PLS}$ in conjunction with economic variables can substantially improve the forecasting performance of all of the forecasts based on economic variables alone. 12 of the 14 forecasts generate positive $R^2_{OS}$s when combining $S^{PLS}$ together with economic variables, ranging from 0.04% to 1.08%. And the MSFEs for 5 forecasts are significantly less than the historical average MSFE according to the MSFE-adjusted statistics.

In summary, Table 5 shows that aligned investor sentiment captured by $S^{PLS}$ substantially improves the out-of-sample predictability of $s^{BW}$. $S^{PLS}$ displays out-of-sample forecasting power for aggregate stock market and substantially outperforms all of the economic variables, confirming our previous in-sample results in Tables 2 and 4.

### 4.4 Asset Allocation Implications

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

At the end of period $t$, the investor optimally allocates

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

(16)

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

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

(17)

where $R^f_{t+1}$ is the gross risk-free return. Following Campbell and Thompson (2008), we assume that the investor uses a five-year moving window of past monthly returns to estimate the variance of excess market return and constrain $w_t$ to lie between 0 and 1.5 to exclude short sales and at most 50% leverage. To examine the effect of risk aversion, we consider portfolio rules based on risk aversion coefficients $\gamma$ of 1 and 3, respectively.

The CER of the portfolio is

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

(18)
where $\hat{\mu}_n$ and $\hat{\sigma}^2_n$ are the sample mean and variance, respectively, for the investor’s portfolio over the $q$ forecasting evaluation periods. The CER can be interpreted as the risk-free return that an investor is willing to accept instead of adopting the given risky portfolio.

The CER gain is the difference between the CER for the investor who uses a predictive regression forecast of market return generated by (11) or (12) and the CER for an investor who uses the historical average forecast (15). 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]

Panel A (B) of Table 6 shows that only four (six) of the 14 economic variables have positive CER gains under risk aversion coefficient of 1 (3), respectively. The positive CER gains are often economically small while many negative CER losses are large in magnitude. Three economic variables (NTIS, TBL, TMS) generate consistently positive CER gains across different risk aversion coefficients. TMS performs the best, delivering positive CER gains of 0.40% to 1.20% and high Sharpe ratio of 0.11 to 0.14. In summary, economic variables are of limited economic value for a risk averse investor, in accord with the negative $R^2_{OS}$ statistics in Table 5.

When turning to investor sentiment, as a benchmark, $S^{BW}$ performs as well as or better than most of the economic variables, with a CER gain range of -0.96% to 0.27% and a Sharpe ratio range of 0.10 to 0.11. $S^{PLS}$ stands out again in term of economic value. All of the CER gains for $S^{PLS}$ are consistently positive and economically large, ranging from 1.67% to 2.19%. It means that an investor with a risk aversion coefficient of 1 (3) would be willing to pay annual portfolio management fee up to 2.19% (1.67%) to have access to the predictive regression forecast based on $S^{PLS}$ instead of the historical average forecast. In addition, the Sharpe ratios of portfolios formed on $S^{PLS}$ range from 0.13 to 0.16, which almost double the Sharpe ratio for a buy-and-hold strategy of 0.07 in Table 1.

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

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

In this section, we investigate the forecasting power of aligned investor sentiment $S^{PLS}$ for the cross-section of characteristics portfolios sorted on industry, size, book-to-market, and momentum. This exercise not only helps to strengthen our previous findings for aggregate stock market predictability but also helps to enhance our understanding for the economic sources of return predictability.\(^\text{14}\)

[Insert Table 7 about here]

Panel A of Table 7 reports the estimation results for in-sample univariate predictive regressions for 10 industry portfolios with investor sentiment over the period 1965:07–2010:12.\(^\text{15}\) 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 five 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 Shop, Non-durable, Health, and Utility 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 9 (8; 9) out of 10 portfolios sorted on size (book-to-market; momentum), while $S^{BW}$ only significantly forecasts 9 (5; 5) corresponding characteristics portfolios. Almost all the $R^2$'s of $S^{PLS}$ are much larger the corresponding $R^2$'s of $S^{BW}$, for example, the $R^2$ of $S^{PLS}$ for large cap portfolio is 1.62%, while the corresponding $R^2$ of $S^{BW}$ is 0.26%.\(^\text{16}\)

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\(^{15}\)Monthly value-weighted returns for portfolios sorted on industry, size, book-to-market ratio, and momentum are available from Kenneth French’s data library.

\(^{16}\)The aligned investor sentiment $S^{PLS}$ estimated earlier for explaining the aggregate stock market return is used
Moreover, consistent with the literature, there is a fairly large dispersion of regression slope estimates in the cross-section. Stocks that are small, distressed (high book-to-market ratio), with high growth opportunity (low book-to-market ratio), or past losers are more predictable by investor sentiment.

5. Economic Explanations

What is the possible economic explanation of the cross-sectional variation of investor sentiment’s predictive power for different characteristics portfolios? Baker and Wurgler (2006, 2007) argue that firms that are difficult to value and hard to arbitrage are more predictable by investor sentiment. Stambaugh, Yu, and Yuan (2012) show that stocks in the short leg of cross-sectional investment strategy are more predictable by investor sentiment. In Section 5.3 of this paper, we further show that stocks that have the highest cash flow predictability are most predictable by investor sentiment, potentially driven by the market underreaction to cash flow information.

5.1 Cash Flow Predictability and Discount Rate Predictability

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

Fama and French (1989) and Cochrane (2008, 2011), among others, argue that aggregate stock market predictability comes from the time variation in discount rate.\footnote{The time variation in discount rate can be driven by rational reasons such as ICAPM and market volatility risk in Merton (1973, 1980), long run risk in Bansal and Yaron (2004), and disaster risk in Gabaix (2012), or behavioral reasons such as habit formation in Campbell and Cochrane (1999) and prospect theory in Barberis, Huang, and Santos (2001).} Under the discount rate channel, high $S^{PLS}$ predicts lower future stock market return because it predicts lower discount rate driven by lower risk aversion or lower expected investment risk.

On the other hand, $S^{PLS}$ may represent investors’ biased belief about future cash flow not justified by economic fundamental (Baker and Wurgler, 2007). Since $S^{PLS}$ is a negative predictor for future stock market return, the cash flow channel implies that the lower stock market return under 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 more stronger.

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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.\(^{18}\)

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


$$ R_{t+1} = k + DG_{t+1} - \rho D/P_{t+1} + D/P_t, \tag{19} $$

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 $\rho$ is a positive log-linearization constant. (19) implies that if $S_{t}^{PLS}$ helps to predict next period market return $R_{t+1}$ beyond the information contained in $D/P_t$, it must predict either $DG_{t+1}$ or $D/P_{t+1}$ (or both). Since $DG_{t+1}$ and $D/P_{t+1}$ represent separately cash flow and discount rate in our setting, the forecasting power of $S_{t}^{PLS}$ for $DG_{t+1}$ and $D/P_{t+1}$ would point to the cash flow predictability channel and discount rate predictability channel, respectively.\(^{19}\)

Panel A of Table 8 reports the estimation results for in-sample bivariate predictive regressions over the 1965–2011 sample period

$$ Y_{t+1} = \alpha + \beta S_{t}^{PLS} + \psi D/P_{t} + \nu_{t+1}, \quad Y = DG, D/P, \tag{20} $$

\(^{18}\)The overly optimistic cash flow forecasts relative to the rational expectation under high sentiment can be driven by various reasons, including overreaction to good cash flow news due to over-extrapolation and representativeness bias (Kahneman and Tversky, 1974), underreaction to bad cash flow news due to conservatism bias (Edwards, 1968; Barberis, Shleifer and Vishny, 1998) or cognitive dissonance (Festinger, 1957; Antoniou, Doukas, and Subrahmanyam, 2013), gradual information diffusion (Hong and Stein, 1999), and Bayesian learning (Timmermann, 1993, 1996; Lewellen and Shanken, 2002), among others.

\(^{19}\)Campbell and Shiller (1988), Campbell and Ammer (1993), Campbell and Vuolteenaho (2004), Campbell, Polk, and Vuolteenaho (2010), and others use a VAR method to decompose stock return into cash flow news and discount rate news. However, Chen and Zhao (2009) show that the VAR news decomposition method is quite sensitive to the choice of state variables. In addition, Wen and Zhou (2013) argue that this approach is not suitable for examining the source of return predictability, since it implicitly assumes that all predictability is generated through time-varying discount rate channel. Nonetheless, we generate qualitatively similar results based on the VAR method.
where $DG_{t+1}$ is the annual log dividend growth rate on the S&P 500 index from year $t$ to $t+1$, $D/P_{t+1}$ is the log dividend price ratio on the S&P 500 index at the end of year $t+1$, and $S^PLS_t$ is the aligned investor sentiment index at the end of year $t$. Following the literature, we focus on annual data in order to avoid spurious predictability arising from within-year seasonality, and $DG_{t+1}$ and $D/P_{t+1}$ are constructed following Cochrane (2008, 2011) based on total market returns and market returns without dividends.

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

$Lagged sentiment$ displays distinct patterns for cash flow and discount rate predictability. According to Panel A of Table 8, the slope estimate of $S^PLS$ for $DG_{t+1}$ in predictive regression (20) is negative, with statistical significance at the 10% level based on the one-sided wild bootstrapped $p$-value. The predictive regression slope estimate of $S^PLS$ for $D/P_{t+1}$ however is virtually equal to zero and statistically insignificant.20

Based on the joint predictability perspective in (19), the significant negative predictability of $S^PLS$ for $DG_{t+1}$ and no predictability for $D/P_{t+1}$ jointly indicate that $S^PLS$ should present significantly negative predictive power for excess market return, which is in accord with the evidence of negative market return predictability of $S^PLS$ in Tables 2 and 4. Moreover, Panel B of Table 8 shows that $S^BW$ can not forecast both $DG_{t+1}$ and $D/P_{t+1}$, which is also consistent with the evidence of insignificant market return predictability of $S^BW$ in Panel B of in Table 2 and the joint predictability perspective.

In summary, the strong predictability of $S^PLS$ for $DG_{t+1}$ and weak predictability for $D/P_{t+1}$ in Table 8 indicates that the negative return predictability of $S^PLS$ for aggregate stock market is coming from the cash flow channel, different from the popular time-varying discount rate interpretation of market return predictability in the literature. Our findings hence support Baker and Wurgler (2007) that the predictability of investor sentiment seems to represent investors’ irrational belief about future cash flow not justified by economic fundamental.

20In an unreported table, we find that $S^PLS$ cannot forecast future dividend-price ratio even when $S^PLS$ is constructed by applying PLS to the six individual sentiment measures and dividend-price ratio.
5.2 Market Volatility Risk

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

We estimate the following predictive regression model

$$LVOL_{t+1} = \alpha + \beta S^{PLS}_t + \psi LVOL_t + \nu_{t+1}, \quad (21)$$

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

$$SVAR_{t+1} = \sum_{i=1}^{N_{t+1}} R^2_{i,t+1}, \quad (22)$$

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).\(^{21}\)

We are interested in the slope coefficient $\beta$ on $S^{PLS}$ in (21). Given that $S^{PLS}$ is negatively associated with future aggregate stock market return in Tables 2 and 4, the volatility risk-based argument implies that high $S^{PLS}$ should predict lower aggregate stock market volatility and thus lower market risk, which in turn decreases the equity risk premium (discount rate). However, in an unreported table, we find that $S^{PLS}$ indeed contains positive forecasting power for market volatility, with a $\beta = 0.028$ and a $t$-statistic of 2.10, inconsistent with the volatility risk-based hypothesis.

In summary, while we cannot fully rule out the risk-based explanation, it seems unlikely that market volatility risk is driving the predictive power of $S^{PLS}$ for stock market return.\(^{22}\) To the

\(^{21}\)Stock market volatility is positively skewed and leptokurtic, which may distort statistical inferences in predictive regression. We hence focus on forecasting the log market volatility, following Andersen, Bollerslev, Diebold, and Ebens (2001) and Paye (2012). Stock market volatility is very persistent in dynamics, which may generate 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 (21) 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.

\(^{22}\)Aggregate cash flow is associated with aggregate consumption and the investor typically requires higher risk premium when the consumption growth is lower. Since high $S^{PLS}$ predicts lower aggregate cash flow in Table 8, a
extent that high investor sentiment proxies for more noise trading, our findings appear to provide further supports for the behavioral explanation of De Long, Shleifer, Summers, and Waldmann (1990) where high noise trading leads to excessive volatility.23

5.3 Market Underreaction and Return Predictability of Investor Sentiment

In this section, we consider the hypothesis that market underreaction to relevant cash flow information generates the negative predictive power of investor sentiment for stock returns. Many studies suggest that investors may not pay attention to or be able to perform the rational expectations to extract the information from the asset prices due to limited information-processing capacity, leading to market underreaction and return predictability. For example, Merton (1987), Hirshleifer and Teoh (2003), and Hirshleifer, Lim, and Teoh (2009), Hirshleifer, Hsu, and Li (2013), and 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, Lim, and Stein (2000), Hong, Torous, and Valkanov (2007), Cohen and Frazzini (2008), and Menzly and Ozbas (2010) show that fundamental information diffuses gradually in the stock market due to market frictions and bounded rationality. Festinger (1957) and Antoniou, Doukas, and Subrahmanyam (2013) show that, owing to cognitive dissonance, investors underreact to bad (good) public information contradicting their sentiment when they are in high (low) sentiment.

In this paper, we use a cross-sectional regression framework to investigate the underreaction explanation of the predictive power of investor sentiment. Specifically, we examine whether the ability of investor sentiment to forecast stock returns is associated with its ability to forecast cash flows. If the underreaction hypothesis holds, firms that are most predictable by investor sentiment should have the highest cash flow predictability as well. Hong, Torous, and Valkanov (2007) test the gradual information diffusion theory using this cross-sectional regression framework and show that industry returns that are positively (negatively) cross-serially correlated with the market are also positively (negatively) cross-serially correlated with future economic fundamental.

We focus on the cross-section of stocks sorted by size as a proxy for investor underreaction. Small firms receive less attention from investors, are difficult to arbitrage, and therefore, should rational risk-based theory will most likely require higher expected stock market return under high $S_{PLS}$, inconsistent with the evidence of lower stock market return following high $S_{PLS}$. Thus, it seems that cash flow risk or consumption risk can not explain the forecasting power of $S_{PLS}$ for stock market return.

23 Antweiler and Frank (2004) also find that higher sentiment, proxied by the number of messages posted and the bullishness of these messages posted on the Yahoo Finance and Raging Bull stock message boards, predicts higher future stock market volatility for a set of individual stocks.
have slower stock price reactions to the cash flow information contained in sentiment and lead to greater predictability. Hong, Lim, and Stein (2000) test the gradual information diffusion theory of Hong and Stein (1999) using size portfolios and show that momentum strategy is more profitable for small firms. Hirshleifer and Teoh (2003) theoretically demonstrate that size can be an investor attention proxy, and Hirshleifer, Hsu, and Li (2013) use size portfolios to test the limited investor attention theory and show that the predictive power of innovation efficiency is stronger among small size firms.

Empirically, we begin by using aligned investor sentiment $S_{PLS}$ to separately forecast cash flows of each size portfolio

$$DG^j_{t+1} = \alpha_j + \phi_j S_{PLS}^j + \vartheta^j_{t+1}, \quad j = 1, \ldots, 10,$$

(23)

where $DG^j_{t+1}$ is annual log dividend growth rate from year $t$ to $t+1$ for one of the 10 size portfolios, which is constructed using total returns and returns without dividends following Cochrane (2008, 2011). The predictive regression slope coefficients, $\phi_j$s, measure the ability of investor sentiment to forecast the cross-section of stock cash flows.

We then use $S_{PLS}$ to separately forecast size portfolio returns

$$R^j_{t+1} = \alpha_j + \beta_j S_{PLS}^j + \epsilon^j_{t+1}, \quad j = 1, \ldots, 10,$$

(24)

where $R^j_{t+1}$ is the monthly log excess returns for one of the 10 size portfolios. The slope estimates $\beta_j$ then measure the ability of investor sentiment to forecast the cross-section of stock returns (annualized by multiplying 12).

Lastly, we run the cross-section regression

$$\beta_j = a + g \phi_j + e_j.$$

(25)

We are interested in the slope coefficient $g$ in (25). If the underreaction hypothesis holds, we expect a positive relationship between $\beta_j$ and $\phi_j$, i.e., $g > 0$. In other words, portfolios with strong return exposures to investor sentiment should have strong cash flow exposures to investor sentiment (e.g., Hong, Torous, and Valkanov, 2007).

As expected, the OLS estimate of $g$ in (25) is 0.60, with a heteroskedasticity-consistent $t$-statistic of 9.46 and an $R^2$ of 80.5%, indicating significantly positive relationship between $\beta_j$ and

---

24 The stock return data are available from Kenneth French’s data library.

25 In an unreported table, we find that both $S_{PLS}$ can significantly forecast the dividend growth for many size portfolios, and the predictive power is higher for small size portfolios.
Thus, size portfolios with higher return predictability with $S_{PLS}$ also have higher cash flow predictability. In particular, small firms that are more predictable by $S_{PLS}$ with larger negative $\beta_j$ also have the higher cash flow predictability by $S_{PLS}$ with larger negative $\phi_j$.

In summary, our findings support the hypothesis that market underreaction to cash flow information leads to the negative predictive power of investor sentiment for stock returns. This exercise also deepens our understanding on how cash flow predictability channel generates the predictive ability of investor sentiment, as documented in Section 5.1 and Table 8.

6. Conclusion

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

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


Figure 1. The Investor Sentiment Index, 1965:07–2010:12. The solid line depicts the aligned investor sentiment index $S^{PLS}$ extracted from the cross-section of six individual investor sentiment measures of Baker and Wurgler (2006) to forecast stock market return by applying the partial least squares. The dashed line depicts the Baker and Wurgler (2006) investor sentiment index $S^{BW}$ as the first principle component of the six individual 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 measure is standardized and regressed on the growth of industrial production, the growth of durable consumption, the growth of non-durable 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. Vertical bars correspond to NBER-dated recessions.
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.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Skew.</th>
<th>Kurt.</th>
<th>Min.</th>
<th>Max.</th>
<th>$\rho(1)$</th>
<th>SR</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^m$ (%)</td>
<td>0.31</td>
<td>4.46</td>
<td>-0.67</td>
<td>5.41</td>
<td>-24.84</td>
<td>14.87</td>
<td>0.06</td>
<td>0.07</td>
</tr>
<tr>
<td>$R^f$ (%)</td>
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<td>0.25</td>
<td>0.72</td>
<td>4.33</td>
<td>0.00</td>
<td>1.36</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td>$S^{PLS}$</td>
<td>0.00</td>
<td>1.00</td>
<td>1.03</td>
<td>4.72</td>
<td>-2.46</td>
<td>3.77</td>
<td>0.73</td>
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</tr>
<tr>
<td>$S^{BW}$</td>
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<td>1.00</td>
<td>0.10</td>
<td>3.19</td>
<td>-2.58</td>
<td>2.69</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td>DP</td>
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<td>0.42</td>
<td>-0.37</td>
<td>2.24</td>
<td>-4.52</td>
<td>-2.75</td>
<td>0.99</td>
<td></td>
</tr>
<tr>
<td>DY</td>
<td>-3.56</td>
<td>0.42</td>
<td>-0.38</td>
<td>2.26</td>
<td>-4.53</td>
<td>-2.75</td>
<td>0.99</td>
<td></td>
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<tr>
<td>EP</td>
<td>-2.82</td>
<td>0.47</td>
<td>-0.77</td>
<td>5.26</td>
<td>-4.84</td>
<td>-1.90</td>
<td>0.99</td>
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<td>DE</td>
<td>-0.74</td>
<td>0.32</td>
<td>3.08</td>
<td>18.97</td>
<td>-1.22</td>
<td>1.38</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td>SVAR (%)</td>
<td>0.23</td>
<td>0.45</td>
<td>9.48</td>
<td>115.62</td>
<td>0.01</td>
<td>6.55</td>
<td>0.49</td>
<td></td>
</tr>
<tr>
<td>BM</td>
<td>0.52</td>
<td>0.28</td>
<td>0.57</td>
<td>2.25</td>
<td>0.12</td>
<td>1.21</td>
<td>0.99</td>
<td></td>
</tr>
<tr>
<td>NTIS</td>
<td>0.01</td>
<td>0.02</td>
<td>-0.84</td>
<td>3.78</td>
<td>-0.06</td>
<td>0.05</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td>TBL (%)</td>
<td>5.49</td>
<td>2.95</td>
<td>0.72</td>
<td>4.33</td>
<td>0.03</td>
<td>16.30</td>
<td>0.98</td>
<td></td>
</tr>
<tr>
<td>LTY (%)</td>
<td>7.29</td>
<td>2.40</td>
<td>0.89</td>
<td>3.34</td>
<td>3.03</td>
<td>14.82</td>
<td>0.99</td>
<td></td>
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<tr>
<td>LTR (%)</td>
<td>0.65</td>
<td>3.06</td>
<td>0.40</td>
<td>5.55</td>
<td>-11.24</td>
<td>15.23</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td>TMS (%)</td>
<td>1.79</td>
<td>1.55</td>
<td>-0.33</td>
<td>2.63</td>
<td>-3.65</td>
<td>4.55</td>
<td>0.95</td>
<td></td>
</tr>
<tr>
<td>DFY (%)</td>
<td>1.07</td>
<td>0.47</td>
<td>1.70</td>
<td>6.71</td>
<td>0.32</td>
<td>3.38</td>
<td>0.96</td>
<td></td>
</tr>
<tr>
<td>DFR (%)</td>
<td>0.01</td>
<td>1.46</td>
<td>-0.29</td>
<td>10.02</td>
<td>-9.75</td>
<td>7.37</td>
<td>-0.06</td>
<td></td>
</tr>
<tr>
<td>INFL (%)</td>
<td>0.36</td>
<td>0.35</td>
<td>-0.20</td>
<td>7.20</td>
<td>-1.92</td>
<td>1.79</td>
<td>0.61</td>
<td></td>
</tr>
</tbody>
</table>
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

\[ R_{t+1} = \alpha + \beta S^k_t + \epsilon_{t+1}, \quad k = PLS, BW, EW \]

where \( R_{t+1} \) denotes the monthly log excess return (in percentage) on the S&P 500 index from \( t \) to \( t + 1 \). \( S^PLS_t \) is the aligned investor sentiment index at period \( t \) extracted by applying the partial least squares to six individual investor sentiment measures, \( S^{BW}_t \) is the Baker and Wurgler (2006) investor sentiment index as the first principle component of six individual investor sentiment measures, and \( S^{EW}_t \) is the naive investor sentiment index with equal absolute weight on each individual investor sentiment measure. All of the three investor sentiment indexes (\( S^PLS, S^{BW}, \) and \( S^{EW} \)) are standardized to have zero mean and unit variance, and are orthogonal to macroeconomic variables to remove the effect of business cycle conditions. We report the regression slope coefficients, heteroskedasticity-consistent \( t \)-statistics, as well as \( R^2 \) statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on one-sided wild bootstrapped \( p \)-values. The sample period is over 1965:07–2010:12.

<table>
<thead>
<tr>
<th>Panel A: Aligned Investor Sentiment, ( S^PLS )</th>
<th>( \alpha ) (%)</th>
<th>( t )-stat</th>
<th>( \beta ) (%)</th>
<th>( t )-stat</th>
<th>( R^2 ) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.31*</td>
<td>1.62</td>
<td>-0.55**</td>
<td>-2.53</td>
<td>1.54</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Baker and Wurgler (2006) Investor Sentiment, ( S^{BW} )</th>
<th>( \alpha ) (%)</th>
<th>( t )-stat</th>
<th>( \beta ) (%)</th>
<th>( t )-stat</th>
<th>( R^2 ) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.31*</td>
<td>1.61</td>
<td>-0.24</td>
<td>-1.21</td>
<td>0.30</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Naive Investor Sentiment, ( S^{EW} )</th>
<th>( \alpha ) (%)</th>
<th>( t )-stat</th>
<th>( \beta ) (%)</th>
<th>( t )-stat</th>
<th>( R^2 ) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.31*</td>
<td>1.61</td>
<td>-0.28*</td>
<td>-1.41</td>
<td>0.41</td>
<td></td>
</tr>
</tbody>
</table>
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 (S). The sample period is over 1965:07–2010:12.

<table>
<thead>
<tr>
<th></th>
<th>CEFD</th>
<th>TURN</th>
<th>NIPO</th>
<th>RIPO</th>
<th>PDND</th>
<th>S</th>
<th>$S^{BW}$</th>
<th>$S^{PLS}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CEFD</td>
<td>0.35</td>
<td>0.50</td>
<td>0.01</td>
<td>0.44</td>
<td>0.02</td>
<td>0.12</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>TURN</td>
<td>0.45</td>
<td>0.50</td>
<td>0.01</td>
<td>0.45</td>
<td>0.02</td>
<td>0.12</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>NIPO</td>
<td>0.39</td>
<td>0.32</td>
<td>0.01</td>
<td>0.43</td>
<td>0.02</td>
<td>0.12</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>RIPO</td>
<td>0.51</td>
<td>0.52</td>
<td>0.50</td>
<td>0.47</td>
<td>0.06</td>
<td>0.48</td>
<td>0.07</td>
<td></td>
</tr>
<tr>
<td>PDND</td>
<td>0.40</td>
<td>0.34</td>
<td>0.49</td>
<td>0.01</td>
<td>0.02</td>
<td>0.12</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>S</td>
<td>0.47</td>
<td>0.50</td>
<td>0.50</td>
<td>0.08</td>
<td>0.49</td>
<td>0.38</td>
<td>0.06</td>
<td></td>
</tr>
<tr>
<td>$S^{BW}$</td>
<td>0.55</td>
<td>0.53</td>
<td>0.51</td>
<td>0.03</td>
<td>0.43</td>
<td>0.03</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td>$S^{PLS}$</td>
<td>0.54</td>
<td>0.52</td>
<td>0.50</td>
<td>0.40</td>
<td>0.46</td>
<td>0.19</td>
<td>0.64</td>
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Table 4
Alternative Return Predictors
Panel A reports in-sample estimation results for the univariate predictive regression models based on one of the alternative return predictors

\[ R_{t+1} = \alpha + \psi Z_k^t + \epsilon_{t+1}, \quad k = 1, \ldots, 14, \]

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

\[ R_{t+1} = \alpha + \beta S_{t}^{PLS} + \psi Z_k^t + \epsilon_{t+1}, \quad k = 1, \ldots, 14. \]

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

<table>
<thead>
<tr>
<th>Panel A: Univariate Predictive Regressions</th>
<th>Panel B: Bivariate Predictive Regressions</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \psi ) (%)</td>
<td>( t )-stat</td>
</tr>
<tr>
<td>DP</td>
<td>0.47</td>
</tr>
<tr>
<td>DY</td>
<td>0.54</td>
</tr>
<tr>
<td>EP</td>
<td>0.21</td>
</tr>
<tr>
<td>DE</td>
<td>0.36</td>
</tr>
<tr>
<td>SVAR</td>
<td>-1.09***</td>
</tr>
<tr>
<td>BM</td>
<td>0.15</td>
</tr>
<tr>
<td>NTIS</td>
<td>-3.70</td>
</tr>
<tr>
<td>TBL</td>
<td>-0.07</td>
</tr>
<tr>
<td>LTY</td>
<td>0.00</td>
</tr>
<tr>
<td>LTR</td>
<td>0.15**</td>
</tr>
<tr>
<td>TMS</td>
<td>0.23**</td>
</tr>
<tr>
<td>DFY</td>
<td>0.46</td>
</tr>
<tr>
<td>DFR</td>
<td>0.18</td>
</tr>
<tr>
<td>INFL</td>
<td>0.18</td>
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</table>
Table 5
Out-of-sample Forecasting Results

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

<table>
<thead>
<tr>
<th>Panel A: Investor Sentiment</th>
<th>Panel B: Economic Variables</th>
<th>Panel C: $S^{PLS}$ and Economic Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2_{OS}$ (%), $MSFE$-adjusted</td>
<td>$R^2_{OS}$ (%), $MSFE$-adjusted</td>
<td>$R^2_{OS}$ (%), $MSFE$-adjusted</td>
</tr>
<tr>
<td>$S^{PLS}$</td>
<td>1.26</td>
<td>1.43*</td>
</tr>
<tr>
<td>$S^{PLS}$ + DP</td>
<td>0.29</td>
<td>0.90</td>
</tr>
<tr>
<td>$S^{PLS}$ + DY</td>
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<td>0.92</td>
</tr>
<tr>
<td>$S^{PLS}$ + EP</td>
<td>0.72</td>
<td>1.02</td>
</tr>
<tr>
<td>$S^{PLS}$ + DE</td>
<td>0.04</td>
<td>0.69</td>
</tr>
<tr>
<td>$S^{PLS}$ + SVAR</td>
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<td>0.59</td>
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<tr>
<td>$S^{PLS}$ + BM</td>
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<td>0.86</td>
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<tr>
<td>$S^{PLS}$ + NTIS</td>
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<td>1.76**</td>
</tr>
<tr>
<td>$S^{PLS}$ + TBL</td>
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<td>1.24</td>
</tr>
<tr>
<td>$S^{PLS}$ + LTY</td>
<td>1.08</td>
<td>1.28*</td>
</tr>
<tr>
<td>$S^{PLS}$ + LTR</td>
<td>0.69</td>
<td>1.46*</td>
</tr>
<tr>
<td>$S^{PLS}$ + TMS</td>
<td>0.72</td>
<td>1.33*</td>
</tr>
<tr>
<td>$S^{PLS}$ + DFY</td>
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<td>0.41</td>
</tr>
<tr>
<td>$S^{PLS}$ + DFR</td>
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<td>0.98</td>
</tr>
<tr>
<td>$S^{PLS}$ + INFL</td>
<td>1.05</td>
<td>1.49*</td>
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35
Table 6
Asset Allocation Results
Panels A and B report the portfolio performance measures for a mean-variance investor with a risk aversion coefficient ($\gamma$) of 1 and 3, 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. $\Delta$ is the annualized certainty equivalent return gain (in percentage) for an investor who uses the predictive regression forecast instead of the historical average benchmark forecast. The weight on stocks in the investors portfolio is restricted to lie between 0 and 1.5. The monthly Sharpe ratio (SR) is the mean portfolio return based on the predictive regression forecast in excess of the risk-free rate divided by the standard deviation of the excess portfolio return. The out-of-sample aligned investor sentiment index $S^{PLS}$ and out-of-sample Baker and Wurgler (2006) investor sentiment index $S^{BW}$ are estimated recursively using the data available through period of forecast formation $t$. The out-of-sample evaluation period is over 1985:01–2010:12.

<table>
<thead>
<tr>
<th></th>
<th>Panel A: $\gamma = 1$</th>
<th></th>
<th>Panel B: $\gamma = 3$</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>$\Delta$ (%)</td>
<td>SR</td>
<td>$\Delta$ (%)</td>
</tr>
<tr>
<td>Investor Sentiment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$S^{PLS}$</td>
<td>2.19</td>
<td>0.16</td>
<td>1.67</td>
</tr>
<tr>
<td>$S^{BW}$</td>
<td>-0.96</td>
<td>0.11</td>
<td>0.27</td>
</tr>
<tr>
<td>Economic Variables</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DP</td>
<td>-4.84</td>
<td>0.06</td>
<td>-3.59</td>
</tr>
<tr>
<td>DY</td>
<td>-5.05</td>
<td>0.06</td>
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</tr>
<tr>
<td>EP</td>
<td>-1.64</td>
<td>0.11</td>
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</tr>
<tr>
<td>DE</td>
<td>-1.59</td>
<td>0.10</td>
<td>-1.23</td>
</tr>
<tr>
<td>SVAR</td>
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<td>0.11</td>
<td>0.07</td>
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<tr>
<td>BM</td>
<td>-3.40</td>
<td>0.08</td>
<td>-1.47</td>
</tr>
<tr>
<td>NTIS</td>
<td>0.22</td>
<td>0.12</td>
<td>0.11</td>
</tr>
<tr>
<td>TBL</td>
<td>0.15</td>
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<td>0.09</td>
</tr>
<tr>
<td>LTY</td>
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<td>0.11</td>
<td>-0.12</td>
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<tr>
<td>LTR</td>
<td>-2.25</td>
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<td>-0.53</td>
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<tr>
<td>TMS</td>
<td>1.20</td>
<td>0.14</td>
<td>0.40</td>
</tr>
<tr>
<td>DFY</td>
<td>-3.72</td>
<td>0.07</td>
<td>-2.39</td>
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<tr>
<td>DFR</td>
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<tr>
<td>INFL</td>
<td>0.17</td>
<td>0.12</td>
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</tr>
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</table>
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

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

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 slope coefficients, heteroskedasticity-consistent $t$-statistics, as well as $R^2$ statistics. To save space, we do not report the intercept in the regressions. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on one-sided wild bootstrapped $p$-values. Portfolio returns are value-weighted and available from Kenneth French’s data library. The sample period is over 1965:07–2010:12.

<table>
<thead>
<tr>
<th></th>
<th>$S_t^{PLS}$ (%)</th>
<th>$t$-stat</th>
<th>$R^2$ (%)</th>
<th>$S_t^{BW}$ (%)</th>
<th>$t$-stat</th>
<th>$R^2$ (%)</th>
</tr>
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<td>0.50</td>
<td>-0.13</td>
<td>-0.54</td>
<td>0.04</td>
</tr>
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<td>0.91</td>
<td>-0.27</td>
<td>-1.17</td>
<td>0.27</td>
</tr>
<tr>
<td>Energy</td>
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<td>-3.08</td>
<td>2.09</td>
<td>-0.44**</td>
<td>-1.84</td>
<td>0.64</td>
</tr>
<tr>
<td>Technology</td>
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<td>2.21</td>
<td>-0.72**</td>
<td>-2.22</td>
<td>1.10</td>
</tr>
<tr>
<td>Telecom</td>
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<td>0.05</td>
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<td><strong>Panel B: Size Portfolios</strong></td>
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<td></td>
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<td>1.52</td>
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<td>-0.66***</td>
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<td>-0.59**</td>
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<td>-0.54**</td>
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<td>-0.50**</td>
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<td>1.06</td>
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<td>1.35</td>
<td>-0.29*</td>
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Table 7 (Continued)

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<th>$S_{PLS}^t$ (%)</th>
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<th>$R^2$ (%)</th>
<th>$S_{BW}^t$ (%)</th>
<th>$t$-stat</th>
<th>$R^2$ (%)</th>
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<td><strong>Panel C: Book-to-market Portfolios</strong></td>
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<td>-0.98</td>
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<tr>
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<td>-1.29</td>
<td>0.32</td>
</tr>
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</tr>
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<td>-0.33*</td>
<td>-1.57</td>
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<tr>
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<td>-0.31*</td>
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<td>-0.39*</td>
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<td><strong>Panel D: Momentum Portfolios</strong></td>
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<tr>
<td>Loser</td>
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<td>-0.84**</td>
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<tr>
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<tr>
<td>4</td>
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<tr>
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<td>-0.68***</td>
<td>-2.97</td>
<td>2.12</td>
<td>-0.33*</td>
<td>-1.56</td>
<td>0.50</td>
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<tr>
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<td>-1.16</td>
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<td>-0.62**</td>
<td>-3.12</td>
<td>1.82</td>
<td>-0.30*</td>
<td>-1.53</td>
<td>0.43</td>
</tr>
<tr>
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<td>1.76</td>
<td>-0.43**</td>
<td>-2.04</td>
<td>0.72</td>
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<tr>
<td>Winner</td>
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<td>-2.45</td>
<td>1.44</td>
<td>-0.67***</td>
<td>-2.52</td>
<td>1.10</td>
</tr>
</tbody>
</table>
Table 8
Forecasting Dividend Growth and Dividend Price Ratio with Investor Sentiment
This table reports in-sample estimation results for the bivariate predictive regressions

\[ Y_{t+1} = \alpha + \beta S_k^t + \psi D/P_t + \upsilon_{t+1}, \quad Y = DG, D/P, \quad k = PLS, BW, \]

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

<table>
<thead>
<tr>
<th></th>
<th>( \beta )</th>
<th>( t )-stat</th>
<th>( \psi )</th>
<th>( t )-stat</th>
<th>( R^2 ) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Aligned Investor Sentiment, ( S_k^{PLS} )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( DG ) (%)</td>
<td>-3.46*</td>
<td>-2.35</td>
<td>3.55</td>
<td>0.73</td>
<td>10.3</td>
</tr>
<tr>
<td>( D/P )</td>
<td>-0.00</td>
<td>-0.09</td>
<td>0.95***</td>
<td>19.33</td>
<td>89.8</td>
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<tr>
<td>Panel B: Baker and Wurgler (2006) Investor Sentiment, ( S_k^{BW} )</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>( DG ) (%)</td>
<td>-2.02</td>
<td>-1.29</td>
<td>4.71</td>
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<tr>
<td>( D/P )</td>
<td>-0.01</td>
<td>-0.55</td>
<td>0.95***</td>
<td>19.56</td>
<td>89.9</td>
</tr>
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</table>
IA.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).²⁶

- 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.
- 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).
- Term spread, TMS: difference between the long-term yield and Treasury bill rate.

²⁶The data are available at Amit Goyal’s website, http://www.hec.unil.ch/agoyal.
• 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.

**IA.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

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

(IA.1)

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

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

$$x_{i,t+1} = \rho_{i,x,0} + \rho_{i,x,1} x_{i,t} + \phi_{i,x,t+1}, \quad i = 1, ..., N,$$

(IA.2)

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

(IA.3)

Define

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

(IA.4)

$$\hat{\phi}_{z,t+1}^c = Z_{i,t+1} - \hat{\rho}_{i,Z,0} - \hat{\rho}_{i,Z,1} Z_{i,t}, \quad i = 1, ..., M,$$

(IA.5)

where

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

(IA.6)
and
\[(\hat{\rho}_{i,0}^c, \hat{\rho}_{i,1}^c), \ i = 1, \ldots, M, \]  

(IA.7)
denote vectors of reduced-bias estimates of the AR(1) parameters in (IA.2) and (IA.3), 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:

\[
\tilde{R}_t, t+1 = \tilde{R}_m + \bar{\varepsilon}_{t+1} w_{t+1}, 
\]

(IA.8)

\[
\tilde{x}_{i,t+1} = \hat{\rho}_{i,x,0}^c + \hat{\rho}_{i,x,1}^c \tilde{x}_{i,t} + \tilde{\varepsilon}_{i,t+1} w_{t+1}, \ i = 1, \ldots, N, 
\]

(IA.9)

\[
\tilde{Z}_{t,t+1} = \hat{\rho}_{i,Z,0}^c + \hat{\rho}_{i,Z,1}^c \tilde{Z}_{i,t} + \tilde{\varepsilon}_{i,t+1} w_{t+1}, \ i = 1, \ldots, M, 
\]

(IA.10)

where \(\tilde{R}_m\) is the sample mean of \(R^m_{t+1}\), \(w_{t+1}\) is a draw from the standard normal distribution, \(\tilde{x}_{i,0} = x_{i,0} (i = 1, \ldots, N)\), and \(\tilde{Z}_{i,0} = Z_{i,0} (i = 1, \ldots, M)\). Observe that we multiply the fitted residuals \(\tilde{\varepsilon}_{t+1}\) in (IA.8), each \(\hat{\phi}_{i,x,t+1}^c\) in (IA.9), and each \(\hat{\phi}_{i,Z,t+1}^c\) in (IA.10) 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 (IA.9) and (IA.10) helps to ensure that we adequately capture the persistence in the predictors.

Using the pseudo sample of observations for

\[
\{(\tilde{R}_{t+1}^m, \tilde{x}_{1,t}, \ldots, \tilde{x}_{N,t}, \tilde{Z}_{1,t}, \ldots, \tilde{Z}_{M,t})\}^{T-1}_{t=0}, 
\]

(IA.11)

we estimate the slope coefficients and the corresponding \(t\)-statistics for univariate predictive regressions based on each investor sentiment index in (8) or each macroeconomic variable in (9), and the bivariate predictive regressions based on aligned investor sentiment and each macroeconomic variable in (10). Note that we compute the aligned investor sentiment index, Baker and Wurgler (2006) investor sentiment index, and naive investor sentiment index in (8) and (10) using the pseudo sample of \(\{\tilde{x}_{i,t}\}^{T-1}_{t=0} (i = 1, \ldots, N)\) and \(\{\tilde{R}_{t+1}^m\}^{T-1}_{t=0}\), so that it accounts for the estimated regressors in the predictive regressions. We store the \(t\)-statistics for all of the predictive regression-
s. Repeating this process 2,000 times yields empirical distributions for each of the $t$-statistics. For a given $t$-statistic, the empirical $p$-value is the proportion of the bootstrapped $t$-statistics greater (less) than the $t$-statistic for the original sample.

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

$$\hat{\varepsilon}_t^j = R_t^j - (\hat{\alpha}^j + \sum_{i=1}^{N} \hat{\beta}_i^j x_{i,t}), \quad j = m, 1,...,C, \quad (IA.12)$$

where $\hat{\alpha}^j$ ($j = m, 1,...,C$) and $\hat{\beta}_i^j$ ($i = 1,...,N$, and $j = m, 1,...,C$) are estimated by regressing excess market return ($j = m$) or each of the excess characteristics portfolio returns ($j = 1,...,C$) on a constant and all of the $N$ individual investor sentiment proxies. We continue to assume that $x_{i,t}$ follows an AR(1) process and use (IA.2), (IA.4), and (IA.9). In accord with the null, we build up a pseudo sample of observations for excess returns on the market and characteristics portfolios

$$\tilde{R}_t^j = \bar{R}_t^j + \hat{\varepsilon}_t^j w_{t+1}, \quad j = m, 1,...,C. \quad (IA.13)$$

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

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

$$\hat{\upsilon}_t^Y = Y_t + (\hat{\alpha}_Y + \sum_{i=1}^{N} \hat{\beta}_i^Y x_{i,t} + \hat{\psi}^{D/P}_t), \quad Y = DG, D/P. \quad (IA.14)$$

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 (IA.2), (IA.4), and (IA.9). We simulate $R_t^m$ using (IA.1) and (IA.8). In accord with the null, we build up a pseudo sample of observations for dividend growth and dividend price ratio

$$\tilde{Y}_t = \hat{\alpha}_Y + \hat{\psi}^{D/P}_t + \hat{\upsilon}_t^Y w_{t+1}, \quad Y = DG, D/P. \quad (IA.15)$$
We use this process to simulate data for dividend growth and dividend price ratio, and compute the aligned investor sentiment index and Baker and Wurgler (2006) investor sentiment index using the pseudo sample. We then use the pseudo sample to compute the slope coefficients and the corresponding $t$-statistics for bivariate predictive regressions based on each investor sentiment index in Table 8. Repeating this process 2,000 times, the empirical $p$-value is the proportion of the bootstrapped $t$-statistics greater (less) than the $t$-statistic for the original sample.

Fourth, we alternate the previous wild bootstrap procedure to simulate data for the predictive regressions on the log aggregate stock market volatility in Section 5.2 under the null. Let

$$\hat{\nu}_{t+1} = LVOL_{t+1} - (\hat{\alpha} + \sum_{i=1}^{N} \hat{\beta}_i x_{i,t} + \hat{\psi} LVOL_t). \quad \text{(IA.16)}$$

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 (IA.2), (IA.4), and (IA.9). We simulate $R^m_t$ using (IA.12) and (IA.13). In accord with the null, we generate a pseudo sample of observations for log market volatility

$$\tilde{LVOL}_{t+1} = \hat{\alpha} + \hat{\psi} \tilde{LVOL}_t + \hat{\nu}_{t+1} w_{t+1}. \quad \text{(IA.17)}$$

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


