Manager Sentiment and Stock Returns

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Abstract

In this paper, we construct a manager sentiment index based on the aggregated textual tone of conference calls and financial statements. We find that manager sentiment is a strong negative predictor of future aggregate stock market returns, with monthly in-sample and out-of-sample R^2 of 9.75% and 8.38%, respectively, which is far greater than the predictive power of other previously-studied macroeconomic variables. Its predictive power is also stronger than and is complimentary to the popular investor sentiment indexes. Moreover, manager sentiment also negatively predicts future aggregate earnings and cross-sectional stock returns, particularly for those firms that are either hard to value or difficult to arbitrage.

JEL classifications: C53, G11, G12, G17

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1. Introduction

Many studies in behavioral finance examine the role of investor sentiment in asset pricing. Both theoretical models and empirical results suggest that overly optimistic or pessimistic investor sentiment can lead prices to diverge from their fundamental values (e.g., De Long, Shleifer, Summers, and Waldmann 1990; Shefrin, 2008). A measure of investor sentiment developed by Baker and Wurgler (2006) has been used in hundreds of studies to understand the role of sentiment in various investor decisions.[1] In contrast, scant research examines the role of aggregate manager sentiment on market outcomes. This is somewhat surprising given managers' information advantage about their companies over other interested parties such as outside investors, and also given managers' first-hand ability to create value for stocks. At the same time, managers are not immune from behavioral biases and may deviate from fully rational (e.g., Malmendier and Tate 2005; Baker and Wurgler 2012). Theoretically, manager sentiment can have both a numerator effect (i.e., investors' estimates of expected future cash flows) and a denominator effect (i.e., discount rate) on stock prices. Empirically, it is an open question whether the effects are significant for stock returns.

In this paper, we provide an aggregate manager sentiment index constructed based on the aggregated textual tone in firm conference calls and financial statements that are known to reflect corporate managers' common optimism or pessimism.[2] While our index construction follows the dictionary methods of Tetlock (2007), Feldman, Govindaraj, Livnat, and Segal (2010), Loughran and McDonald (2011), and Price, Doran, Peterson, and Bliss (2012), among others, our study has two major differences. First, we provide an aggregate index to gauge the overall manager sentiment in the market and its impact on aggregate and cross-sectional stock returns, while these studies focus on firm-level measures for predicting firm-level outcome variables. In this aspect, Bochkay

[1] The latest Google article citations of Baker and Wurgler (2006) exceed 1850.

[2] We use textual disclosures in conference calls and financial statements here because they seem to reflect managers' subjective opinions, beliefs, and projections and capture majority of information available in the marketplace (Li 2008, 2010; Blau, DeLisle, and Price 2015; Brochet, Kolev, and Lerman 2015). Henry (2008) provides an early study of manager sentiment using earnings press releases of a sample in the telecommunications and computer industry.

and Dimitrov (2015) seem to be the first and the only other study at present that also constructs an aggregate index, but they do not include firm conference calls when constructing the index and they focus on studying managers' qualitative disclosures. Second, we compute a monthly index from both available voluntary and mandatory firm disclosures filed within each month, while other studies use quarterly firm disclosures given their analysis of firm-level characteristics. By constructing our manager sentiment index at the monthly frequency, it is comparable in time frequency to investor sentiment and to other macroeconomic predictors that are commonly used for forecasting monthly stock returns.

We assess the ability of the manager sentiment index to predict stock market returns relative to various other macroeconomic predictors. Specifically, we consider a set of fifteen well-known macroeconomic variables used by Goyal and Welch (2008), such as the short-term interest rate (Fama and Schwert 1977; Breen, Glosten, and Jagannathan 1989; Agn and Bekaert 2007), dividend yield (Fama and French 1988; Campbell and Yogo 2006; Ang and Bekaert 2007), earnings-price ratio (Campbell and Shiller 1988), term spreads (Campbell 1987; Fama and French 1988), book-to-market ratio (Kothari and Shanken 1997; Pontiff and Schall 1998), stock volatility (French, Schwert, and Stambaugh 1987; Guo 2006), inflation (Fama and Schwert 1977; Campbell and Vuolteenaho 2004), corporate issuing activity (Baker and Wurgler 2000), and consumption-wealth ratio (Lettau and Ludvigson, 2001).

We also compare the manager sentiment index to five alternative sentiment indexes documented in the literature: 1) the Baker and Wurgler (2006) investor sentiment index, which is the first principle component of six stock market-based sentiment proxies; 2) the Huang, Jiang, Tu, and Zhou (2015) aligned investor sentiment index, which is estimated using the more efficient partial least square method from Baker and Wurglers sentiment proxies; 3) the University of Michigan consumer sentiment index based on household surveys; 4) the Conference Board consumer confidence index also based on household surveys; and 5) the Da, Engelberg, and Gao (2015) Financial and Economic Attitudes Revealed by Search (FEARS) investor sentiment index based on daily Internet search volume from Google Trend.

We find evidence that manager sentiment strongly and negatively predicts aggregate stock market returns. Based on available data from January 2003 to December 2004, we employ the standard predictive regressions by regressing excess market returns on the lagged manager sentiment index. We find that manager sentiment yields a large in-sample R^2 of 9.75% and a one-standard deviation increase in manager sentiment is associated with a -1.26% decrease in expected excess market return for the next month. Using out-of-sample tests for data from January 2007 to December 2014, we continue to find a large positive out-of-sample R^2_{OS} of 8.38%. For comparative purposes, the average in-sample R^2 of other macroeconomic variables is only 1.18% over the same time period (with a max of 5.72% for the SVAR, stock return variance). In untabulated analysis, we also find that most macroeconomic variables fail to beat the simple historical average forecast in out-of-sample tests; the average out-of-sample R^2_{OS} is -3.14% (with a max of 1.74% for the NTIS, net equity expansion).

Moreover, the widely used Baker and Wurgler (2006) investor sentiment index has in- and out-of-sample R^2s of 5.11% and 4.53%, respectively, which are lower than those of the manager sentiment index. In addition, the Huang, Jiang, Tu and Zhou (2015) aligned investor sentiment index has 8.45% and 3.14% in- and out-of-sample R^2s, respectively, which are also lower than those of the manager sentiment index. Theoretically, a priori, we have no reason to believe that manager sentiment will perform better or worse than investor sentiment in predicting the market, nor do we have strong reason to believe the two are highly correlated. Interestingly, however, we find that the manager sentiment index and the aligned investor sentiment index have a low positive correlation of 0.13, indicating that they are likely complementary in their information impact. Indeed, when using both sentiment measures jointly as predictors, the R^2 is 16.7%, which is almost equal to the sum of two individual R^2s. Further econometric forecast encompassing tests confirm these findings.

We further examine the economic value of stock market forecasts based on the manager sentiment index. Following Kandel and Stambaugh (1996) and Campbell and Thompson (2008), among others, using the out-of-sample predictive regression forecasts, we compute the certainty equivalent return (CER) gain and Sharpe Ratio for a mean-variance investor who optimally allocates across equities and the risk-free asset. We find that the manager sentiment index generates large economic gains for the investor, with an annualized CER gain of 7.92%, indicating that an investor with a risk aversion of five would be willing to pay an annual portfolio management fee of up to 7.92% to have access to the predictive regression forecasts based on manager sentiment rather than using the historical average. The CER gain remains economically large after accounting for transaction costs, with a net-of-transactions-costs CER gain of 7.86%. The monthly Sharpe ratio of manager sentiment is about 0.17, which is much higher than the market Sharpe ratio of -0.02 over the same sample period.

We also examine the relationship between manager sentiment and subsequent aggregate earnings to explore the cash flows channel of return predictability. We find that the manager sentiment index, similar to the investor sentiment index, negatively and significantly forecasts future aggregate earnings growth. The finding indicates that the negative return predictability of manager sentiment is potentially driven by managers overly optimistic (pessimistic) projections of future cash flows that is not justified by fundamentals, when sentiment is high (low).

Cross-sectionally, we find that manager sentiment also negatively predicts the cross-section of stock returns, and the predictability is concentrated among stocks with high beta, high idiosyncratic volatility, young age, small market cap, unprofitable, non-dividend-paying, low fixed asset, high R&D, distressed (high B/M ratio, high D/P ratio, low investment), and high growth opportunities (low D/P, high investment). The results indicate that the negative effects of manager sentiment are particularly stronger for stocks that are speculative, hard to value, or difficult to arbitrage, consistent with Baker and Wurgler (2006, 2007). Moreover, in unreported analyses, we find that manager sentiment also generally outperforms investor sentiment in the cross-section and that the two are complementary, similar to our results for aggregate market returns.

Our paper is related to research on the relation between aggregate financial disclosures and stock market returns. Penman (1987) finds that variation in aggregate earnings news can explain the variation in aggregate stock market returns. Kothari, Lewellen, and Warner (2005) find that aggregate earnings growth is negatively related to market returns. Anilowski, Feng and Skinner (2007) find that managers earnings guidance captures aggregate earnings news and find some evidence that increases in upward (downward) guidance are positively (negatively) associated with monthly market returns but no evidence at the quarterly horizon. In contrast, we find that aggregate manager sentiment *negatively* predicts market returns from a month up to a one year horizon. Manager sentiment thus appears to be distinct from management guidance, with the former arguably reflecting managements overly optimistic projection of future earnings.

Our paper is also related to literature on the relation between financial disclosures and investor sentiment. Bergman and Roychowdhury (2008) find that managers reduce the frequency of long-term earnings forecasts over high-sentiment periods. Seybert and Yang (2012) find that managers of speculative and hard-to-value firms issue guidance more frequently during high-sentiment periods. Brown, Christensen, Elliott, and Mergenthaler (2012) provide evidence that managers are more likely to disclose pro forma earnings in periods of high sentiment. Hribar and McInnis (2012) find that when sentiment is high, analysts' earning forecasts are relatively more optimistic for uncertain or difficult-to-value firms. What remains unclear is whether managers are caught by sentiment or whether they rationally exploit sentiment-driven investors (Lang and Lundholm 2000). For example, Bochkay and Dimitrov (2015) show that managers become more optimistic in their qualitative disclosures under high investor sentiment. In this paper, we contribute to literature and find that manager sentiment negatively predicts future aggregate earnings and stock returns, and the negative predictability is much stronger for hard to value or difficult to arbitrage firms. Our study provides evidence supporting that managers, similar to investors, as a whole could be driven by sentiment, consistent with the behavioral view instead of the rational view.

The rest of the paper is organized as follows. Section 2 discusses the data and the construction of the manager sentiment index. Section 3 investigates the in-sample forecasting power of manager sentiment for stock returns of the aggregate market portfolio and compares manager sentiment with macroeconomic variables and alternative sentiment proxies. Section 4 examines the out-of-sample forecasting power of manager sentiment and its economic value for asset allocation. Section 5 investigates the forecasting power of manager sentiment for future aggregate earnings growth. Section 6 explores the cross-sectional forecasting power of manager sentiment for portfolios sorted by propensity to speculate and limits to arbitrage. Section 7 concludes.

2. Data and Methodology

2.1 Construction of manager sentiment index, S^{MS}

We form the aggregated manager sentiment index, S^{MS}, as the average of two individual manager sentiment proxies: the conference call tone (S^{CC}) and the financial statement tone including 10-K and 10-Q reports (S^{FS}). The manager sentiment indexes are measured monthly from 2003:01 to 2014:12. We first describe each individual tone measure separately and then discuss how to construct the overall manager sentiment index.

Conference call tone, S^{CC}, is the average difference between the number of positive words in earnings conference call transcripts and the number of negative words scaled by the total word count. Negative and positive words are classified based on the financial word dictionaries from Loughran and McDonald (2011), which develop word lists for business applications that better reflect tone in financial and accounting text.[3] Price, Doran, Peterson, and Bliss (2012), among others, suggest that the conference call tone can serve as a sentiment index of manager disclosure, and find that the conference call tone significantly predicts firm-level abnormal returns and post-earnings announcement drift. We take S^{CC} as the monthly equally-weighted average conference call tone from 2003:01 to 2014:12 across firms, which covers 144 consecutive months during the post Regulation FD period. Prior to this period, conference call transcript availability is limited.

Specifically, we identify firms conducting conference calls by first matching all non-financial, non-utility firms on Compustat with non-missing total assets to their corresponding unique Factiva

[3] See https://www3.nd.edu/~mcdonald/Word_Lists.html.

identifiers using the company name provided by Compustat. For the 11,336 unique Compustat firms, we find Factiva identifiers for 6,715 firms. Using each firm's unique identifier, we then search Factiva's FD Wire for earnings conference calls made between 2003 and 2014 and find 113,570 total call transcripts for 5,859 unique firms. Conference calls held during the sample period discuss firm performance starting from the fourth quarter of 2002 to the third quarter of 2014 due to the lag between the close of each quarter and the dates of the corresponding conference calls. The distribution of the monthly number of conference calls displays a seasonal pattern due to earnings seasons over our sample period. To remove seasonality and to iron out idiosyncratic jumps, we calculate S^{CC} as the four-month moving average.

Financial statement tone, S^{FS}, is the average difference between the number of positive words in 10-Ks and 10-Qs and the number of negative words scaled by the total word count. Again, negative and positive words are classified based on the financial word dictionaries from Loughran and McDonald (2011). Li (2010), Feldman, Govindaraj, Livnat, and Segal (2010), Loughran and McDonald (2011), among others, suggest that the financial statement tone is a sentiment proxy and is linked to firm-level returns, trading volume, volatility, fraud, and earnings. We obtain 264,335 10-Ks and 10-Qs for 10,414 unique firms from the EDGAR website (www.sec.gov), and calculate S^{FS} as the monthly equally-weighted average financial statement tone from 2003:01 to 2014:12 using a four-month moving average. In Table 1, we find that while both S^{CC} and S^{FS} capture manager sentiment, the correlation between them is fairly low, 0.21, indicating that conference calls and financial statements likely contain complementary information about manager sentiment.

[Insert Table 1 about here]

We then form a composite manager sentiment index, S^{MS}, as the average of the two individual tone measures. Since both measures likely contain information about manager sentiment as well as idiosyncratic non-sentiment noise, the averaged manager sentiment index thus helps to capture the common manager sentiment component in conference calls and 10-Ks and 10-Qs and diversify away the idiosyncratic noise. The index is in a parsimonious form,

$$S^{\mathrm{MS}} = 0.5\, S^{\mathrm{CC}} + 0.5\, S^{\mathrm{FS}}, \tag{1}$$

where, following Baker and Wurgler (2006, 2007), each of the individual aggregate tone measures has been standardized. The manager sentiment index, S^{MS}, has several appealing properties. First, each individual measure enters with the correct sign and with equal weight. Second, the index helps to smooth out extreme values in the individual measures. Third, the weight on each individual tone measure is equal, which is easy to calculate and is robust to parameter uncertainty and model instability.[4]

Following Stambaugh, Yu, and Yuan (2012), we also calculate a manager sentiment dummy, S^{D}, classifying each month as following high (equal to 1) or low (equal to 0) sentiment periods based on the managerial sentiment index S^{MS}. A high-sentiment month is one in which the value of S^{MS} in the previous month is above the median value for the sample period, and the low-sentiment months are those with below-median values.

As a robustness check, we also estimate a sophisticated regression-combined manager sentiment index,

$$S^{\mathrm{RC}} = 0.368\, S^{\mathrm{CC}} + 0.632\, S^{\mathrm{FS}}, \tag{2}$$

where, following Cochrane and Piazzesi (2005), the combination weights on the individual measures are optimally estimated by running regressions of excess market returns on individual tone measures in terms of a single factor,

$$R^m_{t+1} = \alpha + \beta(\Upsilon^{\mathrm{CC}} S^{\mathrm{CC}}_t + \Upsilon^{\mathrm{FS}} S^{\mathrm{FS}}_t) + \varepsilon_{t+1}. \tag{3}$$

In the above specification (3), the regression coefficients β, Υ^{CC}, and Υ^{FS} are not separately

[4]In finance literature, Timmermann (2006) and Rapach, Strauss, and Zhou (2010) find that the simple "1/N"-weighted combination forecast often beats forecasts with sophisticated optimally estimated weights in environments with complex and constantly evolving data generating processes.

identified since one can double the β and halve each Υ and get the same regression. We normalize the weights by imposing that their sum is equal to one, $\Upsilon^{CC} + \Upsilon^{FS} = 1$, such that the weights are uniquely determined by the data.

[Insert Figure 1 about here]

Figure 1 shows that the manager sentiment index S^{MS} appears to reflect anecdotal accounts of time-series variation in sentiment levels. Specifically, the manager sentiment index was low in the early 2000s after the Internet bubble. Sentiment then subsequently rose to a peak and dropped sharply to a trough during the 2008 to 2009 subprime crisis. Manager sentiment then rose again recently in the early 2010s.

2.2 Other data

We conduct most of our empirical tests at the aggregate stock market level or at the single-sorted characteristic portfolio level using the standard monthly frequency. The excess market return is equal to the monthly return on the S&P 500 index (including dividends) minus the risk-free rate, available from Goyal and Welch (2008) and Amit Goyal's website. We obtain cross-sectional stock returns on various portfolios single sorted on proxies for subjectivity of valuation or limits to arbitrage either directly from Ken French's website or calculated using individual stock prices and returns from CRSP and Compustat.

For comparison purpose, we also consider five alternative sentiment indexes documented in the literature,[5]

- Baker and Wurgler (2006) investor sentiment index, S^{BW}, which is the first principle component of six stock market-based sentiment proxies, including the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity

[5]The updated investor sentiment indexes S^{BW} and S^{HJTZ} up to 2014 are available from Guofu Zhou's website, http://apps.olin.wustl.edu/faculty/zhou/. The consumer sentiment indexes S^{MCS} and S^{CBC} are available from University of Michigan's Survey Research Center and Conference Board, respectively. The FEARS sentiment index S^{FEARS} from July 2004 to December 2011 is available from Zhi Da's website, http://www3.nd.edu/ zda/.

share in new issues, and the dividend premium;

- Huang, Jiang, Tu, and Zhou (2015) aligned investor sentiment index, S^{HJTZ}, which exploits the information in Baker and Wurgler's six investor sentiment proxies more efficiently using the partial least square method;
- University of Michigan consumer sentiment index, S^{MCS}, based on telephone surveys on a nationally representative sample of households;
- Conference Board consumer confidence index, S^{CBC}, based on mail surveys on a random sample of U.S. households;
- Da, Engelberg, and Gao (2015) Financial and Economic Attitudes Revealed by Search (FEARS) investor sentiment index, S^{FEARS}, based on the volume of Internet searches related to household concerns (e.g., "recession", "unemployment", and "bankruptcy").

These alternative sentiment indexes, especially the Baker and Wurgler's investor sentiment index S^{BW}, have been widely used in a number of studies such as Baker and Wurgler (2006, 2007, 2011, 2012), Bergman and Roychowdhury (2008), Yu and Yuan (2011), Baker, Wurgler, and Yuan (2012), Stambaugh, Yu, and Yuan (2012), Brown, Christensen, Elliott, and Mergenthaler (2012), Hribar and McInnis (2012), Mian and Sankaraguruswamy (2012), and others.

According to Figure 1, we find that the manager sentiment index, S^{MS}, seems to capture similar sentiment fluctuations with the investor sentiment indexes S^{BW} and S^{HJTSZ}, although they are constructed very differently with different information sets. Consistent with Figure 1, Table 1 indicates that the manager sentiment index S^{MS} has a relatively high positive correlation of 0.53 with Baker and Wurgler's investor sentiment index S^{BW}, but low correlations with the other four alternative sentiment indexes, ranging from -0.24 (S^{FEARS}) to 0.21 (S^{CBC}).

One might argue that the explanatory power of the manager sentiment index for stock returns may come from its contained information about business cycle condition. For instance, managers may become optimistic for rational reasons like good expected economic condition. To control for the influence of business cycle, we consider 15 monthly economic variables that are linked directly to economic fundamentals and risk,[6] which 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), inflation rate (INFL), and consumption-wealth ratio (CAY). Details on these economic predictors are provided in the Appendix.

3. Predictive Regression Analysis

3.1 Manager sentiment and aggregate market returns

Consider the standard predictive regression model,

$$R^m_{t+1} = \alpha + \beta S^{\text{MS}}_t + \varepsilon_{t+1}, \tag{4}$$

where R^m_{t+1} is the excess aggregate market return, i.e., the monthly return on the S&P 500 index in excess of the risk-free rate, and S^{MS}_t is the manager sentiment index defined as the average of the standardized aggregate manager tone extracted from conference calls and 10-Ks and 10-Qs. In addition, for comparison, we also consider S^{RC}, the alternative regression-combined managerial sentiment index, and four individual tone measures. Each manager sentiment index and individual tone measure in (4) is standardized to have zero mean and unit variance.

The null hypothesis of interest is that manager sentiment has no predictive ability, $\beta = 0$. In this case, (4) reduces to the constant expected return model, $R^m_{t+1} = \alpha + \varepsilon_{t+1}$. Because finance theory suggests a negative sign on β, we test $H_0 : \beta = 0$ against $H_A : \beta < 0$, which is closer to theory than the common alternative of $\beta \neq 0$. Econometrically, Inoue and Kilian (2004) encourage

[6] The economic variables are reviewed in Goyal and Welch (2008), and the updated data for the first 14 variables are available from Amit Goyal's website, http://www.hec.unil.ch/agoyal/, and the consumption-wealth ratio is available from Sydney C. Ludvigson's website, http://www.econ.nyu.edu/user/ludvigsons/.

the use of the one-sided alternative hypothesis to increases the power of the test.

Several econometric issues may have an adverse impact on the statistical inferences we draw from Equation (4). First, if a predictor is highly persistent, the OLS regression may generate spurious results (Ferson, Sarkissian, and Simin 2003). Second, due to the well-known Stambaugh (1999) small-sample bias, the coefficient estimate of the predictive regression can be biased in a finite sample, which may distort the t-statistic when the predictor is highly persistent and correlated with the excess market return. To alleviate potential concerns with these two issues, we base our inferences on the empirical p-values that we obtain using a wild bootstrap procedure that accounts for the persistence in predictors, correlations between the excess market return and predictor innovations, and general forms of return distribution. [7]

[Insert Table 2 about here]

Table 2 reports the in-sample estimation results of the predictive regressions (4). Panel A provides the results for the manager sentiment index, S^{MS}. The regression slope on S^{MS}, β, is -1.26, which is economically large and statistically significant at the 1% level based on the wild bootstrap p-value, with a Newey-West t-statistic of -3.57. Therefore, S^{MS} is a significant negative market predictor: high manager sentiment is associated with low excess aggregate market return in the next month. This finding is consistent with our hypothesis that S^{MS} as a sentiment index leads to market-wide over-valuation (under-valuation) when S^{MS} is high (low), leading to subsequent low (high) stock returns.

Interestingly, our finding of a negative relation between the manager sentiment index S^{MS} and aggregate market return is in sharp contrast with the relation at the firm-level. For example, Loughran and McDonald (2011) find that a higher proportion of negative words from the 10-Ks and 10-Qs is associated with more negative excess returns in the filing period at the firm level.

[7] The details of the wild bootstrap procedure is untabulated but available on request. 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.

Price, Doran, Peterson, and Bliss (2012) also find a positive association between the conference call tone and abnormal returns at the firm level. Therefore, the firm-level tone effects do not extend to the market level and our aggregate evidence is more consistent with the managerial sentiment explanation rather than fundamental information explanation. This finding is consistent with Hirshleifer, Hou, and Teoh (2009) who also find opposite relationship for the return predictability of accruals and cash flows at the market level versus the firm level.

Economically, the regression coefficient suggests that a one-standard deviation increase in S^{MS} is associated with a -1.26% decrease in expected excess market return for the next month. Recall that the average monthly excess market return during our sample period is 0.76% (α in (4) and Table 2), thus the slope of -1.26% implies that the expected excess market return based on S^{MS} varies by about 1.5 times larger than its average level, which signals strong economic significance (Cochrane 2011). In addition, S^{MS} generates a large R^2 of 9.75%. If this level of predictability can be sustained out-of-sample, it will be of substantial economic significance (Kandel and Stambaugh 1996). Indeed, Campbell and Thompson (2008) show that, given the large unpredictable component inherent in the monthly market returns, a monthly out-of-sample R^2 statistic of 0.5% can generate significant economic value. This point will be analyzed further in Section 4.1.

Panel B provides the estimation results for the regression-combined manager sentiment index, S^{RC}. The regression slope on S^{RC} is -1.28, with a Newey-West t-statistic of -3.67, which is slightly larger than that of S^{MS} in Panel A, suggesting that the optimally-weighted S^{RC} can further improve the return predictability upon S^{MS}, in the in-sample fitting context. The R^2 of 10.3% is also slightly larger than the 9.75% reported in Panel A for S^{MS}. However, Rapach, Strauss, and Zhou (2009) show that the sophisticated optimally weighted forecast may underperform the naive equally-weighted forecast in a more realistic out-of-sample setting due to parameter uncertainty and model instability. We will show later in Sections 4.1 and 4.2 that this is also true in our case here.

For comparison, Panel C of Table 2 reports the predictive abilities of four individual aggregate tone measures separately. Both S^{CC}, the equally-weighted average conference call tone, and S^{FS}, the equally-weighted average financial statement tone are significant negative return predictors, consistent with the theoretical predictions. S^{FS} has relatively larger in-sample predictability, with an R^2 of 8.10% vis-á-vis 4.05% of S^{CC}, consistent with its higher weight in forming the S^{RC} index. As a robustness check, we also examine the forecasting power of value-weighted average conference call tone, S^{CCv}, and value-weighted average financial statement tone, S^{FSv}. We detect significant negative return predictability again, but the forecasting power is weaker than those of the corresponding equally-weighted tone measures. The finding is consistent with Baker and Wurgler (2006) that since small firms are hard to value and difficult to arbitrage, they are more sensitive to sentiment than large firms. Most importantly, we observe that S^{MS} consistently beats all the individual tone measures, confirming Baker and Wurgler (2006, 2007) that a composite sentiment index is more desirable than individual proxies.

From an economic point of view, while the overall R^2 is interesting, it is also important to analyze the predictability during business-cycles to better understand the fundamental driving forces. Following Rapach, Strauss, and Zhou (2010) and Henkel, Martin, and Nardari (2011), we compute the R^2 statistics separately for economic recessions (R^2_{rec}) and expansions (R^2_{exp}),

$$R^2_{\mathrm{c}} = 1 - \frac{\sum_{t=1}^{T} I_t^{\mathrm{c}}(\hat{\varepsilon}_{i,t})^2}{\sum_{t=1}^{T} I_t^{\mathrm{c}}(R_t^m - \bar{R}^m)^2} \qquad c = \mathrm{rec},\ \exp \tag{5}$$

where I_t^{rec} ($I_t^{\exp}$) is an indicator that takes a value of one when month t is in an NBER recession (expansion) period and zero otherwise; $\hat{\varepsilon}_{i,t}$ is the fitted residual based on the in-sample estimates of the predictive regression model in (4); $\bar{R}^m$ is the full-sample mean of R_t^m; and T is the number of observations for the full sample. Note that, unlike the full-sample R^2 statistic, the R^2_{rec} and R^2_{exp} statistics can be both positive or negative.

Columns 6 and 7 of Table 2 report the R^2_{rec} and R^2_{exp} statistics. Panels A and B show that the return predictability is concentrated over recessions for the manager sentiment indexes S^{MS}

and S^{RC}. For example, over recessions, S^{MS} has a large R^2_{rec} of 21.4%. In contrast, over expansions, S^{MS} has a much smaller R^2_{exp} of 0.74%. Panel C shows that, consistent with the manager sentiment indexes, the individual tone measures also present much stronger predictability during recessions vis-á-vis expansions. In summary, the return predictability of manager sentiment is concentrated over recessions, consistent with Huang, Jiang, Tu, and Zhou (2015) for investor sentiment indexes and Rapach, Strauss, and Zhou (2010) and Henkel, Martin, and Nardari (2011) for other macroeconomic variables.

In the last two columns of Table 2, we divide the whole sample into high and low sentiment periods to investigate the possible economic sources of the return predictability of S^{MS}. Following Stambaugh, Yu, and Yuan (2012), we classify a month as high (low) sentiment if the manager sentiment level in the previous month is above (below) its median value for the sample period, and compute the R^2_{high} and R^2_{low} statistics for the high and low sentiment periods, respectively, in a manner similar to (5).

Empirically, we find that the predictive power of S^{MS} in Panel A is fairly large during both high sentiment and low sentiment periods, although the predictability is stronger during high sentiment periods. For example, over high sentiment periods, S^{MS} has an R^2_{high} of 12.9%. In contrast, over low sentiment periods, S^{MS} has an smaller R^2_{low} of 6.93%. For the individual tone measures, Panel C reports that the predictability of S^{FS} is stronger during high sentiment periods, but S^{CC} displays stronger predictability during low sentiment periods. Comparing Panels A and C, the more balanced forecasting performance of S^{MS} over high and low sentiment periods is potentially due to the fact that S^{MS} summarizes information in both tone measures S^{CC} and S^{FS}, which have stronger predictive power in low and high sentiment periods, respectively. In short, consistent with Shen and Yu (2013) and Huang, Jiang, Tu, and Zhou (2015) for investor sentiment, we also find that manager sentiment's predictive power is stronger over high sentiment periods, during which mispricing is more likely due to short-sale constraints.

3.2 Predictability with longer horizons

Although we perform most of our empirical tests on manager sentiment over the usual one month horizon, in this subsection, we investigate its forecasting power over longer horizons. Manager sentiment is highly persistent and long-term in nature and hence may have a long run effect on stock market. In addition, due to limits of arbitrage, mispricings from manager sentiment may not be eliminated completely by arbitrageurs over a short horizon. Brown and Cliff (2004, 2005) show that survey-based investor sentiment has significant return predictability over long run horizons exceeding one year. Baker, Wurgler, and Yuan (2012) show that global sentiment in year $t-1$ predicts significantly the following 12 month country-level market returns over 1980–2005. Huang, Jiang, Tu and Zhou (2015) show that aligned investor sentiment S^{HJTZ} presents significant forecasting power for up to a one-year forecasting horizon.

[Insert Table 3 about here]

Table 3 reports the in-sample estimation results of the manager sentiment index S^{MS} on the excess market return over horizons from one month to three years. For comparison, we also report results for the regression-combined manager sentiment S^{RC}. Panel A shows that S^{MS} can significantly predict the long run excess market return for up to three years. The in-sample forecasting power increases as the horizon increases and then declines. Specifically, the in-sample R^2 of S^{MS} peaks at the 9-month forecasting horizon of 27.1%; the absolute value of the regression coefficient on S^{MS} generally increases as horizon increases and begins to stabilizes at 24 months. At the annual horizon, a one-standard deviation positive shock to S^{MS} predicts a -8.58% decrease in the aggregate stock market return over the next one year. In addition, we obtain qualitatively similar findings for S^{RC} in Panel B.

In sum, the manager sentiment index S^{MS} significantly predicts stock market returns not only at the usual one month horizon but also over long run horizons up to three years into the future, with a peak at the 9-month horizon.

3.3 Comparison with economic predictors

In this subsection, we compare the forecasting power of the manager sentiment index S^{MS} with economic predictors and examine whether its forecasting power is driven by omitted economic variables related to business cycle fundamentals or changes in macroeconomic risks.

First, we consider the predictive regression on a single economic variable,

$$R_{t+1}^{m} = \alpha + \psi Z_t^k + \varepsilon_{t+1}, \qquad k = 1, ..., 16, \tag{6}$$

where Z_t^k is one of the 15 individual economic variables described in Section 2.2 and in the Appendix or the ECON factor which is the first principal component (PC) extracted from the 15 individual economic variables.

[Insert Table 4 about here]

Panel A of Table 4 reports the estimation results for (6). Out of the 15 individual economic predictors, only stock return variance (SVAR), net equity expansion (NTIS), Treasury bill rate (TBL), and long-term yield (LTY) exhibit significant predictive abilities for the market at the 10% or better significance levels. Among these four significant economic variables, three of them have R^2s larger than 1.5% (SVAR, NTIS, and LTY), and one has an R^2 larger than 5% (*SVAR*). The last row of Panel A shows that the ECON factor, the first PC extracted from the 15 economic variables, is insignificant in forecasting excess market return, with a small R^2 of only 0.12%. Hence, S^{MS} outperforms all 15 individual economic predictors and the PC common factor, ECON, in forecasting the monthly excess market returns in-sample.

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

$$R_{t+1}^{m} = \alpha + \beta S_t^{\text{MS}} + \psi Z_t^k + \varepsilon_{t+1}, \qquad k = 1, ..., 16. \tag{7}$$

The coefficient of interest is the regression slope β on S_t^{MS}. We test $H_0 : \beta = 0$ against $H_A : \beta < 0$ based on the wild bootstrapped p-values.

Panel B of Table 4 shows that the estimates of the slope β in (7) range from -1.10 to -1.95, all of which are negative and economically large, in line with the results in the earlier predictive regression (4) reported in Table 2. More importantly, β remains statistically significant at the 1% or better level when augmented by the economic predictors. The R^2s in (7) range from 9.83% to 15.3%, which are substantially larger than those reported in Panel A based on the economic predictors alone. These results demonstrate that the return predictability of the manager sentiment index S^{MS} is not driven by macroeconomic fundamentals and it contains sizable sentiment forecasting information complementary to what is contained in the economic predictors.

3.4 Comparison with alternative sentiment indexes

In this subsection, we empirically compare the manager sentiment index S^{MS} with five alternative sentiment indexes documented in the literature, and examine whether the forecasting power of S^{MS} is a substitute for or is complementary to investor sentiment. Theoretically, a priori, there are no strong reasons to believe that investor sentiment will perform better or worse than manager sentiment in predicting the stock market. As insiders, managers are better informed about their firms than outside investors and have the first-hand ability to create value for firms. At the same time, recent research shows that managers are also often subject to cognitive biases and may not be fully rational. Therefore, while the literature generally exclusively focus on investor sentiment in forecasting stock returns, in practice, investor and manager sentiment likely coexist.

We run the the following predictive regressions of monthly excess market return (R_{t+1}^m) on the lagged manager sentiment index, S^{MS}, with controls for alternative sentiment indexes, S_t^{k},

$$R_{t+1}^m = \alpha + \beta S_t^{\text{MS}} + \delta S_t^k + \varepsilon_{t+1}, \qquad k = \text{BW}, \text{HJTZ}, \text{MCS}, \text{CBC}, \text{FEARS}, \tag{8}$$

where S^{BW} denotes the Baker and Wurgler (2006) investor sentiment index, S^{HJTZ} denotes the Huang, Jiang, Tu, and Zhou (2015) aligned investor sentiment index, S^{MCS} denotes the University of Michigan consumer sentiment index, S^{CBC} denotes the Conference Board consumer confidence index, and S^{FEARS} denotes the Da, Engelberg, and Gao (2015) FEARS investor sentiment index (over the sample period 2004:07−2011:12 due to data constraints). Detailed descriptions of these alternative sentiment indexes are provided in Section 2.2. To test the incremental forecasting information contained in S_t^{MS}, we test $H_0 : \beta = 0$ against $H_A : \beta < 0$ based on the wild bootstrapped p-values.

[Insert Table 5 about here]

As a benchmark, the first column of Table 5 shows that the manager sentiment index S^{MS} is a significant negative predictor for the market, with a large R^2 of 9.75%. In the second column, the widely used Baker and Wurgler (2006) investor sentiment index S^{BW} has an in-sample R^2 of 5.11%, which is much lower than the predictability of S^{MS}, although S^{BW} is indeed a significant negative predictor for the excess market return. Interestingly, in the third column, when including both S^{MS} and S^{BW} jointly as return predictors in a bivariate predictive regression, S^{MS} remains significant but S^{BW} becomes insignificant, and the R^2 of the bivariate regression is equal to 10.3%, which is similar to that of using S^{MS} alone. These findings are consistent with the high correlation of 0.53 between S^{MS} and S^{BW} in Table 1, indicating that S^{MS} empirically dominates S^{BW} in forecasting the stock market.

The fourth column of Table 5 shows that the Huang, Jiang, Tu and Zhou (2015)'s aligned investor sentiment index S^{HJTZ}, which is an alternative investor sentiment index generated by exploring the the same six stock market-based sentiment proxies of Baker and Wurgler (2006) more efficiently, generates a larger R^2 of 8.45%, with statistical and economic significance. However, S^{HJTZ}'s predictability, in term of in-sample R^2, is still smaller than that of S^{MS}, although the difference is economically small. More interesting, the fifth column shows that when combining S^{MS} together with S^{HJTZ}, the bivariate predictive regression generates an in-sample R^2 of 16.7%, almost equal to the sum of the individual R^2s of the univariate regressions, revealing that the predictive power of the manager sentiment index S^{MS} and the aligned investor sentiment index S^{HJTZ} are almost perfectly complimentary to each other, consistent with their low correlation in Table 1.

The sixth to eleventh columns of Table 5 show that the return predictability of the University of Michigan consumer sentiment index (S^{MCS}), the Conference Board consumer confidence index (S^{CBC}), and the Da, Engelberg, and Gao (2015)'s FEARS investor sentiment index (S^{FEARS}) are smaller than that of S^{MS}, ranging from 0.26% to 2.71%. Most importantly, they each become statistically insignificant when controlling for S^{MS} in bivariate regressions, while S^{MS} remains consistently significant and negative. In the last column, we run a kitchen-sink regression that includes all the sentiment indexes in one long regression. We find that S^{MS} remains statistically significant and economically large, while the coefficients on the other sentiment indexes become more volatile due to serious multicollinearity problem.

In short, the manager sentiment index S^{MS} contains additional sentiment information beyond exiting sentiment indexes in forecasting the stock market. In addition, S^{MS} is almost perfectly complimentary to the aligned investor sentiment index S^{HJTZ} in forecasting.

3.5 Forecast encompassing test

To further assess the relative information content between the manager sentiment index S^{MS} and the other five alternative sentiment indexes, we conduct a forecast encompassing test. 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.

[Insert Table 6 about here]

Table 6 reports p-values for the Harvey, Leybourne, and Newbold (1998) forecast encompassing test. The first row of Table 6 shows that the manager sentiment index S^{MS} encompasses the two individual tone measures as well as four alternative sentiment indexes at conventional significance levels except S^{HJTZ}, indicating S^{MS} contains complementary forecasting information beyond S^{HJTZ}. The second and third rows show that neither S^{CC} nor S^{FS} encompass S^{MS}, indicating that both individual tone measures contain differentiated information and the potential gains in combining individual tone measures into a composite manager sentiment index to fully make use of relevant information, as discussed in Table 2. In addition, the fourth to eighth rows of Table 6 show that none of the five alternative sentiment indexes can significantly encompass S^{MS} and its components S^{CC} and S^{FS}, suggesting that the manager sentiment index S^{MS} contains incremental sentiment forecasting information beyond existing sentiment measures.

4. Economic Value

4.1 Out-of-sample R^2_{OS}

In this section, we investigate the out-of-sample forecasting performance of the manager sentiment index. Goyal and Welch (2008), among others, argue that out-of-sample tests are more relevant for investors and practitioners for assessing genuine return predictability in real time, although the in-sample predictive analysis provides more efficient parameter estimates and thus more precise return forecasts. In addition, out-of-sample tests are much less affected by the econometrics issues such as the over-fitting concern, small-sample size distortion and the Stambaugh bias than in-sample regressions (Busetti and Marcucci, 2012). Hence, we investigate the out-of-sample predictive performance of the manager sentiment index, S^{MS}.

The key requirement for out-of-sample forecasts at time t is that we can only use information available up to t to forecast stock returns at $t+1$. Following Goyal and Welch (2008), and many others, we run the out-of-sample predictive regressions recursively on each lagged manager sentiment measure,

$$\hat{R}^m_{t+1} = \hat{\alpha}_t + \hat{\beta}_t S^k_{1:t;t} \tag{9}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates from regressing $\{R^m_{s+1}\}_{s=1}^{t-1}$ on a constant and a recursively estimated sentiment measure $\{S^k_{1:t;s}\}_{s=1}^{t-1}$. Similar to our in-sample analogues in Table 2, we investigate the out-of-sample forecasting performance of the recursively estimated manager sentiment index, S^{MS}, the regression-combined manager sentiment index, S^{RC}, the conference call tone, S^{CC}, and the financial statement tone, S^{FS}. In addition, we also consider the combination forecast of manager sentiment proxies, S^{C}, that is widely used in the forecasting literature and often beats sophisticated optimally estimated forecasting weights (Timmermann, 2006). Rapach, Strauss, and Zhou (2009) show that a simple equally-weighted average of univariate regression forecasts can consistently predict the market risk premium. It is hence of interest to see how well it performs in the context of using the two individual tone measures. For comparison purse, we also examine the out-of-sample forecasting performance of the five alternative sentiment indexes as in Table 5.

Let p be a fixed number chosen for the initial sample training, so that the future expected return can be estimated at time $t = p+1, p+2, \ldots, T$. Hence, there are q $(= T - p)$ out-of-sample evaluation periods. That is, we have q out-of-sample forecasts: $\{\hat{R}^m_{t+1}\}_{t=p}^{T-1}$. Specifically, we use the data over 2003:01 to 2006:12 as the initial estimation period, so that the forecast evaluation period spans over 2007:01 to 2014:12. 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.[8]

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

[8] 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.

average benchmark,

$$R_{\mathrm{OS}}^2 = 1 - \frac{\sum_{t=p}^{T-1}(R_{t+1}^m - \hat{R}_{t+1}^m)^2}{\sum_{t=p}^{T-1}(R_{t+1}^m - \bar{R}_{t+1}^m)^2}, \tag{10}$$

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

$$\bar{R}_{t+1}^m = \frac{1}{t}\sum_{s=1}^{t} R_s^m. \tag{11}$$

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 $(-\infty, 1]$. If $R_{OS}^2 > 0$, then the forecast $\hat{R}_{t+1}^m$ outperforms the historical average $\bar{R}_{t+1}^m$ in terms of MSFE.

We test the statistical significance of R_{OS}^2 using the MSFE-adjusted statistic of Clark and West (2007) (MSFE–*adj* statistic). It 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: $R_{\mathrm{OS}}^2 \leq 0$ against $H_A : R_{OS}^2 > 0$. Clark and West (2007) show that this test has an asymptotically standard normal distribution when comparing forecasts from the nested models. 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's MSFE to be smaller than the predictive regression model's MSFE under the null. The MSFE-adjusted statistic accounts for the negative expected difference between the historical average MSFE and predictive regression MSFE under the null, so that it can reject the null even if the R_{OS}^2 statistic is negative.

[Insert Table 7 about here]

Panel A of Table 7 shows that the manager sentiment index S^{MS} exhibits strong out-of-sample predictive ability for the aggregate market, with an R_{OS}^2 of 8.38%. The Clark and West (2007)

MSFE–*adj* statistic of S^{MS} is 2.55, suggesting that the MSFE of S^{MS} is significantly smaller than that of the historical average at the 1% or better significance level. The R^2_{OS} of S^{MS} is economically large and exceeds substantially all the other R^2_{OS}s in Table 7, including all other manager sentiment measures in Panel A and all five alternative sentiment indexes in Panel B. The two manager tone components S^{CC} and S^{FS} have significant forecasting power, with R^2_{OS}s of 1.77% and 6.85%, respectively, both of which are smaller than the predictability of S^{MS}, indicating the forecasting gains that result from combining information from two tone measures into a composite manager sentiment index. In addition, the fourth and fifth columns of Table 7 show that the predictability of the manager sentiment index S^{MS} and its individual tone measures S^{CC} and S^{FS} is concentrated over recessions, confirming our earlier in-sample findings in Table 2.

The recursively estimated regression-combined manager sentiment index, S^{RC}, generates a positive R^2_{OS} of 5.70%, hence, while the sophisticated optimally-estimated S^{RC} slightly outperforms the equally-weighted index S^{MS} in the in-sample fitting context (see Table 2), it substantially underperfoms S^{MS} in the more realistic out-of-sample setting. Consistent with Rapach, Strauss, and Zhou (2010), the combination forecast S^{C} generates a large R^2_{OS} of 7.94%, with statistical significance at the 5% level. These findings are largely consistent with Goyal and Welch (2008) that while sophisticated estimated models may have good in-sample fitting, their out-of-sample performance tends to be worse due to large estimation error.

For comparison, Panel B of Table 7 shows the out-of-sample performance of the five alternative sentiment indexes. Among the five indexes, two investor sentiment indexes S^{BW} and S^{HJTZ} are positive and significant, with R^2_{OS}s of 4.54% and 3.14%, respectively. The R^2_{OS}s of other three sentiment indexes S^{MCS}, S^{CBC}, and S^{FEARS} are negative, indicating forecasting loss relative to the historical average benchmark. Nevertheless, all the R^2_{OS}s of the alternative sentiment indexes are substantially lower than the R^2_{OS} of manager sentiment index S^{MS}.

In summary, this section shows that the manager sentiment S^{MS} displays strong out-of-sample forecasting power for the aggregate stock market. In addition, S^{MS} substantially outperforms all the other manager sentiment measures and alternative investor sentiment indexes documented in the literature in an out-of-sample setting, consistent with the results of our in-sample regression analysis in Section 2.

4.2 Asset allocation implications

In this section, we further examine the economic value of stock return predictability of the manager sentiment index S^{MS} from an asset allocation perspective. Following Kandel and Stambaugh (1996), Campbell and Thompson (2008) and Ferreira and Santa-Clara (2011), among others, we compute the certainty equivalent return (CER) gain and Sharpe Ratio for a mean-variance investor who optimally allocates across equities and the risk-free asset using the out-of-sample predictive regression forecasts.

At the end of period t, the investor optimally allocates

$$w_t = \frac{1}{\gamma}\frac{\hat{R}^m_{t+1}}{\hat{\sigma}^2_{t+1}} \tag{12}$$

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

$$R^p_{t+1} = w_t R^m_{t+1} + R^f_{t+1}, \tag{13}$$

where R^f_{t+1} is the risk-free return. Following Campbell and Thompson (2008), we assume that the investor uses a five-year moving window of past monthly returns to estimate the variance of the excess market return and constrains w_t to lie between 0 and 1.5 to exclude short sales and to allow for at most 50% leverage.

The CER of the portfolio is

$$\mathrm{CER}_p = \hat{\mu}_p - 0.5\gamma\hat{\sigma}^2_p, \tag{14}$$

where $\hat{\mu}_n$ and $\hat{\sigma}_n^2$ are the sample mean and variance, respectively, for the investor's portfolio over the q forecasting evaluation periods. The CER gain is the difference between the CER for the investor who uses a predictive regression forecast of market return generated by (9) and the CER for an investor who uses the historical average forecast (11). 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. To examine the adverse effect of transaction costs, we also consider the case of 50bps transaction costs, which is generally considered as a relatively high number.

[Insert Table 8 about here]

Table 8 shows that the manager sentiment index S^{MS} generates large economic gains for the mean-variance investor, consistent with its large R_{OS}^2 statistics in Table 7. Specifically, S^{MS} has a large positive annualized CER gain of 7.92%, indicating that an investor with a risk aversion of five would be willing to pay an annual portfolio management fee up to 7.92% to have access to the predictive regression forecasts based on S^{MS} instead of using the historical average forecast. The CER gain remains economically large after accounting for transaction costs, with a net-of-transactions-costs CER gain of 7.86%. The monthly Sharpe ratio of S^{MS} is about 0.17, which is much higher than the market Sharpe ratio, -0.02, over the same sample period with a buy-and-hold strategy.

The rest of Panel A shows that all the other manager sentiment or tone measures also generate large economic gains for the investor. The annualized CER gains vary from 6.64% (S^{RC}) to 10.6% (S^{FS}), and the net-of-transactions-costs CER gains vary from 6.56% (S^{RC}) to 10.5% (S^{FS}). In addition, all the monthly Sharpe ratios are also economically large, in the range of 0.13 (S^{RC} and S^{CC}) to 0.22 (S^{FS}).

Panel B of Table 8 shows that, out of the five alternative sentiment indexes, the two investor sentiment indexes S^{BW} and S^{HJTZ} generate large economic gains for the investor, while the gains from the other three indexes are limited. Specifically, without transaction costs, S^{BW} and S^{HJTZ} generate both large CER gains (9.06% for S^{BW} and 8.79% for S^{HJTZ}) and large Sharpe ratios (0.19 for S^{BW} and 0.18 for S^{HJTZ}), and the economic gains remain large after accounting for transaction costs. However, while S^{MCS} and S^{FEARS} can generate fairly large CER gains (4.17% for S^{MCS} and 5.80% for S^{FEARS}), their Sharpe ratios are low, 0.03 and 0.01, respectively. S^{MCS} only generates small CER gain of 0.62% and a negative Sharpe ratio of -0.03.

Overall, Table 8 demonstrates that the manager sentiment index S^{MS} can generate sizable economic value for an investor from an asset allocation perspective. The results are robust to common levels of transaction costs.

5. Manager Sentiment and Aggregate Earnings

In this section, we investigate the forecasting power of the manager sentiment index S^{MS} for future aggregate earnings growth. Thus far we have focused on forecasting market returns with manager sentiment; however, stock prices are determined not only by discount rates but also by expectations about future cash flows. Therefore, the negative return predictability of the manager sentiment index may come from investors' biased beliefs about future earnings unjustified by economic fundamentals in hand (e.g., Bower 1981; Johnson and Tversky 1983; Wright and Bower 1992; Baker and Wurgler 2007). Specifically, when manager sentiment is high (low), the market may have overly optimistic (pessimistic) expectations for future earnings, leading to overvaluation (undervaluation) and subsequent low (high) stock returns.

Our empirical analysis focuses on forecasting future aggregate earnings growth, which has been widely examined and used in similar studies in the literature (e.g., Campbell and Shiller 1988; Fama and French 2000; Menzly, Santos, and Veronesi 2004; Lettau and Ludvigson 2005; Cochrane 2008, 2011; Binsbergen and Koijen 2010; Huang, Jiang, Tu, and Zhou 2015). We employ the following predictive regressions,

$$\mathrm{EG}_{t\to t+12} = \alpha + \beta S_t^{\mathrm{MS}} + \psi \mathrm{E/P}_t + \delta \mathrm{EG}_t + \upsilon_{t\to t+12}, \tag{15}$$

where $\mathrm{EG}_{t\to t+12}$ is the annual growth rate of twelve-month moving sums of aggregate earnings on the S&P 500 index, which is available from Robert Shiller's website and from Goyal and Welch (2008). Following previous studies, we include controls for the lagged earnings-to-price ratio ($\mathrm{E/P}_t$) and lagged earnings growth (EG_t), and focus on annual horizon data to avoid spurious earnings growth predictability arising from within-year seasonality.[9] We are interested in the regression slope β, and test $H_0 : \beta = 0$ against $H_A : \beta < 0$, to examine whether the manager sentiment index , S_t^{MS}, contains information about future aggregate earnings growth.

[Insert Table 9 about here]

Table 9 reports the estimation results of forecasting annual aggregate earnings growth in (15). The first two columns show that manager sentiment S^{MS} contains significant negative forecasting power for future aggregate earnings growth $\mathrm{EG}_{t\to t+12}$. According to the first column, the regression slope estimate on S^{MS} for $\mathrm{EG}_{t\to t+12}$ is -0.46, with a Newey-West t-statistic of -2.26. Hence, a one-standard deviation increase in S^{MS} is associated with a -46% decrease in $\mathrm{EG}_{t\to t+12}$ for the next year, revealing that aggregate earnings growth is highly predictable with manager sentiment over our sample period. This point is further confirmed by the large R^2 of 35.6% for the univariate predictive regression for $\mathrm{EG}_{t\to t+12}$ with S^{MS}.

The negative predictability of manager sentiment for next-year aggregate earnings growth is consistent with our previous finding on negative market return predictability reported in Section 3.1 and Table 2. The finding suggests that aggregate manager sentiment index captures systematically biased beliefs about future cash flows rather than fundamental information. The aggregate-level

[9]In unreported tables, we find similar but weaker results for aggregate dividend growth, which is consistent with Fama and French (2001) that there is a steep-downward trend in the fraction of U.S. firms paying dividends, and that the dividends are subject to smoothing.

evidence contrasts with the positive association between firm-level manager sentiment (tone) and subsequent firm-level earnings documented in Feldman, Govindaraj, Livnat, and Segal (2010), Li (2010), Loughran and McDonald (2011), and Price, Doran, Peterson, and Bliss (2012). However, the finding is consistent with Huang, Jiang, Tu, and Zhou (2015) which find negative negative association between sentiment and aggregate earnings growth for the aligned investor sentiment index, and Hribar and McInnis (2012) which find negative association between sentiment and analysts' earnings forecasts errors for the Baker and Wurgler's investor sentiment index.

In the second column of Table 9, we further control for lagged earnings-to-price ratio ($\mathrm{E/P}_t$) and annual earnings growth rate (EG_t), and find that the aggregate earnings growth predictability of S^{MS} remains robust when controlling for these two aggregate earnings related controls. In addition, both lagged earnings-to-price ratio ($\mathrm{E/P}_t$) and lagged annual earnings growth (EG_t) are insignificant negative predictors for $\mathrm{EG}_{t\to t+12}$, indicating weak mean-reversion in aggregate earnings growth.

For comparison, in the third to last columns, we examine the aggregate earnings growth predictably of the regression-combined manager sentiment index, S^{RC}, the conference call tone, S^{CC}, and the financial statement tone, S^{FS}. We find that all of these alternative manager sentiment measures present significant negative predictive power for $\mathrm{EG}_{t\to t+12}$, consistent with S^{MS}. Specifically, S^{RC} has a regression slope of -0.42 and an R^2 of 29.8%, which is statistically significant but smaller than the predictability of S^{MS}. Both tone measures of S^{CC} and S^{FS} generate large earnings growth predictability, with R^2s of 35.9% and 13.7%, respectively. Thus, S^{CC} contains relatively greater information content about future aggregate earnings growth than S^{FS}, which is in sharp contrast with their relative importance in forecasting aggregate market returns, again confirming their complementary roles.

In short, Table 9 shows that manager sentiment is a negative indicator for future cash flows, and high manager sentiment is negatively associated with next-year aggregate earnings growth. Our findings hence suggest that, when manager sentiment is high, the market suffers from overly optimistic belief about future aggregate cash flow (earnings) growth, which causes market overvaluation. When bad cash flows news are gradually revealed to investors, the overvaluation diminishes and stock prices fall, leading to low low future returns.

6. Manager Sentiment and Characteristic Portfolio Returns

As highlighted by Shleifer and Vishny (1997), Baker and Wurgler (2006, 2007) and Stambaugh, Yu, and Yuan (2012), firms that are hard to value tend to be more sensitive to irrational speculation from sentiment investors. Moreover, the sentiment-driven misvaluation is more likely to sustain in the presence of limits to arbitrage, when informed arbitrageurs move slowly to exploit the profit opportunities. Therefore, manager sentiment's forecasting power may also have cross-sectional effects, and may be stronger among stocks that are more speculative, difficult to value, or hard to arbitrage, similar to investor sentiment. In this section, we explore the cross-sectional variation of manager sentiment's effects on stock returns. These cross-sectional tests not only help to strengthen our previous findings for aggregate stock market predictability, but also help to enhance our understanding for the economic channels through which manager sentiment impacts asset prices.

Following Baker and Wurgler (2006, 2007), we consider 11 well-documented decile portfolios formed on single sorting on firm characteristics, including beta, idiosyncratic volatility, firm age, size, earnings-to-book equity ratio (profit), dividends-to-book equity ratio (dividend), PPE-to-total asset ratio (fixed asset), R&D-to-total asset ratio (R&D), book-to-market ratio (B/M), dividends-to-price ratio (D/P), and total asset growth (investment), which are related to subjectivity of valuation and limits to arbitrage.

- Beta, the Scholes-Williams (1977) beta for daily common stock returns over a year available from CRSP. Baker, Bradley, and Wurgler (2011) argue that high-beta stocks are more prone to speculate and are more difficult to arbitrage due to institutional frictions.

- Idiosyncratic volatility, the standard deviation of the residuals from regressing daily stock returns on market returns over a year. Barberis and Xiong (2010) and Baker, Bradley, and Wurgler (2011) suggest that high-volatility stocks are more speculative, and Wurgler and Zhuravskaya (2002) and Stambaugh, Yu, and Yuan (2015) use idiosyncratic volatility as a proxy for limits to arbitrage.
- Age, the number of years listed in Compustat. Baker and Wurgler (2006, 2007) argue that young firms are more difficult to value and are hard to arbitrage.
- Size, the price per share multiplied by the number of shares outstanding, available from Ken French's website. Small firms are difficult to arbitrage.
- Profit, earnings (defined as revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses) divided by book equity available from Ken French's website. Baker and Wurgler (2006, 2007) argue that the valuation of unprofitable firms is difficult and they have higher limits to arbitrage.
- Dividend, total dividends divided by book equity. Similar to earnings, non-dividend-paying stocks are speculative and difficult to arbitrage.
- Fixed asset, property, plant, and equipment (PPE) divided by total assets as a proxy for asset tangibility. Baker and Wurgler (2006, 2007) argue that firms with high fixed asset are hard to value and are speculative.
- R&D, research and development expense (R&D) divided by total assets. Similar to fixed assets, R&D proxies for asset intangibility, and firms with high R&D are hard to value.
- B/M, the book to market equity ratio available from Ken French's website. Baker and Wurgler (2006, 2007) argue that low B/M firms have high growth opportunities, high B/M firms are distressed, and firms in the middle are stable. Both high growth firms (low B/M) and distressed firms (high B/M) are hard to value and difficult to arbitrage.
- D/P, the total dividends to market equity ratio available from Ken French's website. Similar to B/M, low D/P firms have high growth opportunities, while high D/P firms are distressed.
- Investment, the year-to-year change in total assets divided by lagged total assets available

from Ken French's website. High-investment firms are high growth stocks, while low-investment firms are distressed.

We form value-weighted monthly decile portfolios based on the above firm characteristics. Decile 1 refers to firms in the lowest decile, decile 5 refers to firms in the middle, and decile 10 refers to firms in the highest decile. We then look for patterns in the cross-section of decile portfolios conditional on manager sentiment. We expect that, as in Baker and Wurgler (2006, 2007), manager sentiment should present stronger forecasting power for stocks that are speculative and hard to value (i.e., high beta, high volatility, young, unprofitable, non-dividend-paying, with high intangible assets, and high growth), and/or difficult to arbitrage (i.e., high beta, high volatility, young, small, unprofitable, high growth, and distressed).

[Insert Figure 2 about here]

Figure 2 reports the average monthly excess returns for two-way sorts based on the 11 firm characteristics and manager sentiment over the sample period 2003:01–2014:12. To identify the cross-sectional effects of manager sentiment on stock returns, we classify monthly returns as following periods of high or low manager sentiment relative to its median value. We then calculate average returns separately over high and low manager sentiment period and the return differences between high and low manager sentiment periods.

The results in Figure 2 strongly support our hypothesis that the effects of manager sentiment on stock prices are stronger among stocks that are speculative, hard to value, or difficult to arbitrage. Panel A shows that when sentiment is low, high beta firms earn substantially higher future returns than those with low beta; however, when sentiment is high, high beta firms earn surprisingly lower returns. These findings suggest that aggregate manager sentiment more strongly impacts high beta stocks than those low beta ones, consistent with our hypothesis and Baker and Wurgler (2006). These findings also indicate that the low beta anomaly only exists during high manager sentiment periods, when misvaluation is more likely, consistent with Stambaugh, Yu, and Yuan (2012) and Antoniou, Doukas, and Subrahmanyam (2015). In the rest of Figure 2, we obtain generally similar findings for the other firm characteristics, and find that firms with high idiosyncratic volatility, young age, small market cap, unprofitable, non-dividend-paying, distressed (high B/M, high D/P, low investment), and high growth opportunities (low D/P, high investment) tend to react more strongly to manager sentiment, with higher returns following low manager sentiment and lower returns following periods of high manager sentiment.[10]

We then employ predictive regressions to further investigate the cross-sectional effects of manager sentiment on stock returns. In Figure 2, we compute average returns for each decile portfolio of each firm characteristic during high and low sentiment periods based on a simple binary high-low manager sentiment classification. The predictive regression analysis, however, allows us to incorporate the continuous information of the manager sentiment index and to conduct formal statistical tests. We run the predictive regressions

$$R^j_{t+1} = \alpha + \beta S^{\mathrm{MS}}_t + \varepsilon^j_{t+1}, \tag{16}$$

where the dependent variable R^j_{t+1} is either the monthly excess returns or long-short return spreads (based on sensitivity to sentiment) of the 11 decile portfolios based on firm characteristics, and S^{MS} is the lagged manager sentiment index, with hypothesis testing based on wild bootstrapped p-values.

[Insert Table 10 about here]

Table 10 reports the estimation results of the predictive regressions of (16). Specifically, the left panel of Table 10 shows that all of the regression slope estimates for S^{MS} are significant and negative; thus the negative predictability of manager sentiment for subsequent stock returns is pervasive in the cross-section. More importantly, we detect large cross-sectional variation in the the regression slope estimates β. Specifically, firms with high beta, high idiosyncratic volatility, young

[10]While the direction of return predictability for asset tangibility characteristics such as fixed assets and R&D are consistent with our hypothesis in Figure 2, Table 10 shows that the patterns are statistically insignificant, similar to the results reported in Baker and Wurgler (2006).

age, small market cap, low profitability, low dividends, low fixed assets, high R&D, high distress (high B/M, high D/P, low investment), and high growth opportunities (low D/P, high investment) are generally more predictable by manager sentiment, consistent with our hypothesis and with the two-way sort results in Figure 2. In addition, the return predictability is economically large. For example, the regression coefficient in the first row and decile 10 suggests that a one-standard deviation increase in the manager sentiment index S^{MS} is associated with a -3.55% decrease in one-month-ahead expected excess return for high beta firms.

The right panel of Table 10 provides additional formal tests that investigate whether manager sentiment can forecast various long-short spread portfolios formed based on sensitivity to sentiment (10-1 for volatility, profitability and tangibility related measures; and 10-5 or 5-1 for distress and growth measures). The results again confirm our hypothesis that speculative, hard to value, or difficult to arbitrage stocks are more predictable by manager sentiment. For example, a one-standard deviation increase in the manager sentiment index S^{MS} is associated with a -2.34% decrease in the return spread between the high beta and low beta stocks (10-1), with statistical significance at the 1% level. Therefore, manager sentiment has a significantly stronger impact for high beta stocks than low beta stocks. We obtain similar findings for other characteristics including idiosyncratic volatility, age, size, profitability, and dividends as reported in the 10-1 column, and for distress (high B/M, high D/P, low investment) and high growth opportunities (low D/P, high investment) as reported in the 10-5 and 5-1 columns.

7. Conclusion

In this paper, we propose a manager sentiment index constructed based on average managerial tone of conference calls and 10-Ks and 10-Qs. We find that manager sentiment significantly predicts stock returns with higher (lower) future market returns following periods of low (low) manager sentiment. We find that its predictive power is far greater than commonly used macroeconomic variables, and it outperforms existing investor sentiment measures. We also find that manager sentiment is complimentary to investor sentiment in forecasting stock returns, implying that managers and investors have substantially different sentiment impacts to valuations. Moreover, we find that manager sentiment is a strong negative predictor of future aggregate earnings growth, implying that managers' biased belief about future cash flows at least partially plays a role in explaining the predictability of manager sentiment. Finally, we find that manager sentiment also strongly forecasts the cross-section of stock returns, particularly for stocks that are hard to value or difficult to arbitrage.

Overall, our empirical results suggest that manager sentiment has strong negative forecasting power for stock returns both at the market level and at the cross-sectional level. The predictability holds for both in-sample and out-of-sample tests, and can generate large economic value for the investor from an asset allocation perspective. While investor sentiment has been widely used to examine a variety of financial issues, the manager sentiment index, which contains complementary information to the existing sentiment measures, may also yield a number of future applications in accounting and finance.

Appendix

A.1 Detailed description of economic variables

This section describes the 15 economic variables used in Table 4, which are popular return predictors documented in the literature and are closely linked to economic fundamentals and risk. They are computed at the monthly level and are described in more detail in Goyal and Welch (2008).

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

- Inflation, INFL: calculated from the CPI (all urban consumers); following Goyal and Welch (2008), inflation is lagged for two months relative to stock market return to account for the delay in CPI release.
- Consumption-wealth ratio, CAY: residual of regressing consumption on asset wealth and labor income from Lettau and Ludvigson (2001). The data is from Professor Martin Lettau's webpage.

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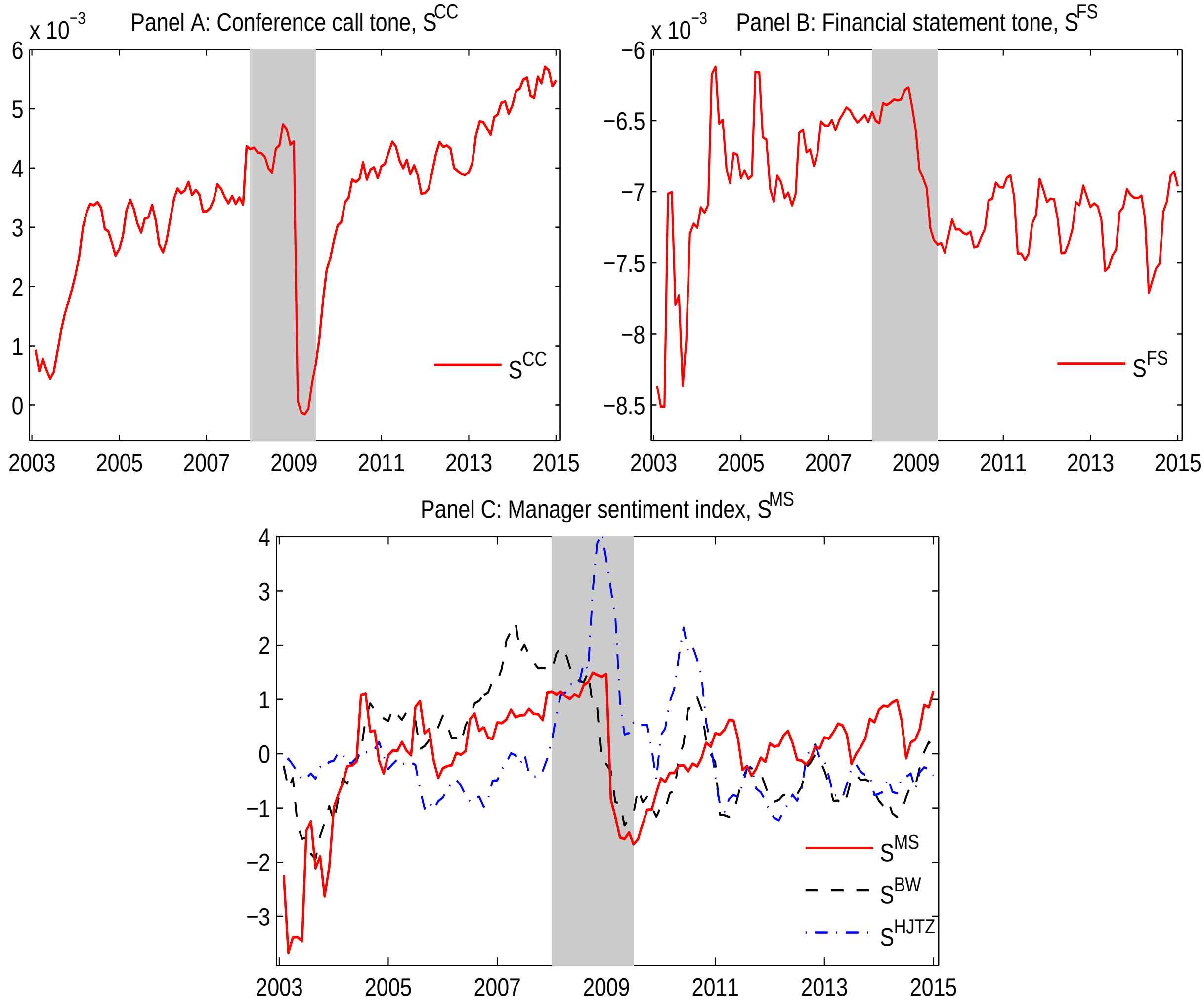

Figure 1: The manager sentiment index, 2003:01−2014:12

Panel A depicts the monthly time series of the aggregate conference call tone, S^{CC}. Panel B depicts the monthly time series of the aggregate financial statement tone using both 10-Ks and 10-Qs, S^{FS}. The solid line in Panel C depicts the manager sentiment index, S^{MS}, which is the average of S^{CC} and S^{FS}. Each individual tone measure is standardized, equally-weighted, and smoothed with a four month moving average. The dashed and dotted lines in Panel C depict the Baker and Wurgler (2006) investor sentiment index S^{BW} and the Huang, Jiang, Tu, and Zhou (2015) aligned investor sentiment index S^{HJTZ}, respectively, extracted from six stock market-based sentiment proxies. All the sentiment indexes in Panel C are standardized to have zero mean and unit variance. The vertical bars correspond to NBER-dated recessions.

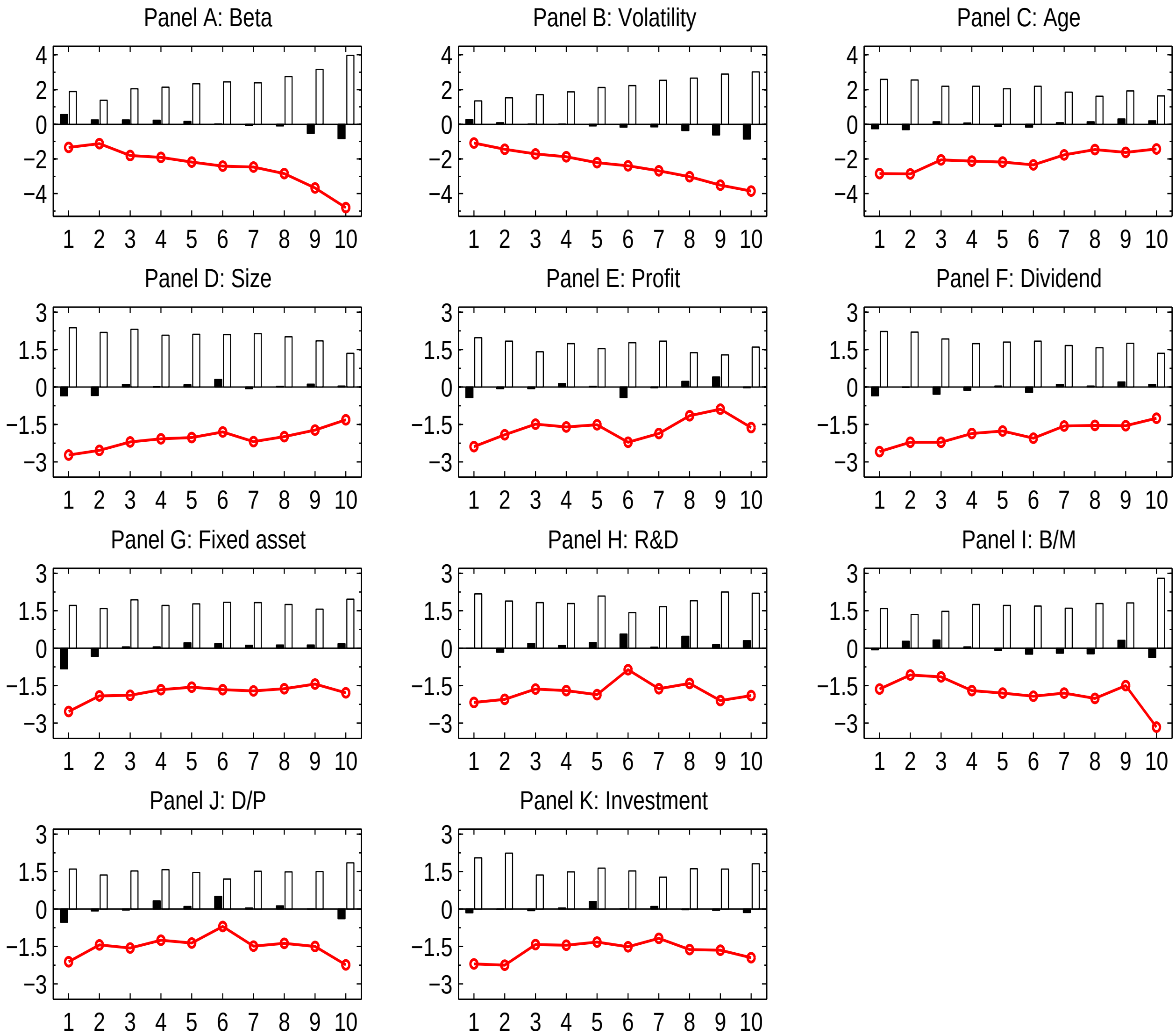

Figure 2: Two-way sorts on firm characteristics and high and low manager sentiment
Panels A to K plot the average monthly excess returns (in percentage) of 11 decile portfolios formed on single sorting based on firm characteristics following periods of high and low manager sentiment. Decile 1 refers to firms in the lowest decile, and decile 10 refers to firms in the highest decile. The firm characteristics include beta, idiosyncratic volatility, firm age, firm size, earnings-to-book equity ratio (profit), dividends-to-book equity ratio (dividend), PPE-to-total asset ratio (fixed asset), R&D-to-total asset ratio, book-to-market ratio (B/M), dividends-to-price ratio (D/P), and total asset growth (investment), which are related to the propensity to speculate or limits to arbitrage. The solid bars are returns following high sentiment periods, and the clear bars are returns following low sentiment periods, as classified based on the median level of the manager sentiment index, S^{MS}. The solid lines are the return differences across high and low manager sentiment periods. The sample period is 2003:01−2014:12.

Table 1: Sentiment indexes correlations

	S^{MS}	S^{RC}	S^{CC}	S^{FS}	S^{BW}	S^{HJTZ}	S^{MCS}	S^{CBC}	S^{FEARS}
S^{MS}	1.00								
S^{RC}	0.98	1.00							
S^{CC}	0.78	0.63	1.00						
S^{FS}	0.78	0.89	0.21	1.00					
S^{BW}	0.53	0.58	0.20	0.61	1.00				
S^{HJTZ}	0.13	0.17	-0.07	0.24	0.32	1.00			
S^{MCS}	-0.06	-0.05	-0.08	-0.02	0.12	-0.48	1.00		
S^{CBC}	0.21	0.22	0.10	0.22	0.43	-0.50	0.87	1.00	
S^{FEARS}	-0.24	-0.23	-0.17	-0.19	-0.14	-0.28	0.04	0.01	1.00

This table provides the correlations for various measures of sentiment, including the manager sentiment index, S^{MS}, the regression-combined manager sentiment index, S^{RC}, the conference call tone, S^{CC}, the financial statement tone, S^{FS}, the Baker and Wurgler (2006) investor sentiment index, S^{BW}, the Huang, Jiang, Tu, and Zhou (2015) aligned investor sentiment index, S^{HJTZ}, the University of Michigan consumer sentiment index, S^{MCS}, the Conference Board consumer confidence index, S^{CBC}, and the Da, Engelberg, and Gao (2015) Financial and Economic Attitudes Revealed by Search (FEARS) investor sentiment index, S^{FEARS}. The sample period is 2003:01−2014:12 (2004:07−2011:12 for S^{FEARS} due to data constraints).

Table 2: Manager sentiment and aggregate market return

	α (%)	t-stat	β (%)	t-stat	R^2 (%)	R^2_{rec}	R^2_{exp}	R^2_{high}	R^2_{low}
Panel A: Manager sentiment index									
S^{MS}	0.76	2.39	-1.26	-3.57	9.75	21.4	0.74	12.9	6.93
Panel B: Regression-combined manager sentiment index									
S^{RC}	0.76	2.40	-1.28	-3.67	10.3	22.2	0.89	15.1	5.77
Panel C: Individual tone measures									
Equally-weighted tone									
S^{CC}	0.76	2.32	-0.81	-2.13	4.05	9.43	-0.09	0.87	6.84
S^{FS}	0.76	2.37	-1.15	-3.25	8.10	16.70	1.47	15.10	1.96
Value-weighted tone									
S^{CCv}	0.76	2.31	-0.76	-1.89	3.57	8.30	-0.06	0.75	6.04
S^{FSv}	0.76	2.34	-0.95	-3.13	5.52	9.75	2.27	7.33	3.94

This table provides the in-sample estimation results for the predictive regressions of excess market return on lagged manager sentiment,

$$R^m_{t+1} = \alpha + \beta S^k_t + \varepsilon_{t+1},$$

where R^m_{t+1} denotes the monthly excess aggregate stock market return (in percentage) and S^k_t denotes each lagged manager sentiment predictor. Panel A presents results using the manager sentiment index, S^{MS}, which is the equally-weighted average of standardized conference call tone and financial statement tone. Panel B presents results using the regression-combined manager sentiment index, S^{RC}, with the weights on the tone measures S^{CC} and S^{FS} optimally estimated using a regression approach. Panel C reports the results of four individual tone measures separately, including the equally-weighted conference call tone, S^{CC}, the equally-weighted financial statement tone, S^{FS}, and the corresponding value-weighted conference call tone, S^{CCv}, and the value-weighted financial statement tone, S^{FSv}. All the manager sentiment indexes and individual tone measures are standardized to have zero mean and unit variance. The regression coefficients, Newey-West t-statistics, and R^2 are reported. R^2_{rec} (R^2_{exp}) statistics are calculated over NBER-dated business-cycle recessions (expansions), and R^2_{high} (R^2_{low}) are calculated over high (low) sentiment periods, respectively. A month is classified as high (low) sentiment if the manager sentiment index in the previous month is above (below) the median value for the entire time series. The sample period is 2003:01−2014:12.

Table 3: Manager sentiment and long-horizon predictability

	Forecasting horizon (h-month)						
	1	3	6	9	12	24	36
Panel A: Manager sentiment index, S^{MS}							
β (%)	-1.26	-3.85	-6.03	-7.73	-8.58	-11.6	-12.4
t-stat	-3.57	-4.11	-3.21	-2.97	-2.54	-2.11	-2.50
R^2 (%)	9.75	24.9	25.8	27.1	25.4	20.4	16.2
Panel B: Regression-combined manager sentiment index, S^{RC}							
β (%)	-1.28	-3.82	-6.01	-7.84	-8.77	-11.7	-12.6
t-stat	-3.67	-4.08	-3.18	-2.98	-2.55	-2.08	-2.48
R^2 (%)	10.3	24.6	25.8	28.3	27.1	21.4	17.4

This table reports the h-month ahead long-horizon forecasting results for excess market returns on lagged manager sentiment,

$$R^m_{t\to t+h} = \alpha + \beta S^k_t + \varepsilon_{t\to t+h}, \qquad k = \mathrm{MS},\ \mathrm{RC},$$

where $R^m_{t\to t+h}$ is the h-month ahead excess market return from month t to $t+h$ (in percentage), S^{MS} in Panel A is the manager sentiment index, and S^{RC} in Panel B is the regression-combined manager sentiment index. All the manager sentiment indexes are standardized to have zero mean and unit variance. The regression coefficients, Newey-West t-statistics, and R^2 are reported. The sample period is 2003:01−2014:12.

Table 4: Comparison with economic variables

	Panel A: Univariate regressions $R^m_{t+1} = \alpha + \psi Z^k_t + \varepsilon_{t+1}$			Panel B: Bivariate regressions $R^m_{t+1} = \alpha + \beta S^{\mathrm{MS}}_t + \psi Z^k_t + \varepsilon_{t+1}$				
	ψ (%)	t-stat	R^2 (%)	β (%)	t-stat	ψ (%)	t-stat	R^2 (%)
DP	0.11	0.20	0.08	-1.26	-3.58	0.11	0.23	9.83
DY	0.31	0.63	0.61	-1.24	-3.54	0.25	0.56	10.1
EP	-0.22	-0.48	0.30	-1.42	-3.39	0.38	0.77	10.5
DE	0.21	0.42	0.26	-1.34	-3.37	-0.25	-0.49	10.1
SVAR	-0.96	-2.05	5.72	-1.18	-3.45	-0.85	-1.89	14.2
BM	0.20	0.49	0.25	-1.33	-3.52	0.43	1.04	10.9
NTIS	0.84	1.76	4.33	-1.10	-3.16	0.45	0.97	10.9
TBL	-0.41	-1.63	1.04	-1.22	-3.40	-0.15	-0.59	9.88
LTY	-0.54	-1.99	1.79	-1.37	-3.85	-0.75	-2.75	13.1
LTR	0.31	0.69	0.58	-1.29	-3.60	0.42	0.96	10.8
TMS	0.16	0.63	0.16	-1.39	-3.52	-0.36	-1.27	10.4
DFY	-0.26	-0.46	0.43	-1.31	-3.68	-0.44	-0.86	10.9
DFR	0.57	0.91	2.02	-1.19	-3.46	0.36	0.62	10.5
INFL	0.45	1.08	1.27	-1.26	-3.66	0.45	1.19	11.0
CAY	-0.12	-0.16	0.10	-1.95	-3.88	-1.18	-2.48	15.3
ECON	0.13	0.31	0.12	-1.30	-3.64	0.30	0.69	10.4

Panel A reports the in-sample estimation results for the univariate predictive regressions of monthly excess market return on one of the lagged economic variables, Z^k_t,

$$R^m_{t+1} = \alpha + \psi Z^k_t + \varepsilon_{t+1}, \qquad k = 1, ..., 16,$$

where R^m_{t+1} is the monthly excess aggregate stock market return (in percentage), and Z^k_t is one of the 15 individual economic variables given in the the first 15 rows of the first column or the ECON factor which is the first principal component factor extracted from the 15 individual economic variables. Panel B reports the in-sample estimation results for the bivariate predictive regressions on both the lagged manager sentiment index S^{MS}_t and Z^k_t,

$$R^m_{t+1} = \alpha + \beta S^{\mathrm{MS}}_t + \psi Z^k_t + \varepsilon_{t+1}, \qquad k = 1, ..., 16.$$

We report the regression coefficients, Newey-West t-statistics, and the R^2. A detailed description of the economic variables is provided in the Appendix. The sample period is 2003:01−2014:12.

Table 5: Comparison with alternative sentiment indexes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
S^{MS}	-1.26		-1.08		-1.16		-1.25		-1.27		-1.71	-1.59
	[-3.57]		[-2.79]		[-3.48]		[-3.53]		[-3.44]		[-3.29]	[-2.64]
S^{BW}		-0.91	-0.34									1.72
		[-2.96]	[-1.08]									[1.76]
S^{HJTZ}				-1.17	-1.06							-2.05
				[-2.24]	[-2.13]							[-2.18]
S^{MCS}						0.22	0.15					2.07
						[0.55]	[0.38]					[1.82]
S^{CBC}								-0.21	0.05			-3.39
								[-0.51]	[0.14]			[-2.18]
S^{FEARS}										0.75	0.35	-0.12
										[1.96]	[0.97]	[-0.30]
R^2 (%)	9.75	5.11	10.3	8.45	16.7	0.31	9.88	0.26	9.76	2.71	15.9	27.6

This table reports the estimation results for the predictive regressions of monthly excess market return (R^m_{t+1}, in percentage) on the lagged manager sentiment index, S^{MS}, with controls for alternative sentiment indexes in the literature, S^{k}_t,

$$R^m_{t+1} = \alpha + \beta S^{\mathrm{MS}}_t + \delta S^k_t + \varepsilon_{t+1}.$$

In the first 11 columns, we run either univariate or bivariate predictive regressions on S^{MS} and on one of the five alternative sentiment indexes, including the Baker and Wurgler (2006)investor sentiment index based on six sentiment proxies from stock market (S^{BW}), the Huang, Jiang, Tu, and Zhou (2015) aligned investor sentiment index based on six market-based sentiment proxies (S^{HJTZ}), the University of Michigan consumer sentiment index based on household surveys (S^{MCS}), the Conference Board consumer confidence index based on household surveys (S^{CBC}), and the Da, Engelberg, and Gao (2015) Financial and Economic Attitudes Revealed by Search (FEARS) investor sentiment index based on daily Internet search volume from households (S^{FEARS}, over the sample period 2004:07−2011:12). In the last column, we run a kitchen-sink regression that includes all sentiment indexes in one long regression. The regression coefficients, Newey-West t-statistics, and R^2s are reported. The sample period is 2003:01−2014:12.

Table 6: Forecast encompassing tests

	S^{MS}	S^{CC}	S^{FS}	S^{BW}	S^{HJTZ}	S^{MCS}	S^{CBC}	S^{FEARS}
S^{MS}		0.68	0.28	0.26	0.04	0.47	0.51	0.39
S^{CC}	0.00		0.02	0.02	0.04	0.46	0.47	0.35
S^{FS}	0.08	0.18		0.30	0.03	0.45	0.51	0.27
S^{BW}	0.00	0.06	0.04		0.05	0.40	0.55	0.13
S^{HJTZ}	0.02	0.16	0.04	0.16		0.55	0.40	0.36
S^{MCS}	0.00	0.04	0.00	0.00	0.03		0.32	0.02
S^{CBC}	0.00	0.02	0.00	0.00	0.03	0.30		0.02
S^{FEARS}	0.00	0.03	0.03	0.07	0.05	0.40	0.47	

This table reports p-values for the Harvey, Leybourne, and Newbold (1998) statistic for various sentiment indexes. The statistic corresponds to a one-sided (upper-tail) test of the null hypothesis that the predictive regression forecast for the monthly excess market return 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 are the manager sentiment index, S^{MS}, the conference call tone, S^{CC}, the financial statement tone, S^{FS}, the Baker and Wurgler (2006) investor sentiment index, S^{BW}, the Huang, Jiang, Tu, and Zhou (2015) aligned investor sentiment index, S^{HJTZ}, the University of Michigan consumer sentiment index, S^{MCS}, the Conference Board consumer confidence index, S^{CBC}, and the Da, Engelberg, and Gao (2015) Financial and Economic Attitudes Revealed by Search (FEARS) investor sentiment index, S^{FEARS}. The sample period is 2003:01−2014:12 (2004:07−2011:12 for S^{FEARS} due to data constraints).

Table 7: Out-of-sample forecasting results

	R^2_{OS} (%)	MSFE-*adj*	$R^2_{OS,\mathrm{rec}}$ (%)	$R^2_{OS,\mathrm{exp}}$ (%)
Panel A: Manager sentiment measures				
S^{MS}	8.38***	2.55	18.8	-1.20
S^{RC}	5.70**	1.68	14.7	-5.97
S^{C}	7.94**	2.07	12.8	-7.27
S^{CC}	1.77*	1.52	19.0	1.83
S^{FS}	6.85***	2.44	15.1	-4.50
Panel B: Alternative sentiment measures				
S^{BW}	4.54***	2.56	5.60	3.57
S^{HJTZ}	3.14**	1.66	9.38	-1.91
S^{MCS}	-4.85	-0.09	-2.02	-7.45
S^{CBC}	-3.00	-0.71	-5.02	-1.14
S^{FEARS}	-0.53	1.82	1.12	-4.35

This table reports the out-of-sample performances of various sentiment measures in predicting the monthly excess market return. Panel A provides the results using the manager sentiment index, S^{MS}, the regression-combined manager sentiment index, S^{RC}, the combination forecast of manager sentiment proxies, S^{C}, and the two individual manager sentiment proxies of conference call tone, S^{CC}, and financial statement tone, S^{FS}. Panel B provides results using the Baker and Wurgler (2006) investor sentiment index, S^{BW}, the Huang, Jiang, Tu, and Zhou (2015) aligned investor sentiment index, S^{HJTZ}, the University of Michigan consumer sentiment index, S^{MCS}, the Conference Board consumer confidence index, S^{CBC}, and the Da, Engelberg, and Gao (2015) FEARS investor sentiment index, S^{FEARS}. All of the out-of-sample forecasts are estimated recursively using data available at the forecast formation time t. R^2_{OS} is the Campbell and Thompson (2008) out-of-sample R^2 measuring the reduction in mean squared forecast error (MSFE) for the competing predictive regression forecast relative to the historical average benchmark forecast. MSFE-*adj* is the Clark and West (2007) MSFE-adjusted 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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. $R^2_{OS,\mathrm{rec}}$ ($R^2_{OS,\mathrm{exp}}$) statistics are calculated over NBER-dated business-cycle recessions (expansions). The out-of-sample evaluation period is 2007:01–2014:12 (2007:01–2011:12 for S^{FEARS} due to data constraint).

Table 8: Asset allocation results

	No transaction cost		50pbs transaction cost	
Predictor	CER gain (%)	Sharpe ratio	CER gain (%)	Sharpe ratio
Panel A: Manager sentiment measures				
S^{MS}	7.92	0.17	7.86	0.17
S^{RC}	6.64	0.13	6.56	0.13
S^{C}	8.11	0.16	8.06	0.16
S^{CC}	6.73	0.13	6.71	0.13
S^{FS}	10.6	0.22	10.5	0.22
Panel B: Alternative sentiment measures				
S^{BW}	9.06	0.19	8.97	0.19
S^{HJTZ}	8.79	0.18	8.73	0.17
S^{MCS}	4.17	0.03	4.15	0.03
S^{CBC}	0.62	-0.03	0.59	-0.03
S^{FEARS}	5.80	0.01	5.61	-0.01

This table reports the portfolio performance measures for a mean-variance investor with a risk aversion coefficient of five who allocates monthly between equities and risk-free bills using the out-of-sample predictive regression forecast of the excess market return based on various sentiment measures. Panel A provides the results using the manager sentiment index, S^{MS}, the regression-combined manager sentiment index, S^{RC}, the combination forecast of manager sentiment proxies, S^{C}, and the two individual manager sentiment proxies of conference call tone, S^{CC}, and financial statement tone, S^{FS}. Panel B provides results using the Baker and Wurgler (2006) investor sentiment index, S^{BW}, the Huang, Jiang, Tu, and Zhou (2015) aligned investor sentiment index, S^{HJTZ}, the University of Michigan consumer sentiment index, S^{MCS}, the Conference Board consumer confidence index, S^{CBC}, and the Da, Engelberg, and Gao (2015) FEARS investor sentiment index, S^{FEARS}. CER gain is the annualized certainty equivalent return gain for the investor. The monthly Sharpe ratio 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 portfolio weights are estimated recursively using data available at the forecast formation time t. The out-of-sample evaluation period is 2007:01–2014:12 (2007:01–2011:12 for S^{FEARS} due to data constraints).

Table 9: Manager sentiment and aggregate earnings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
S_t^{MS}	-0.46	-0.41						
	[-2.26]	[-1.92]						
S_t^{RC}			-0.42	-0.38				
			[-2.22]	[-1.86]				
S_t^{CC}					-0.46	-0.42		
					[-2.95]	[-1.95]		
S_t^{FS}							-0.28	-0.30
							[-2.09]	[-1.80]
$\mathrm{E/P}_t$		-0.11		-0.16		-0.04		-0.29
		[-0.60]		[-1.03]		[-0.19]		[-2.20]
EG_t		-0.12		-0.12		-0.04		-0.09
		[-0.97]		[-0.96]		[-0.32]		[-0.78]
R^2 (%)	35.6	42.6	29.8	40.9	35.9	37.6	13.7	35.2

This table reports the estimation results for the predictive regressions of annual aggregate earnings growth ($\mathrm{EG}_{\mathrm{t}\rightarrow\mathrm{t}+12}$) on the lagged manager sentiment index, S^{MS}, with controls for lagged earnings-to-price ratio ($\mathrm{E/P}_t$) and lagged annual aggregate earnings growth (EG_t),

$$\mathrm{EG}_{t\rightarrow t+12} = \alpha + \beta S_t^{\mathrm{MS}} + \psi \mathrm{E/P}_t + \delta \mathrm{EG}_t + \upsilon_{t\rightarrow t+12},$$

where $\mathrm{EG}_{t\rightarrow t+12}$ is the annual growth rate of twelve-month moving sums of aggregate earnings on the S&P 500 index. For comparison, we also report estimation results for the regression-combined manager sentiment index, S^{RC}, the conference call tone, S^{CC}, and the financial statement tone, S^{FS}. The regression coefficients, Newey-West t-statistics, and R^2 are reported. The sample period is 2003:01−2014:12.

Table 10: Manager sentiment and characteristic portfolio returns

		Deciles										Comparisons		
		1	2	3	4	5	6	7	8	9	10	10−1	10−5	5−1
Beta	β (%)	-1.21	-1.08	-1.60	-1.65	-1.71	-1.87	-1.88	-2.18	-2.61	-3.55	-2.34	-1.84	-0.51
	t-stat	[-4.67]	[-4.00]	[-4.19]	[-3.78]	[-3.28]	[-3.36]	[-3.17]	[-3.16]	[-3.23]	[-3.60]	[-2.84]	[-3.15]	[-1.21]
Volatility	β (%)	-1.04	-1.24	-1.40	-1.57	-1.85	-1.96	-2.28	-2.59	-3.07	-3.37	-2.33	-1.52	-0.81
	t-stat	[-2.99]	[-2.93]	[-2.88]	[-2.82]	[-3.18]	[-3.38]	[-3.81]	[-4.26]	[-5.28]	[-4.77]	[-5.10]	[-5.06]	[-2.79]
Age	β (%)	-2.13	-2.31	-1.68	-1.80	-1.70	-1.81	-1.47	-1.26	-1.51	-1.19	0.94	0.51	0.43
	t-stat	[-3.17]	[-3.23]	[-3.76]	[-3.30]	[-3.08]	[-3.08]	[-3.02]	[-2.79]	[-3.73]	[-2.84]	[3.37]	[3.00]	[2.61]
Size	β (%)	-2.40	-2.07	-1.76	-1.68	-1.71	-1.46	-1.67	-1.55	-1.43	-1.18	1.22	0.53	0.69
	t-stat	[-4.94]	[-4.33]	[-3.72]	[-3.84]	[-3.40]	[-3.29]	[-3.31]	[-3.05]	[-2.68]	[-2.94]	[5.47]	[3.00]	[4.34]
Profit	β (%)	-2.18	-1.63	-1.31	-1.40	-1.39	-1.60	-1.54	-0.94	-0.95	-1.26	0.92	0.13	0.79
	t-stat	[-3.48]	[-2.97]	[-2.74]	[-3.10]	[-3.59]	[-2.81]	[-2.81]	[-2.80]	[-2.90]	[-2.68]	[3.67]	[0.68]	[2.83]
Dividend	β (%)	-2.10	-1.86	-1.51	-1.47	-1.40	-1.48	-1.38	-1.30	-1.37	-1.17	0.92	0.22	0.70
	t-stat	[-3.45]	[-3.60]	[-2.87]	[-3.34]	[-2.99]	[-2.50]	[-2.61]	[-3.04]	[-3.24]	[-2.59]	[4.36]	[1.77]	[4.03]
Fixed asset	β (%)	-1.97	-1.69	-1.65	-1.55	-1.57	-1.47	-1.31	-1.35	-1.19	-1.37	0.60	0.20	0.40
	t-stat	[-2.76]	[-2.88]	[-3.63]	[-3.39]	[-3.16]	[-3.47]	[-3.14]	[-2.81]	[-2.66]	[-2.60]	[1.58]	[0.90]	[1.18]
R&D	β (%)	-1.54	-1.48	-1.34	-1.37	-1.62	-1.14	-1.37	-1.61	-2.10	-2.17	-0.63	-0.55	-0.09
	t-stat	[-3.21]	[-2.88]	[-2.78]	[-2.51]	[-2.88]	[-3.33]	[-3.52]	[-4.31]	[-4.74]	[-4.40]	[-1.23]	[-0.91]	[-0.42]
B/M	β (%)	-1.29	-1.17	-1.10	-1.45	-1.43	-1.52	-1.42	-1.66	-1.37	-2.32	-1.03	-0.88	-0.14
	t-stat	[-2.71]	[-3.24]	[-3.51]	[-2.75]	[-3.29]	[-2.86]	[-3.07]	[-2.59]	[-2.85]	[-2.75]	[-2.10]	[-1.84]	[-0.78]
D/P	β (%)	-1.53	-1.35	-1.30	-0.99	-1.19	-0.84	-1.25	-1.22	-1.22	-2.03	-0.51	-0.85	0.34
	t-stat	[-2.64]	[-2.87]	[-2.78]	[-2.63]	[-2.19]	[-3.44]	[-2.21]	[-3.06]	[-3.03]	[-2.54]	[-1.17]	[-2.19]	[2.41]
Investment	β (%)	-1.85	-1.76	-1.25	-1.06	-1.21	-1.27	-1.16	-1.41	-1.39	-1.53	0.32	-0.31	0.64
	t-stat	[-3.47]	[-3.35]	[-3.83]	[-2.51]	[-2.56]	[-3.19]	[-3.23]	[-2.79]	[-2.72]	[-2.86]	[2.35]	[-1.89]	[4.45]

This table reports the regression coefficients (in percentages) and Newey-West t-statistics (in brackets) for the predictive regressions of monthly excess returns of 11 characteristics-based decile portfolios on lagged manager sentiment index (S^{MS}) over the sample period 2003:01−2014:12,

$$R^j_{t+1} = \alpha + \beta S^{\mathrm{MS}}_t + \varepsilon^j_{t+1},$$

where the decile portfolio returns R^j_{t+1} are formed based on firm characteristics such as beta, idiosyncratic volatility, firm age, firm size, earnings-to-book equity ratio (profit), dividends-to-book equity ratio (dividend), PPE-to-total asset ratio (fixed asset), R&D-to-total asset ratio, book-to-market ratio (B/M), dividends-to-price ratio (D/P), and total asset growth (investment). The long-short portfolio returns 10−1,10−5 and 5−1 are computed as the return differences between deciles 10 and 1, deciles 10 and 5, and deciles 5 and 1, respectively. Decile 1 refers to firms in the lowest decile, decile 5 refers to firms in the middle, and decile 10 refers to firms in the highest decile.