Manager Sentiment and Stock Returns

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Current Version: March 2017

*We are grateful to John Doukas, Weiping Li, Tim Loughran, Xingguo Luo, David Rapach, Nick Seybert, Jun Tu, Jianfeng Yu, Bohui Zhang, Hao Zhou, seminar participants at Beijing University, Central University of Finance and Economics, Renmin University, Saint Louis University, Tsinghua University, Wuhan University, Xiamen University, Zhejiang University, and conference participants at the 2016 Asian Financial Association Meetings, 2016 China International Conference in Finance, 2016 Conference on Financial Predictability and Data Science, 2016 Financial Management Association Meetings, and 216 Wealth and Asset Management Research Conference at Washington University in St. Louis for very helpful comments. Send correspondence to Guofu Zhou, Olin School of Business, Washington University in St. Louis, St. Louis, MO 63130; e-mail: zhou@wustl.edu; phone: 314-935-6384.

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Abstract

This paper constructs a manager sentiment index based on the aggregated textual tone of corporate financial disclosures. 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 economically comparable and is informationally complementary to existing measures of investor sentiment. Higher manager sentiment precedes greater corporate investment, lower aggregate earnings, and worse macroeconomic conditions. Moreover, manager sentiment negatively predicts cross-sectional stock returns, particularly for firms that are costly to arbitrage.

JEL classifications: C53, G11, G12, G17

Keywords: Manager Sentiment, Textual Tone, Investor Sentiment, Asset Pricing, Return Predictability

1. Introduction

Many studies in behavioral finance suggest that speculative market sentiment can lead prices to diverge from their fundamental values (e.g., De Long, Shleifer, Summers, and Waldmann 1990; Shefrin, 2008). Empirically, Baker and Wurgler (2006) develop an influential measure of investor sentiment by aggregating information from six stock market-based proxies that has been widely used to explain asset prices.[1] However, there is little research on corporate managers' sentiment. This is somewhat surprising given managers' information advantage about their companies over outside investors. At the same time, like investors, corporate managers are not immune from behavioral biases. As a result, they can be overly optimistic or pessimistic beyond fundamentals, leading to irrational market outcomes (e.g., Malmendier and Tate 2005; Baker and Wurgler 2012; Greenwood and Shleifer 2014).

In this paper, we investigate the asset pricing implications of manager sentiment, focusing on the predictive ability of the aggregated textual tone in firm financial statements and conference calls on future U.S. stock market returns. Intuitively, investors may simply follow managers' tone in financial disclosures, even though their tone may not exactly represent the underlying fundamentals of the firm. Hence, high (low) manager sentiment may drive high (low) investor sentiment, leading to speculative market overvaluation (undervaluation) if overly optimistic (pessimistic) tone is not justified by firms' fundamentals. When the true fundamentals are revealed to the investors gradually, the misvaluation diminishes and the stock price reverses, yielding low (high) future stock returns (Baker and Wurgler 2007). However, it is an open empirical question whether or not such hypothesized effects are significant in the stock market.

We construct a manager sentiment index based on the aggregated textual tone in firm financial statements and conference calls, since qualitative description of the firm's business and financial performance at least partially reflects managers' subjective opinions and beliefs about why their

[1] The latest Google article citations of Baker and Wurgler (2006) exceed 2,500, and the six proxies are the close-end fund discount rate, share turnover, number of IPOs, first-day returns of IPOs, dividend premium, and equity share in new issues.

firms performed as they did over the recent fiscal period and their expectations for future firm performance (Li 2008, 2010; Henry, 2008; Blau, DeLisle, and Price 2015; Brochet, Kolev, and Lerman 2015). Using the standard dictionary method and the Loughran and McDonald (2011) financial and accounting dictionaries, we measure textual tone as the difference between the number of positive and negative words in the disclosure scaled by the total word count of the disclosure, similar to Tetlock (2007), Feldman, Govindaraj, Livnat, and Segal (2010), Loughran and McDonald (2011), Price, Doran, Peterson, and Bliss (2012), and García (2013), among others. However, our study has two major differences from these existing studies. First, while these studies focus on firm-level measures for predicting firm-level outcome variables, we provide an aggregate index to gauge the overall manager sentiment in the market and investigate its impact on both aggregate and cross-sectional stock returns.[2] Second, while other studies use firm disclsoures at the quarterly or annual frequency, we compute a monthly index from both voluntary and mandatory firm disclosures filed within each month. Using a monthly frequency allows us to compare our index with other investor sentiment indexes and with other macroeconomic predictors that are commonly used for forecasting stock returns on a monthly basis.

We find that this new textual tone-based manager sentiment index significantly and negatively predicts future aggregate stock market returns, consistent with behavioral-theoretical predictions. We employ the standard predictive regressions by regressing excess market returns on the lagged manager sentiment index based on data available from January 2003 to December 2014. The manager sentiment index 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 the expected excess market return for the next month. In addition, the predictive power of manager sentiment continues to be robust out-of-sample, generating a large positive out-of-sample R^2_{OS} of 8.38% over the evaluation period from January 2007 to December 2014. Hence, corporate managers as a whole tend to be overly optimistic when the economy and the market peak, and the manager sentiment index is a

[2]One exception is Bochkay and Dimitrov (2015) who also develop a manager sentiment index. However, their index does not use conference calls, and their study focuses on showing their index is a truly sentiment measure while we focus on the predictive power of manager sentiment for future market returns.

contrarian return predictor.

We examine the economic value of stock market forecasts based on manager sentiment. Following Kandel and Stambaugh (1996) and Campbell and Thompson (2008), we compute the certainty equivalent return (CER) gain and Sharpe Ratio for a mean-variance investor who optimally allocates his wealth across equities and the risk-free asset using the out-of-sample predictive regression forecasts. We find that the manager sentiment index generates large economic gains for the investor with an annualized CER gain of 7.92%. The CER gain remains economically large, 7.86%, after accounting for transaction costs. 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 compare the return predictability of manager sentiment to various 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 find that the predictive power of manager sentiment is greater than that of these other macroeconomic predictors, and remains largely unchanged after controlling for them. In particular, the average in-sample R^2 of the macroeconomic predictors is only 1.18% over the same time period (with a max of 5.72% for the SVAR, stock return variance), which is much smaller than the in-sample R^2 of 9.75% of the manager sentiment index. We also find that most macroeconomic variables fail to generate significant out-of-sample forecasts, with an average out-of-sample R^2_{OS} of -3.14% (with a max of 1.74% for the NTIS, net equity expansion), consistent with the literature. This compares poorly with the 8.38% of the index. Hence, manager sentiment provides strong and significant incremental predictive power beyond other macroeconomic variables.

We then compare the manager sentiment index with five existing measures of investor sentiment 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 Wurgler's 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) sentiment index based on daily Internet search volume available from Google Trend. We document four interesting observations. First, we find that the manager sentiment index correlates positively with existing investor sentiment measures. The largest correlation is with the Baker and Wurgler (2006) investor sentiment index at about 0.5. The other correlations are smaller, ranging from 0.1 to 0.2.

Second, there is no significant lead-lag relationship between the manager sentiment index and the existing investor sentiment indexes in the sense of Granger causality, after accounting for the autocorrelation for each sentiment measure. Third, the predictive power of manager sentiment is economically comparable with existing sentiment measures. In particular, we find that 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 the in- and out-of-sample R^2s of the manager sentiment index. Fourth, the forecasting power of the manager sentiment index remains significant after controlling for the five existing investor sentiment measures. For example, when using the manager sentiment index together with existing investor sentiment measures jointly as predictors, the in-sample R^2 is equal to 16.7%, which is almost equal to the sum of two individual R^2s. The econometric forecast encompassing tests confirm that manager sentiment is not a sideshow of existing investor sentiment measures. In summary, while manager sentiment is positively associated with investor sentiment, it contains unique and incremental information about market sentiment beyond existing investor sentiment measures.

We also explore the relationship between manager sentiment and subsequent aggregate earnings growth and macroeconomic growth to explore the cash flow predictability channel. We find that the manager sentiment index, similar to existing investor sentiment indexes, negatively forecasts future aggregate earnings growth and macroeconomic growth (decreases in the Chicago Federal Reverse National Activity Index, CFNAI). This negative manager sentiment-cash flow relationship suggests that the manager sentiment index reflects biased expectations for future cash flows and is unlikely a proxy for fundamental information. In addition, the negative return predictability of manager sentiment is likely to be driven by overly optimistic (pessimistic) forecasts of future cash flows not justified by fundamentals.

We next examine the relationship between manager sentiment and aggregate investment growth to identify a potential source for the negative predictability. We find that periods with high (low) manager sentiment are accompanied by high (low) contemporaneous aggregate investment growth, and the aggregate investment growth rate remains high (low) over the subsequent year then reverses to the mean in two years when the lower (higher) than expected returns to investments are gradually revealed. This finding suggests that managerial investment decisions are influenced by manager sentiment. As a group, managers with overly optimistic (pessimistic) tone tend to overinvest (underinvest) because they overestimate (underestimate) the future cash flows from investments. Our results also suggest that manager sentiment is different from investor sentiment in its stronger influence on firm investments.

We next find that manager sentiment 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, low profitability, no dividends, low fixed assets, high R&D, high distress, and high growth opportunities. These results, consistent with Baker and Wurgler (2006, 2007), suggest that stocks that are speculative and difficult to arbitrage are more sensitive to sentiment-driven mispricing. Moreover, limits to arbitrage is a likely reason for the persistence of the return predictability of the manager sentiment index.

Our paper contributes to the literature on investor sentiment and its role in asset pricing. Baker and Wurgler (2006, 2007, 2011, 2012), Yu and Yuan (2011), Baker, Wurgler, and Yuan (2012), Stambaugh, Yu, and Yuan (2012), Huang, Jiang, Tu, and Zhou (2015), and many others provide strong evidence of return predictability with stock market-based investor sentiment measures. 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 management earnings guidance contributes to the return predictability of investor sentiment. Brown, Christensen, Elliott, and Mergenthaler (2012) find 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' earnings forecasts are relatively more optimistic for uncertain or difficult-to-value firms. Arif and Lee (2014) propose an investment-based sentiment measure. Bochkay and Dimitrov (2015) find that managers' qualitative disclosures tend to be more optimistic under high investor sentiment. In contrast, our paper proposes a new financial disclosure tone-based manager sentiment measure that contains unique and incremental sentiment information beyond existing investor sentiment measures and has greater predictive power than any other measure.

Our paper is related to the literature on the contents and effects of textual corporate disclosures. For example, Henry (2008) provides an early study of manager sentiment using earnings press releases for a sample of firms in the telecommunications and computer industry. Price, Doran, Peterson, and Bliss (2012) use the Henry (2008) word lists to gauge managerial sentiment during quarterly earnings conference calls for public firms. The closest paper to ours is Loughran and McDonald (2011), who create a comprehensive list of sentiment words used in business context. They examine their dictionary's applications for a large sample of 10-Ks from 1994 to 2008 and find, in the cross-section, that firms with high (low) textual-based manager sentiment tend to have higher (lower) stock returns (see Loughran and McDonald (2016) for a recent literature review). In contrast, we provide evidence that aggregate manager sentiment negatively forecasts the time series of future stock returns. Our findings indicate that the positive (negative) information in high (low) firm-level manager sentiment is primarily firm-specific and idiosyncratic, which is diversified away when averaging together, while aggregate manager sentiment mainly reflects systematic sentiment driven by managers' overly optimistic or pessimistic cash flow expectations. We also find that incorporating positive words helps predict stock returns in the aggregate time series, whereas Loughran and McDonald (2011) find only negative word counts have predictive power in the cross-section. In addition, we are the first to show that the effect of manager sentiment is particularly important for firms that are speculative and difficult to arbitrage.

Our paper is also related to research on the relation between aggregate financial disclosures and stock market returns. Penman (1987) finds that aggregate earnings news can explain the 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 year. Manager sentiment thus appears to be distinct from management guidance, with the former arguably reflecting management's overly optimistic or pessimistic projections of future cash flows.

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 it 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, studies its relation to firm investment, and explores its cross-sectional forecasting power for portfolios sorted by propensity to speculate and limits to arbitrage. Section 6 concludes.

2. Data and Methodology

2.1 Construction of the manager sentiment index

We compute the monthly manager sentiment index based on the aggregated textual tone in conference calls and 10-K and 10-Q reports from from 2003:01 to 2014:12. In 2000, the U.S. Securities and Exchange Commission (SEC) issued Regulation Fair Disclosure requiring that publicly-listed companies disclose material information to all investors at the same time. As a result, conference call transcripts began to be publicly available beginning around late 2002. In addition, in 2002, in response to several high-profile accounting scandals (e.g., Enron and Worldcom), Congress passed the Sarbanes-Oxley Act (SOX) mandating strict reforms to improve financial reporting quality and to protect investors from fraud. Among other requirements, SOX requires corporate managers to certify the accuracy of their reported financial statements. Although electronic 10-K and 10-Q filings are available on EDGAR beginning in 1995, SOX may have significantly altered their content. Hence, we construct a monthly manager sentiment index using conference calls and 10-K and 10-Q reports after 2002 to mitigate the impact of the structural break caused by both Regulation Fair Disclosure and SOX.

We identify firms conducting conference calls by first matching all non-financial, non-utility firms on Compustat with positive total assets to their corresponding unique Factiva 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 periods typically correspond to fiscal quarters 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.

We calculate the monthly aggregated conference call tone, S^{CC}, as the simple cross-sectional average of firm-level textual tone, defined as the difference between the number of positive words and the number of negative words scaled by the total word count in each earnings conference call transcript filed in each month. Price, Doran, Peterson, and Bliss (2012), among others, study the firm-level conference call tone as a sentiment measure of managerial disclosure, and find that the conference call tone significantly predicts firm-level abnormal returns and post-earnings announcement drift. We use the bag of words approach to quantify textual tone in documents by counting the number of times a word appears in a given document, ignoring order and punctuation. Negative and positive words are classified based on the financial word dictionaries from Loughran and McDonald (2011), who develop a set of highly influential and widely used word lists for business applications that better reflect tone in financial and accounting text.[3] Since the distribution of the monthly number of conference calls displays a seasonal pattern due to earnings seasons, we smooth the conference call tone index using a four-month moving average weighted by the number of conference calls in each month, in order to remove seasonality and to iron out idiosyncratic jumps. As discussed earlier, the monthly aggregated conference call tone spans from 2003:01 to 2014:12 and covers 144 consecutive months during the post Regulation FD and SOX period.

We then obtain 264,335 10-Ks and 10-Qs for 10,414 unique firms from the EDGAR website (www.sec.gov). We exclude firms in the financial and utility sectors and firms with missing or negative total assets. We compute the textual tone based on the entire document, since Loughran and McDonald (2011) find that the full document and MD&A section often use similar words, and focusing on the MD&A section would lead to a loss of observations. Because the filed documents are often in HTML format, following Li (2008, 2010), we remove all encoded images, tables, exhibits, HTML languages, special symbols, and other non-text items from the documents.

We calculate the monthly financial statement tone, S^{FS}, as 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 for all filings from 2003:01 to 2014:12. Li (2010), Feldman, Govindaraj, Livnat, and Segal (2010), and Loughran and McDonald (2011), among others, use firm-level financial statement tone as a sentiment proxy and find that it is linked to firm-level returns,

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

trading volume, volatility, fraud, and earnings. We form the aggregated tone index based on the negative and positive word classifications in the financial word dictionaries from Loughran and McDonald (2011). Loughran and McDonald (2011) focus on 10-Ks since 10-Qs typically contain less text. Over our sample period, 10-Ks on average contain about 42 thousand words, while 10-Qs contain about 15 thousand words. However, by including 10-Qs in our analysis, we can examine managerial sentiment on a more timely basis and make comparisons to other commonly-used monthly macroeconomic variables. We smooth the monthly index using a four-month moving average weighted by the number of financial reports in each month to remove seasonality and to iron out idiosyncratic jumps.

[Insert Table 1 about here]

The monthly composite manager sentiment index, our focus variable, S^{MS}, is then calculated as the average of the aggregated textual tone in conference calls and financial statements,

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

where S^{CC} is the monthly aggregated conference call tone and S^{FS} is the monthly aggregated financial statement tone. Following Baker and Wurgler (2006, 2007), each individual aggregate tone measure has been standardized to mean zero and unit standard deviation. The S^{MS} index captures the market-wide aggregate manager sentiment in any particular month. In addition, following Stambaugh, Yu, and Yuan (2012), we also calculate a manager sentiment dummy, S^{D}, and classify each month as a high (= 1) or low (= 0) manager sentiment period according to 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.

[Insert Figure 1 about here]

Figure 1 shows that the manager sentiment index S^{MS} reflects 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. In addition, the manager sentiment index seems to capture similar sentiment fluctuations over time with the alternative investor sentiment indexes such as the Baker-Wurgler investor sentiment index, although they are constructed differently with different information sets.

The manager sentiment index has several appealing properties. First, it helps to smooth out noise in the individual measures. As shown in Table 1, although both S^{CC} and S^{FS} capture manager sentiment, the correlation between them is not high, 0.21, indicating that conference calls and financial statements likely contain complementary information about manager sentiment. The averaged manager sentiment index thus captures the common manager sentiment component in conference calls and 10-Ks and 10-Qs and diversifies away the idiosyncratic non-sentiment noise in each individual component. Second, we use both positive and negative words in forming the manager sentiment index. While the negative words tend to have stronger information content than the positive words, the correlation between negative and positive words is not large, and positive words potentially contain incremental information beyond negative words. Third, the index imposes simple equal weights on standardized individual components, which are easy to calculate and robust to parameter uncertainty and model instability. In the same spirit, 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.

Nevertheless, we construct several alternative textual tone measures for robustness purposes. For example, first, we also estimate a sophisticated regression-combined manager sentiment index, $S^{\mathrm{RC}} = 0.37S^{\mathrm{CC}} + 0.63S^{\mathrm{FS}}$, 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,

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

In the above specification (1), the regression coefficients β, Υ^{CC}, and Υ^{FS} are not separately 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, $\Upsilon^{\text{CC}} + \Upsilon^{\text{FS}} = 1$, such that the weights are uniquely determined by the data.

Second, we form value-weighted manager indexes. Generally, the equal-weighted index is preferred to the value-weighted. This is because equal-weighting represents breath more fully. Huang, Jiang, Tu, and Zhou (2015) theoretically argue that, when forming aggregate sentiment indexes, we should place greater weight on individual proxies that are more exposed to sentiment, given that the sentiment index is not a tradable asset. Baker and Wurgler (2006) find that small firms are usually more sensitive to sentiment than large firms. Hence, the value-weighted index can fail to capture that sensitivity.

Third, we compute alternative manager sentiment measures using positive and negative words separately. Loughran and McDonald (2011) and others suggest that, at the firm level, negative words are usually more effective than positive words in measuring tone, potentially attributable to the frequent negation of positive words in the framing of negative news by corporate managers. Interestingly, we find that the aggregated managerial sentiment based on the positive and negative word counts alone are often positively correlated with each other, but the correlation is not very large (about 0.4 for conference calls and 0.2 for 10-Ks and 10-Qs).

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 limits to arbitrage and speculation either directly from Ken French's website or calculated using individual stock prices and returns from CRSP and Compustat.

For comparison purposes, we also consider five existing investor sentiment indexes documented in the literature, which are constructed with data from the stock market, household surveys, or a Google keyword search.[4]

- 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 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 existing investor 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

[4]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/.

(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.

It is possible that the explanatory power of the manager sentiment index for stock returns comes from its information about the business cycle. For instance, managers may use optimistic language for rational reasons like to explain favorable expected economic conditions. To control for the influence of the business cycle, we use 15 monthly economic variables that are linked directly to macroeconomic fundamentals,[5] 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). These variables are defined as follows:

- 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-

[5]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/.

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 the stock market return to account for the delay in the release of the CPI.
- 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.[6]

3. Predictive Regression Analysis

3.1 In-sample predictability tests

We employ the standard predictive regression model for analyzing aggregate stock return predictability:

$$R^m_{t\to t+h} = \alpha + \beta S^{\text{MS}}_t + \varepsilon_{t\to t+h}, \tag{2}$$

where $R^m_{t\to t+h}$ is the h-month ahead excess market return from month t to $t+h$ (in percentage) calculated from the monthly excess aggregate market return R^m_{t+1} (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. Following studies for investor sentiment, S^{MS}_t in the above regression is standardized to have zero mean and

[6]We have also examined the alternative CAY, "cayp" in Goyal and Welch (2008), and found similar results.

unit variance to facilitate comparison and interpretation across predictors. We are interested in testing the significance of β in Eq. (2). The null hypothesis of interest is that manager sentiment has no predictive ability, $\beta = 0$. In this case, (2) reduces to the constant expected return model. For a more powerful test of predictability, Inoue and Kilian (2004) recommend using a one-sided alternative hypothesis on β, we test $H_0 : \beta = 0$ against $H_A : \beta < 0$, as the finance theory suggests a negative sign on β.

It is well known that statistical inferences in Eq. (2) are complicated by several econometric issues. 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. Third, the standard error and the associated t-statistic can be biased with the use of overlapping observations when $h > 1$ (e.g., Hodrick 1992; Goetzmann and Jorion 1993; Nelson and Kim 1993) To address these complications and to make more reliable inferences, we use the heteroskedasticity- and autocorrelation-robust Newey-West t-statistic and compute the wild bootstrapped empirical p-value 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 OLS estimation results of the predictive regressions (2) for the manager sentiment index S^{MS} over each horizon. First, at the monthly horizon, the regression slope on S^{MS}, β, is -1.26, and is 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

[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.

market-wide over-valuation (under-valuation) when S^{MS} is high (low), leading to subsequent low (high) stock returns in the future.

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 (2) 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, 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. At the monthly frequency, 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). This point will be analyzed further in Section 4.1.

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

Table 2 reports the in-sample forecasting results of the manager sentiment index on the excess market return over horizons up to three years. At the quarterly, semi-annual, annual, nine-month, two-year, and three-year horizons, S^{MS} can consistently and significantly predict the long run excess market return. For example, 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. Across horizons, the in-sample forecasting power in term of R^2 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 stabilize at 24 months.

In summary, Table 2 shows that the manager sentiment index is a leading negative predictor for subsequent aggregate stock market returns across horizons. The evidence contributes to the existing market sentiment literature that manager sentiment, similar to investor sentiment, peaks (troughs) in advance of weaker (stronger) stock market performance. Our findings also complement the vast empirical evidence at the firm-level. For example, Loughran and McDonald (2011) find that a higher proportion of negative words from 10-Ks and 10-Qs is associated with more negative excess returns in the filing period at the firm level. Price, Doran, Peterson, and Bliss (2012) also find a positive association between conference call tone and abnormal returns at the firm level. However, while our measures of manager sentiment are not exactly the same, our aggregate evidence at the market level is more consistent with the managerial sentiment explanation rather than the fundamental information explanation. This finding is also consistent with Hirshleifer, Hou, and Teoh (2009) who find a complementary relationship for the return predictability of accruals and cash flows at the market level versus the firm level. Li, Ng, and Swaminathan (2013) also provide an interesting predictive pattern by implied costs of capital. Theoretically, firm-level measures of manager sentiment can contain both systematic and idiosyncratic fundamental information, while the latter should be diversified away when averaging. Hence, aggregate manager sentiment captures largely systematic optimism or pessimism.

3.2 Alternative measures of manager sentiment

In this subsection, we show that our results are robust to a variety of alternative measures of manager sentiment.

First, we consider the regression-combined manager sentiment index, S^{RC}, with the weights on the tone measures optimally estimated using a regression approach. Panel A of Table 3 provides the estimation results for 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}, suggesting that the optimally-weighted S^{RC} can further improve the return predictability of S^{MS}, in the in-sample fitting context. The R^2 of 10.3% is also slightly larger than the 9.75% 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.

[Insert Table 3 about here]

Second, we separately consider S^{CC} and S^{FS}, manager sentiment based on aggregate conference call tone and aggregate financial statement tone, respectively, and their corresponding value-weighted counterparts S^{CCV} and S^{FSV}. Panel A of Table 3 reports the predictive abilities of the four individual aggregate tone measures separately. Both S^{CC} and S^{FS} 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. For the value-weighted tone measures, we also detect significant negative return predictability, but the forecasting power is weaker than that of the corresponding equally-weighted tone measures. This finding is consistent with Baker and Wurgler (2006) that since small firms are difficult to value and 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.

Third, we consider S^{CCP} and S^{CCN}, the conference call tone aggregated on positive and negative word counts separately, as well as S^{FSP} and S^{FSN}, the financial statement tone aggregated on positive and negative word counts separately, respectively. All of these alternative manager sentiment measures are standardized to have zero mean, unit variance, and higher values for higher manager sentiment levels. Panel A of Table 3 reports the predictive abilities of the four individual aggregate tone measures separately. We find that of the four measures, three (S^{CCN}, S^{FSP} and S^{FSN}) are significant negative return predictors, but the forecasting power of S^{FSP} and S^{FSN} are smaller than S^{FS}, which incorporates information from both. Hence, both negative words and positive words are useful, especially for 10-Ks and 10-Qs, in measuring manager sentiment at the aggregate level. This is potentially due to noise reduction when including positive and negative words together. In addition, since corporate managers tend to avoid using negative words, including positive words may provide a better evaluation of manager sentiment at the monthly frequency. Nevertheless, consistent with Loughran and McDonald (2011), we find that manager sentiment based on negative words alone outperforms those based on positive words alone, potentially attributable to the frequent negation of positive words in the framing of negative news by corporate managers.

3.3 Subperiod analysis

First, 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 (e.g., García 2013). 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}),

$$R^2_{\text{c}} = 1 - \frac{\sum_{t=1}^{T} I_t^{\text{c}} (\hat{\varepsilon}_{i,t})^2}{\sum_{t=1}^{T} I_t^{\text{c}} (R_t^m - \bar{R}^m)^2} \qquad c = \text{rec, exp} \tag{3}$$

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 (2); $\bar{R}^m$ 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.

Panel B of Table 3 reports the R^2_{rec} and R^2_{exp} statistics. We find that the return predictability is concentrated over recessions for the manager sentiment index S^{MS}. For example, over recessions, S^{MS} has a large R^2_{rec} of 20.4%. In contrast, over expansions, S^{MS} has a much smaller R^2_{exp} of 0.75%. This finding is consistent with García (2013) and Huang, Jiang, Tu, and Zhou (2015) for investor sentiment indexes and Rapach, Strauss, and Zhou (2010) and Henkel, Martin, and Nardari (2011) for macroeconomic variables. Intuitively, managers tend to become highly optimistic (pessimistic) near business cycle peaks (troughs) due to perhaps an over-extrapolation bias, which will lead to large misvaluation and a strong predictable return reversal. In addition, job losses and uncertainty can increase during recessions that put more distress on investors (García, 2013), which can in turn yield stronger market sensitivity to manager sentiment in these periods.

Second, in Panel B of Table 3, we also 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 (3). Shen and Yu (2013) and Huang, Jiang, Tu, and Zhou (2015) find that sentiment's predictive power is stronger over high sentiment periods, during which mispricing is more likely due to limits to arbitrage and short-sale constraints.

Empirically, we find that the predictive power of S^{MS} is indeed 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 a smaller R^2_{low} of 6.93% though still fairly large economically. In summary, these findings, largely consistent with Shen and Yu (2013) and Huang, Jiang, Tu, and Zhou (2015), suggest that manager sentiment, similar to investor sentiment, has stronger forecasting power when sentiment is higher.

3.4 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,

$$R^m_{t+1} = \alpha + \psi Z^k_t + \varepsilon_{t+1}, \qquad k = 1, ..., 16, \tag{4}$$

where Z^k_t is one of the 15 individual economic variables described in Section 2.2 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 (4). 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 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 the 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^{MS}_t and each economic variable, Z^k_t,

$$R^m_{t+1} = \alpha + \beta S^{\mathrm{MS}}_t + \psi Z^k_t + \varepsilon_{t+1}, \qquad k = 1, ..., 16. \tag{5}$$

The coefficient of interest is the regression slope β on S_t^{MS}.

Panel B of Table 4 shows that the estimates of the slope β in (5) 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 (2) 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 (5) 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.

3.5 Comparison with investor sentiment indexes

In this subsection, we empirically compare the manager sentiment index S^{MS} with existing investor sentiment indexes documented in the literature.

First, in Table 1, we show that the manager sentiment index is contemporaneously associated with investor sentiment, suggesting that managers as a whole share certain elements of sentiment with investors. In this subsection, we further examine whether the forecasting power of S^{MS} is a substitute for or is complementary to investor sentiment. Although the current return predictability literature almost exclusively focuses on investor sentiment in forecasting stock returns, it is of interest to examine the predictive power of manager sentiment and to relation to that of investor sentiment, since managers who are better informed about their firms are also subject to cognitive biases and emotion, similar to investors.

We run the following predictive regressions of the 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},

$$R_{t+1}^m = \alpha + \beta S_t^{\mathrm{MS}} + \delta S_t^k + \varepsilon_{t+1}, \qquad k = \mathrm{BW}, \mathrm{HJTZ}, \mathrm{MCS}, \mathrm{CBC}, \mathrm{FEARS}, \tag{6}$$

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). All investor sentiment indexes are standardized to have zero mean, unit variance, and higher values for higher sentiment levels. Detailed descriptions of these alternative sentiment indexes are provided in Section 2.2.

[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 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 Huang, Jiang, Tu and Zhou (2015) aligned investor sentiment index, S^{HJTZ}, which is an alternative investor sentiment index generated by exploring the same six stock market-based sentiment proxies of Baker and Wurgler (2006) more efficiently, generates an R^2 of 8.45% with statistical significance, which is smaller than that of S^{MS} but greater than that of S^{BW}. The interest question is whether manger investor sentiment can dominate investor sentiment or vice versa. 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 complementary 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) FEARS investor sentiment index (S^{FEARS}) are smaller than that of S^{MS}, whose R^2 values ranging from 0.26% to 2.71%. Most importantly, they each become statistically insignificant when controlling for S^{MS} in the 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 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 multicollinearity.

In short, our findings suggest that the manager sentiment index S^{MS} contains additional and complementary sentiment information beyond exiting investor sentiment indexes in forecasting the stock market.

3.6 Feedback relationship with investor sentiment

In this subsection, we further test the potential feedback relationship between manager sentiment S^{MS} and the existing investor sentiment proxies. Intuitively, it is possible that S^{MS} may simply react to lagged information contained in existing investor sentiment measures (i.e., investor sentiment leads manager sentiment), or lagged S^{MS} may simply drive existing investor sentiment measures (i.e., manager sentiment leads investor sentiment), or, most likely, manager sentiment and investor sentiment capture unique and complementary sentiment information.

To formally analyze the feedback relationship between the manager sentiment index and existing investor sentiment indexes, we estimate the following models,

$$S_t^{\text{MS}} = \alpha + \sum_{i=1}^{s} \delta_i S_{t-i}^{\text{MS}} + \sum_{i=1}^{s} \beta_i S_{t-i}^{\text{k}} + \varepsilon_t, \qquad k = \text{BW}, \text{HJTZ}, \tag{7}$$

and

$$S_t^{\mathrm{k}} = \alpha + \sum_{i=1}^{s} \delta_i S_{t-i}^{\mathrm{k}} + \sum_{i=1}^{s} \beta_i S_{t-i}^{\mathrm{MS}} + \varepsilon_t, \qquad k = \mathrm{BW}, \mathrm{HJTZ}, \tag{8}$$

where S^{MS} denotes the manager sentiment index, and S^{BW} denotes the Baker and Wurgler (2006) investor sentiment index, and S^{HJTZ} denotes the Huang, Jiang, Tu, and Zhou (2015) aligned investor sentiment index.[8] We set $s = 5$ for our lag choice, although alternative choices do not affect the conclusions. The regressions in (7) and (8) are similar to models estimated by Tetlock (2007) and García (2013), and are equivalent to Granger causality tests for a lead-lag relationship between manager sentiment and investor sentiment, after accounting for each variable's own autocorrelation.

[Insert Table 6 about here]

Panel A of Table 6 presents the estimated coefficients for Eq. (7), which measures the feedback effect from each investor sentiment measure to manager sentiment. Panel B from Table 6 presents the estimated coefficients for Eq. (8), which measures the feedback effect from manager sentiment to investor sentiment.

Table 6 shows that the simple models in (7) and (8) could largely explain the time series dynamics of manager sentiment and investor sentiment, with adjusted R^2s of 83% to 94%. Most importantly, Table 6 shows that manager sentiment does not Granger lead investor sentiment, nor does investor sentiment Granger lead manager sentiment. The evidence suggests that the lagged values are the strongest predictors of the current levels for both manager and investor sentiment. These findings indicate that manager sentiment and investor sentiment capture different subsets of sentiment information, and they are complementary in measuring market sentiment.

[8] We focus on S^{BW} and S^{HJTZ} for brevity, but we obtain similar results using S^{MCS}, S^{CBC}, and S^{FEARS}.

3.7 Forecast encompassing test

To further assess the information content of the manager sentiment index S^{MS} relative to 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 7 about here]

Table 7 reports p-values for the Harvey, Leybourne, and Newbold (1998) forecast encompassing test. The first row of Table 7 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 that 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 incremental information and suggesting potential gains in combining the individual tone measures into a composite manager sentiment index to fully make use of the relevant information, as discussed in Table 3. In addition, the fourth to eighth rows of Table 7 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. Under the assumption of a constant data-generating process, in-sample predictive analysis provides more efficient parameter estimates and thus more precise return forecasts. However, as shown by Goyal and Welch (2008) and others, this assumption is not true in practice. In addition, relative to in-sample tests, out-of-sample tests are less affected by econometric issues such as over-fitting, small-sample size distortion, and the Stambaugh bias (Busetti and Marcucci, 2012). Hence, it is of interest for us to 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 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}. In addition, we also consider in our out-of-sample analysis the recursive-regression-combined manager sentiment index, S^{RC}, combined from S^{CC} and S^{FS}, S^{C}. For comparison purposes, we also examine the out-of-sample forecasting performance of the five alternative sentiment indexes as the in-sample analysis of 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 from 2003:01 to 2006:12 as the initial estimation period and the data from 2007:01 to 2014:12 as the forecast evaluation period. The choice of the length of time of the in-sample estimation period balances having enough observations to precisely estimate the initial parameters with the desire for a relatively long out-of-sample period for forecast evaluation.[9]

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 average benchmark,

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

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

$$\bar{R}^m_{t+1} = \frac{1}{t}\sum_{s=1}^{t} R^m_s. \tag{11}$$

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

We test the statistical significance of R^2_{OS} using the MSFE-adjusted statistic of Clark and West (2007) (MSFE–*adj* statistic) which 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 (H_0: $R^2_{\mathrm{OS}} \leq 0$ against H_A : $R^2_{OS} > 0$). 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 MSFE of the benchmark model to be smaller than the MSFE of the predictive regression model under the null. The MSFE-adjusted statistic accounts for the negative expected difference between the historical

[9]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 MSFE and predictive regression MSFE under the null, so that it can reject the null even if the R^2_{OS} statistic is negative.

[Insert Table 8 about here]

Panel A of Table 8 shows that the manager sentiment index S^{MS} exhibits strong out-of-sample predictive ability for the aggregate market, with an R^2_{OS} 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 substantially exceeds all the other R^2_{OS}s in Table 8, in particular, all the five existing investor sentiment indexes in Panel B. In addition, the fourth and fifth columns of Table 8 show that the predictability of the manager sentiment index S^{MS} is concentrated during recessions, confirming our earlier in-sample findings in Table 3.

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 3), 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 8 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 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 the 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

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

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 9 about here]

Table 9 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 8. 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 8.11% (S^{C}), and the net-of-transactions-costs CER gains vary from 6.56% (S^{RC}) to 8.06% (S^{C}). In addition, all the monthly Sharpe ratios are also economically large, in the range of 0.13 (S^{RC}) to

0.16 (S^{C}).

Panel B of Table 9 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 a small CER gain of 0.62% and a negative Sharpe ratio of -0.03.

Overall, Table 9 demonstrates that the manager sentiment index S^{MS} generates sizable economic value for an investor from an asset allocation perspective. The results are robust to common levels of transaction costs.

5. Economic Channels

5.1 Predicting aggregate earnings growth and macroeconomic growth

In this section, we investigate the forecasting power of the manager sentiment index S^{MS} for future aggregate earnings growth and macroeconomic growth to explore the cash flows predictability channel. Thus far we have demonstrated that manager sentiment negatively predicts future aggregate stock market returns. Stock prices are determined by the discounted value of expected future cash flows. Therefore, the negative return predictability of the manager sentiment index may come from investors' biased expectations about future cash flows unjustified by economic fundamentals in hand (Bower 1981; Johnson and Tversky 1983; Wright and Bower 1992; Baker and Wurgler 2007; Hribar and McInnis 2012; Arif and Lee 2014; Huang, Jiang, Tu, and Zhou 2015). Specifically, when manager sentiment is high (low), the market may have overly optimistic (pessimistic) expectations for future cash flows, leading to overvaluation (undervaluation) and subsequent low (high) stock returns.

Our empirical analysis focuses on forecasting future aggregate earnings growth and macroeconomic growth, which have 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,

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

where the dependent variable, $\mathrm{CF}_{t\to t+12}$, is either $\mathrm{EG}_{t\to t+12}$, a measure for aggregate earnings growth, or $\mathrm{CFNAI}_{t\to t+12}$, a measure for macroeconomic growth. $\mathrm{EG}_{t\to t+12}$ 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). $\mathrm{CFNAI}_{t\to t+12}$, which is the twelve-month moving average of CFNAI_t, the monthly Chicago Federal Reverse National Activity Index. Introduced by Stock and Watson (1999), the CFNAI is the first principal component of eighty-five indicators of economic growth drawn from four broad categories of the economy: employment; production and income; personal consumption and housing; and sales, orders, and inventories. This index closely tracks periods of business-cycle expansions and contractions. Lower values of the CFNAI indicate a higher likelihood that a recession is occurring. Following previous studies, we include controls for the lagged earnings-to-price ratio ($\mathrm{E/P}_t$) and lagged earnings growth (EG_t), lagged CFNAI_t, and use an annual horizon to avoid spurious cash flow growth predictability arising from within-year seasonality.[10] We are interested in the regression slope β on S_t^{MS} to examine whether the manager sentiment index reflects biased expectations about future cash flows.

[Insert Table 10 about here]

[10]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.

Panel A of Table 10 reports the estimation results of forecasting annual aggregate earnings growth in (15). The first column shows that manager sentiment S^{MS} contains significant negative forecasting power for future aggregate earnings growth $\mathrm{EG}_{t\to t+12}$. 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 -0.46 decrease in $\mathrm{EG}_{t\to t+12}$ for the next year. This point is further confirmed by the large R^2 of 35.6% for the univariate predictive regression for aggregate earnings growth with S^{MS}. In the second column of Panel A, Table 10, we further control for the lagged earnings-to-price ratio ($\mathrm{E/P}_t$) and lagged 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.

Panel B focuses on forecasting macroeconomic growth. The fifth column documents the univariate relationship between S^{MS} and $\mathrm{CFNAI}_{t\to t+12}$, and shows that higher manager sentiment is associated with deteriorating macroeconomic conditions and a higher likelihood of recession. Specifically, the regression slope estimate on S^{MS} is -0.44 and the Newey-West t-statistic is -2.27. Hence, a one-standard deviation increase in S^{MS} is associated with a -0.44 decrease in $\mathrm{CFNAI}_{t\to t+12}$ for the next year. Note that the mean of $\mathrm{CFNAI}_{t\to t+12}$ is zero and its standard deviation is about 0.7. This finding is robust to controlling for the lagged earnings-to-price ratio ($\mathrm{E/P}_t$) and lagged CFNAI_t.

For robustness, we also report aggregate earnings growth and macroeconomic growth predictability based on the regression-combined manager sentiment index, S^{RC}. We find that the alternative manager sentiment measure also has significant negative predictive power for $\mathrm{EG}_{t\to t+12}$ and $\mathrm{CFNAI}_{t\to t+12}$, consistent with S^{MS}. Specifically, S^{RC} has a regression slope of -0.42 and an R^2 of 29.8% in forecasting aggregate earnings growth, and it has a regression slope of -0.46 and an R^2 of 21.2% in forecasting CFNAI, both of which are statistically significant.

In short, Table 10 shows that manager sentiment is a negative leading indicator for future aggregate earnings and macroeconomic conditions. This finding is largely consistent with the biased execration view that a higher manager sentiment index captures managers' overly optimistic beliefs about future cash flows which leads to overvaluation and lower future stock returns, rather than fundamental information or rational catering.

5.2 Manager sentiment and aggregate investment growth

In this subsection, we examine the relationship between manager sentiment and aggregate investment growth. Having shown that manager sentiment negatively predicts future aggregate stocks returns, aggregate earnings growth, and macroeconomic conditions, we now examine how it relates to firm investments.

We employ the following predictive regressions,

$$\mathrm{IG}_{t+h} = \alpha + \beta S_t^{\mathrm{MS}} + \upsilon_{t+h}, \tag{16}$$

where the dependent variable, IG_{t+h}, is the h-month ahead annual growth rate of aggregate capital expenditures (in percentage) calculated using data from the Compustat database. The forecasting horizon h spans from 0 to 36 months; when $h = 0$, we examine the contemporaneous relationship between manager sentiment and aggregate investment growth.

[Insert Table 11 about here]

The first row of Panel A of Table 11 reports the contemporaneous results. Manager sentiment S^{MS} is positively correlated with contemporaneous aggregate investment growth IG_t. The regression slope estimate on S^{MS} for IG_t is 7.79%, with a Newey-West t-statistic of 6.06. Hence, a one-standard deviation increase in S^{MS} is associated with a 7.79% increase in aggregate investment growth. This positive association is economically strong, which is confirmed by the large R^2 of 37.88%.

The rest of Panel A of Table 11 shows that the positive predictive relationship between manager sentiment and aggregate investment growth persists for about one year. Specifically, higher manager sentiment significantly and positively predicts higher investment growth for the next quarter, half year, and three quarters. While the predictive relationship between manager sentiment and one-year ahead investment growth remains positive, it becomes statistically insignificant. Lastly, high aggregate investment growth following high manager sentiment reverses slightly after two years.

Arif and Lee (2014) show that investor sentiment is contemporaneously associated with increases in aggregate investment. For comparison, we re-estimate Equation (16) replacing the manager sentiment index S^{MS} with the Baker and Wurgler (2006) investor sentiment index S^{BW},

$$\mathrm{IG}_{t+h} = \alpha + \beta S_t^{\mathrm{BW}} + \upsilon_{t+h}. \tag{17}$$

We report the findings in Panel B of Table 11.

Results in the first row of Panel B show that investor sentiment S^{BW} is significantly and positively correlated with contemporaneous aggregate investment growth IG_t, confirming the findings in Arif and Lee (2014). The remaining rows in Panel B provide evidence that, similar to manager sentiment, the positive relationship between investor sentiment and aggregate investment growth persists for about one year, a finding which, to our knowledge, is new to the literature. Moreover, while this positive association between investor sentiment and aggregate investment growth is economically large (i.e., the contemporaneous R^2 is 18.02%), it is much smaller than the corresponding R^2 values for manager sentiment in Panel A. These results suggest that manager sentiment is different from investor sentiment and has a stronger influence on firm investment growth.

In summary, Table 11 shows that periods with high (low) manager sentiment are accompanied by high (low) contemporaneous aggregate investment growth. The aggregate investment growth rate remains high (low) over the subsequent year, then reverses to the mean in two years when the lower (higher) than expected returns to investments are gradually revealed to the manager.

This finding suggests that a higher manager sentiment index captures managers' overly optimistic beliefs about future cash flows which leads to overinvestment. In addition, manager sentiment has a stronger positive impact on firm investment growth relative to investor sentiment.

5.3 Manager sentiment and characteristic-sorted portfolios

In this section, we explore the cross-sectional variation of manager sentiment's effects on stock returns. As highlighted by Shleifer and Vishny (1997), Baker and Wurgler (2006, 2007) and Stambaugh, Yu, and Yuan (2012), the market 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, if our manager sentiment index indeed reflects market sentiment, its forecasting power should be stronger among stocks that are more speculative and difficult to value and to arbitrage. These cross-sectional tests not only strengthen our previous findings for aggregate stock market predictability, but also enhance our understanding of the limits to arbitrage channel through which manager sentiment impacts asset prices.

Following Baker and Wurgler (2006, 2007), we consider 11 well-documented decile portfolios formed by 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 the subjectivity of valuation and limits to arbitrage. These variables are defined as follows:

- 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 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 age, low profitability, non-dividend-paying, high intangible assets, and high growth), and/or difficult to arbitrage (i.e., high beta, high volatility, young age, small, low profitability, high growth, and high distress).

[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 periods and the return differences between high and low manager sentiment periods.

The results in Figure 2 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. For example, 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 with lower beta, consistent with our hypothesis and with 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, low profitability, non-dividend-paying, high distress (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 high manager sentiment.[11]

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

$$R_{t+1}^{j} = \alpha + \beta S_t^{\mathrm{MS}} + \varepsilon_{t+1}^{j}, \tag{18}$$

where the dependent variable R_{t+1}^{j} 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.

[Insert Table 12 about here]

Table 12 reports the estimation results of the predictive regressions of (18). The left panel of Table 12 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 regression slope estimates β: firms with high beta, high idiosyncratic volatility, young 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 the two-way sort results in Figure 2. In addition, the return predictability is economically large. For example, the regression

[11] 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 12 shows that the patterns are statistically insignificant, similar to the results reported in Baker and Wurgler (2006).

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 the one-month-ahead expected excess return for high beta firms.

The right panel of Table 12 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.

In summary, our findings suggest that the predictive power of the manager sentiment index mainly reflects sentiment-driven mispricing instead of rational forces, and limits to arbitrage play an important role in driving the negative manager sentiment-stock return relationship.

6. Conclusion

In this paper, we propose a manager sentiment index constructed based on the 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 (high) 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 complementary to investor sentiment in forecasting stock returns, implying that manager sentiment has a substantially different impact on valuation relative to investor sentiment. Moreover, we find that manager sentiment is a strong negative predictor of future aggregate earnings growth and macroeconomic conditions, and is closely related to firm investments, implying that managers' biased beliefs about future cash flows at least partially explains 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 a strong negative forecasting power for stock returns both at the market level and in the cross-section. The predictability holds for both in-sample and out-of-sample tests, and can generate large economic value for the investors 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.

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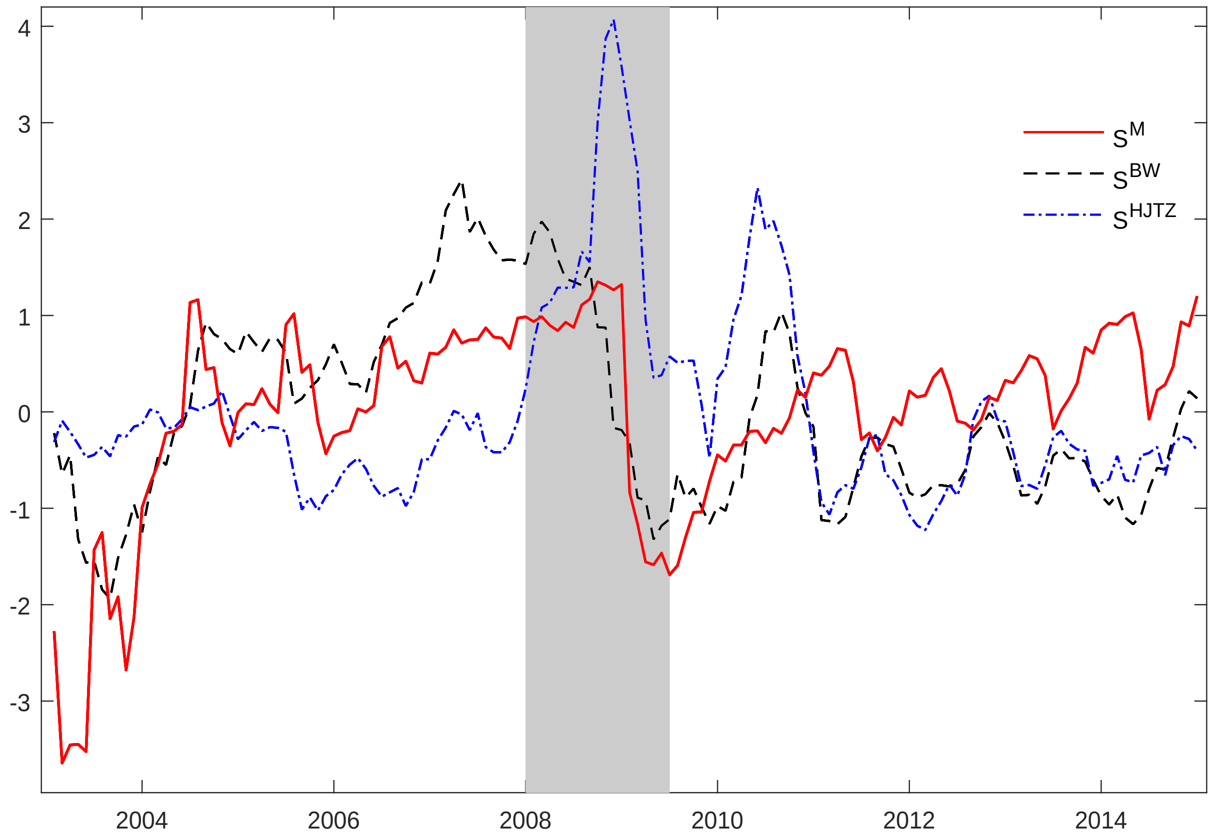

Figure 1: The manager sentiment index, 2003:01−2014:12
The solid line depicts the manager sentiment index, S^{MS}, which is the average aggregate textual tone in conference calls, 10-Qs and 10-Ks filed in each month with a four month moving average. The dashed and dotted lines depict the Baker and Wurgler (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 investor sentiment proxies. All the sentiment measures are standardized to have zero mean and unit variance. The vertical bars correspond to NBER-dated recessions.

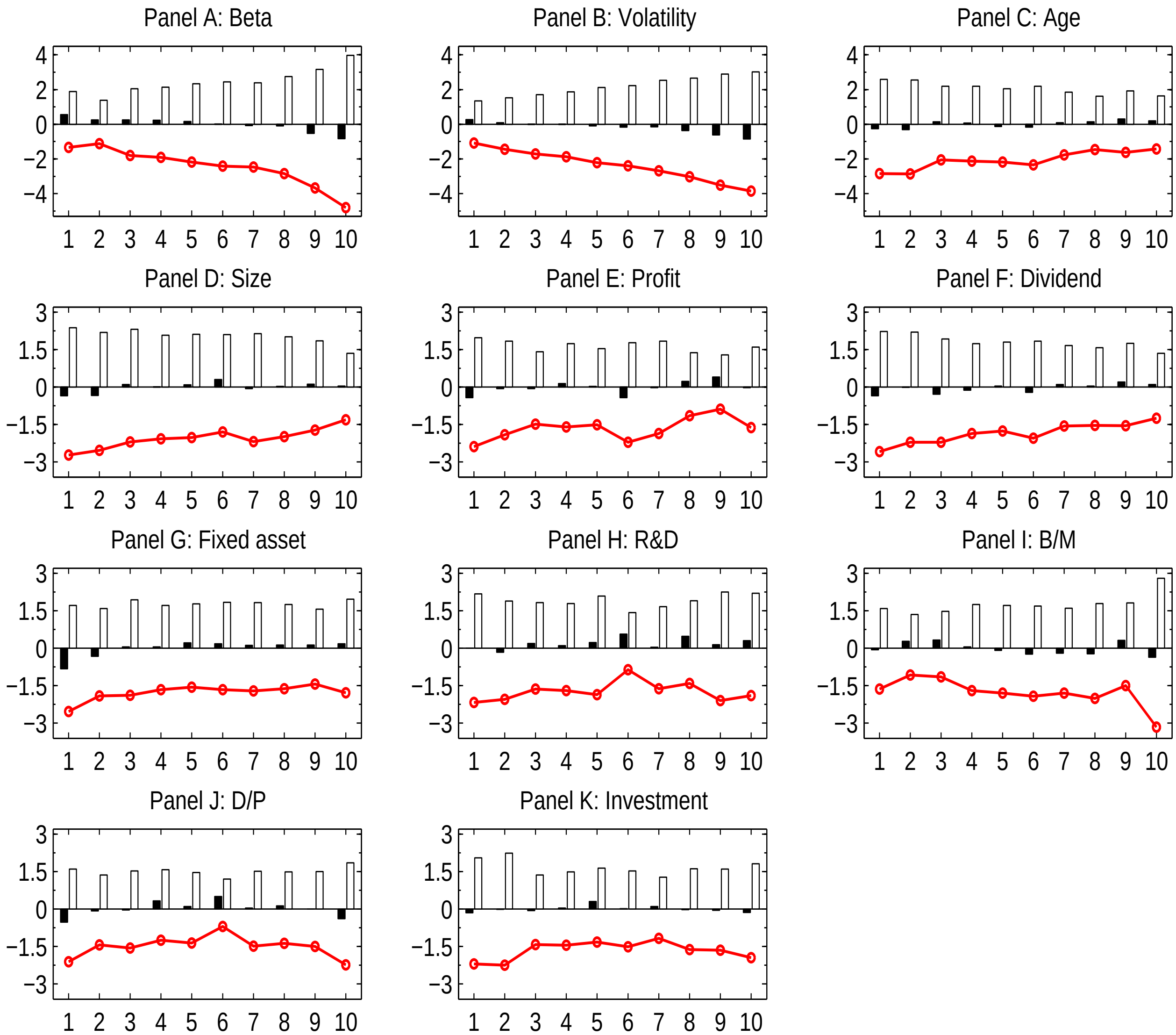

Figure 2: Two-way sorts on firm characteristics and high and low manager sentiment
Panels A to K plot the average monthly excess returns (in percentage) of 11 decile portfolios formed on single sorting based on firm characteristics following periods of high and low manager sentiment. Decile 1 refers 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}	0.79	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	0.37	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

Horizon	α (%)	t-stat	β (%)	t-stat	R^2 (%)
1	0.76	2.39**	-1.26	-3.57***	9.75
3	2.35	2.82***	-3.85	-4.11***	24.92
6	4.59	2.67***	-6.03	-3.21***	25.80
9	6.69	2.58***	-7.73	-2.97***	27.15
12	8.47	2.40**	-8.58	-2.54**	25.39
24	15.27	1.92**	-11.64	-2.11**	20.41
36	20.17	1.56*	-12.43	-2.50**	16.18

This table reports the ordinary least squares estimation results for α, β, and R^2 statistics for the predictive regression model,

$$R^m_{t \to t+h} = \alpha + \beta S^{\mathrm{MS}}_t + \varepsilon_{t \to t+h},$$

where $R^m_{t \to t+h}$ is the h-month ahead excess market return from month t to $t+h$ (in percentage) calculated from the monthly excess aggregate market return R^m_{t+1}, i.e., the monthly return on the S&P 500 index in excess of the risk-free rate. S^{MS}_t is the manager sentiment index defined as the average aggregate manager tone extracted from conference calls and 10-Ks and 10-Qs. S^{MS}_t is standardized to have zero mean and unit variance. The regression coefficients, Newey-West heteroskedasticity- and autocorrelation-robust t-statistics, and R^2 are reported. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, for testing $H_0 : \beta = 0$ against $H_A : \beta < 0$, based on bootstrapped p-values. The sample period is 2003:01−2014:12.

Table 3: Robustness tests

Panel A: Alternative measures of manager sentiment

	β (%)	t-stat	R^2 (%)		β (%)	t-stat	R^2 (%)
S^{RC}	-1.28	-3.67	10.3	S^{CCP}	0.27	0.75	0.53
S^{CC}	-0.81	-2.13	4.05	S^{CCN}	-0.96	-2.51	5.61
S^{FS}	-1.15	-3.25	8.10	S^{FSP}	-0.61	-1.90	2.28
S^{CCV}	-0.76	-1.89	3.57	S^{FSN}	-0.93	-2.57	5.42
S^{FSV}	-0.95	-3.13	5.52				

Panel B: Subperiod analysis

	R^2_{rec}	R^2_{exp}		R^2_{high}	R^2_{low}
Business cycle	20.4	0.75	Sentiment level	12.9	6.93

This table provides additional robustness checks for the monthly in-sample predictive regressions. Panel A reports the OLS estimates of β, Newey-West t-statistics, and R^2 statistics for the predictive regressions on alternative measures of 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). S^k_t denotes each lagged alternative manager sentiment measure, including S^{RC}, the regression-combined manager sentiment index with the weights on each individual tone measures optimally estimated using a regression approach; S^{CC} and S^{FS}, the manager sentiment based on the aggregate conference call tone alone or based on the aggregate financial statement tone alone; S^{CCV} and S^{FSV}, the value-weighted conference call tone and financial statement tone; S^{CCP} and S^{CCN}, the conference call tone aggregated on positive words or negative words counts alone; S^{FSP} and S^{FSN}, the financial statement tone aggregated on positive words or negative words counts alone. All the alternative manager sentiment measures are standardized to have zero mean, unit variance, and higher values for higher manager sentiment levels. Panel B reports the in-sample forecasting power of the manager sentiment index S^{MS} over different sub-sample periods. R^2_{rec} (R^2_{exp}) statistics are calculated over NBER-dated business-cycle recessions (expansions), respectively. 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 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 the 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 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. The sample period is 2003:01−2014:12.

Table 5: Comparison with existing investor 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 the monthly excess market return (R^m_{t+1}, in percentage) on the lagged manager sentiment index, S^{MS}, with controls for alternative investor 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 the 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). All investor sentiment indexes are standardized to have zero mean, unit variance, and higher values for higher sentiment levels. Detailed descriptions of these alternative sentiment indexes are provided in Section 2.2. In the last column, we run a kitchen-sink regression that includes all sentiment indexes in one long regression. The regression coefficients, the heteroskedasticity- and autocorrelation-robust Newey-West t-statistics, and R^2s are reported. The sample period is 2003:01−2014:12.

Table 6: Feedback between manager sentiment and investor sentiment

	Panel A: IS $\Rightarrow$ MS				Panel B: MS $\Rightarrow$ IS			
	$S^{\text{BW}} \Rightarrow S^{\text{MS}}$		$S^{\text{HJTZ}} \Rightarrow S^{\text{MS}}$		$S^{\text{BW}} \Rightarrow S^{\text{MS}}$		$S^{\text{HJTZ}} \Rightarrow S^{\text{MS}}$	
β_1	-0.03	[-0.28]	-0.04	[-0.38]	0.02	[0.21]	-0.01	[-0.13]
β_2	0.22	[0.78]	0.20	[1.37]	0.05	[0.46]	0.14	[1.28]
β_3	-0.11	[-0.36]	-0.24	[-1.69]	-0.01	[-0.17]	-0.14	[-1.12]
β_4	0.19	[0.93]	-0.07	[-0.37]	-0.06	[-0.83]	0.00	[0.03]
β_5	-0.20	[-1.37]	0.07	[0.42]	0.02	[0.49]	0.02	[0.44]
Adj. R^2	0.84		0.83		0.94		0.92	

Panel A reports the OLS estimation results of the following model, testing the feedback effect from investor sentiment to manager sentiment (IS $\Rightarrow$ MS)

$$S_t^{\text{MS}} = \alpha + \sum_{i=1}^{s} \delta_i S_{t-i}^{\text{MS}} + \sum_{i=1}^{s} \beta_i S_{t-i}^{\text{k}} + \varepsilon_t, \qquad k = \text{BW}, \text{HJTZ}.$$

Panel B reports the OLS estimation results of the following model, testing the feedback effect from manager sentiment to investor sentiment (MS $\Rightarrow$ IS)

$$S_t^{\text{k}} = \alpha + \sum_{i=1}^{s} \delta_i S_{t-i}^{\text{k}} + \sum_{i=1}^{s} \beta_i S_{t-i}^{\text{MS}} + \varepsilon_t, \qquad k = \text{BW}, \text{HJTZ},$$

where the choice of lag s is equal to 5, S^{MS} denotes the manager sentiment index, and 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. The regression coefficients β, the corresponding heteroskedasticity- and autocorrelation-robust Newey-West t-statistics (in brackets), and R^2s are reported. The sample period is 2003:01−2014:12.

Table 7: 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 8: Out-of-sample forecasting results

	R^2_{OS} (%)	MSFE-*adj*	$R^2_{OS,\text{rec}}$ (%)	$R^2_{OS,\text{exp}}$ (%)
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
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 performance 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}, and the combination forecast of manager sentiment proxies S^{CC} and S^{FS}, S^{C}. 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. $R^2_{OS,\text{rec}}$ ($R^2_{OS,\text{exp}}$) 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 9: 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
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}, and the combination forecast of manager sentiment proxies S^{CC} and S^{FS}, S^{C}. 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 10: Manager sentiment and aggregate earnings growth and macroeconomic growth

	Panel A: Earnings growth				Panel B: CFNAI			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
S_t^{MS}	-0.46	-0.41			-0.44	-0.53		
	[-2.26]	[-1.92]			[-2.27]	[-2.36]		
S_t^{RC}			-0.42	-0.38			-0.46	-0.48
			[-2.22]	[-1.86]			[-2.27]	[-2.24]
EG_t		-0.16		-0.15				
		[-0.97]		[-0.96]				
CFNAI_t						0.22		0.26
						[0.84]		[1.01]
$\mathrm{E/P}_t$		-0.11		-0.16		0.27		0.17
		[-0.60]		[-1.03]		[1.18]		[0.82]
R^2 (%)	35.6	42.6	29.8	40.9	19.8	45.2	21.2	43.1

This table reports the estimation results for the predictive regressions of aggregate earnings growth ($\mathrm{EG}_{\mathrm{t}\rightarrow\mathrm{t}+12}$) and the Chicago Federal Reverse National Activity Index ($\mathrm{CFNAI}_{\mathrm{t}\rightarrow\mathrm{t}+12}$, a composite measure of macroeconomic growth) on the lagged manager sentiment index, S^{MS}, and the regression-combined manager sentiment index, S^{RC}, with controls for lagged aggregate earnings growth (EG_t), lagged CFNAI_t, and lagged earnings-to-price ratio ($\mathrm{E/P}_t$). The regression takes the form

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

where the dependent variable, $\mathrm{CF}_{t\rightarrow t+12}$, is either $\mathrm{EG}_{t\rightarrow t+12}$, which is the annual growth rate of twelve-month moving sums of aggregate earnings on the S&P 500 index, or $\mathrm{CFNAI}_{t\rightarrow t+12}$, which is the twelve-month moving average of CFNAI_t. CFNAI is the first principal component of eighty-five indicators of economic growth and it closely tracks periods of macroeconomic expansions and contractions. The regression coefficients, Newey-West t-statistics, and R^2 are reported. The sample period is 2003:01−2014:12.

Table 11: Manager sentiment and aggregate investment growth

	Panel A: Manager sentiment, S^{MS}					Panel B: Investor sentiment, S^{BW}				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Horizon	α (%)	t-stat	β (%)	t-stat	R^2 (%)	α (%)	t-stat	β (%)	t-stat	R^2 (%)
0	5.74	2.46	7.79	6.06	37.88	6.86	2.29	5.72	2.49	18.02
3	6.36	2.69	7.79	4.65	40.28	7.37	2.49	5.91	2.38	20.61
6	6.82	2.58	6.34	3.82	28.49	7.75	2.52	5.34	2.20	17.64
9	7.14	2.50	4.52	2.75	14.97	8.07	2.48	3.70	1.98	8.58
12	7.45	2.41	1.65	0.85	2.05	8.42	2.51	1.40	0.88	1.23
24	7.33	2.68	-6.13	-2.79	29.26	9.95	3.75	-7.04	-2.35	30.47
36	6.60	1.81	-2.15	-0.92	3.85	5.82	1.41	2.85	1.02	4.91

This table reports the estimation results for α, β, and R^2 statistics for the predictive regressions of aggregate investment growth (IG_{t+h}) on the lagged manager sentiment index (S^{MS}) or the lagged Baker and Wurgler (2006) investor sentiment index (S^{BW}). The regression takes the form

$$\text{IG}_{t+h} = \alpha + \beta S_t^{\text{k}} + \upsilon_{t+h}, \qquad k = \text{MS}, \text{BW}$$

where IG_{t+h} is the h-month ahead annual growth rate of the aggregate capital expenditures (in percentage) calculated from the Compustat database. Forecasting horizon h spans from 0 to 36 months, where 0 refers to the contemporaneous relationship. S_t^{MS} is the manager sentiment index defined as the aggregated textual tone extracted from conference calls and 10-Ks and 10-Qs, and S^{BW} denotes the Baker and Wurgler (2006) investor sentiment index. The regression coefficients, Newey-West heteroskedasticity- and autocorrelation-robust t-statistics, and R^2 are reported. The sample period is 2003:01−2014:12.

Table 12: 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 the 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 the following firm characteristics: 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.