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Manager sentiment and stock returns☆

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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^2s 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 lower aggregate earnings surprises and greater aggregate investment growth. Moreover, manager sentiment negatively predicts cross-sectional stock returns, particularly for firms that are difficult to value and costly to arbitrage.

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 et al., 1990; Shefrin, 2008). Empirically, Baker and Wurgler (2006) propose an investor sentiment index that has been widely used to explain asset prices.[1] Recently, Huang et al. (2015) develop an alternative index which often performs better as it is aligned with the asset returns to be explained, and Zhou (2018) provides a review of the literature. However, there is little research on corporate managers' sentiment. This is somewhat surprising given managers' information advantage about their companies

[1] Their index is based on principal component analysis by aggregating information from six proxies: the closed-end fund discount rate, share turnover, number of initial public offerings (IPOs), first-day returns of IPOs, dividend premium, and equity share in new issues.

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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 relative to 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 its predictability for future U.S. stock market returns. Intuitively, investors may simply follow managers' sentiment in financial disclosures, even though this sentiment may not represent the underlying fundamentals of the firm. Hence, high manager sentiment may lead to speculative market overvaluation. When the true economic fundamentals are revealed to the market gradually, the misvaluation diminishes and stock prices reverse, yielding low future stock returns (Baker and Wurgler, 2007). However, it is an open empirical question whether 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 a qualitative description of the firm's business and financial performance at least partially reflects managers' subjective opinions and beliefs about why their firms performed as they did over the recent fiscal period and their expectations for future firm performance (Li, 2008; 2010; Henry, 2008; Blau et al., 2015; Brochet et al., 2018). 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), Loughran and McDonald (2011), García (2013), and 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 disclosures 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 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 use the out-of-sample forecasts to 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. 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 14 well-known macroeconomic variables used by Goyal and Welch (2008), such as the short-term interest rate (Fama and Schwert, 1977; Breen et al., 1989; Ang 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 et al., 1987; Guo, 2006), inflation (Fama and Schwert, 1977; Campbell and Vuolteenaho, 2004), and corporate issuing activity (Baker and Wurgler, 2000). 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.

We also examine the relationship between manager sentiment and subsequent aggregate earnings surprises to explore the cash flow expectation error channel. We find strong evidence that manager sentiment negatively predicts subsequent aggregate earnings surprises in the next year, consistent with the extrapolative expectations models in Greenwood and Shleifer (2014) and Hirshleifer et al. (2015). In addition, we find that future information about aggregate earnings surprises helps to explain manager sentiment's predictive power for future annual market returns. Our findings suggest that the expectation error for future cash flows is likely the primary force driving manager sentiment's ability to predict future market returns.

We next examine the relationship between manager sentiment and future aggregate investment growth to explore the overinvestment channel. We find that periods with high manager sentiment are accompanied by high aggregate investment growth in the short run up to three quarters, but low subsequent aggregate investment growth in the long run up to two years. Our findings indicate that high manager sentiment captures managers' overly

[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 true sentiment measure while we focus on the predictive power of manager sentiment for future market returns.

optimistic beliefs about future returns to investment which leads to overinvestment, consistent with the extrapolative expectations models for investment of Gennaioli et al. (2016) and the frictions of investment lags in Lamont (2000).

We then compare the manager sentiment index with five existing measures of investor sentiment in the literature: 1) the Baker and Wurgler (2006) investor sentiment index; 2) the Huang et al. (2015) aligned investor sentiment index; 3) the University of Michigan consumer sentiment index; 4) the Conference Board consumer confidence index; and 5) the Da et al. (2015) Financial and Economic Attitudes Revealed by Search (FEARS) sentiment index. We find that the manager sentiment index correlates positively with all these 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.

We then show that manager sentiment is significantly different from existing investor sentiment and it contains unique and incremental information. First, we show that the forecasting power of manager sentiment remains significant after controlling for these existing investor sentiment measures. Second, the econometric forecast encompassing tests also confirm that manager sentiment is not a sideshow of existing investor sentiment measures. Third, the predictive power of manager sentiment is stronger than existing investor 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, there is no significant lead–lag relationship between the manager sentiment index and the existing investor sentiment indexes in the sense of Granger causality. Fifth, in sharp contrast with manager sentiment, investor sentiment contains insignificant incremental information for future aggregate earnings surprises. Sixth, high manager sentiment is strongly tied to overinvestment, but the link between investor sentiment and overinvestment is weak.

Manager sentiment also negatively predicts the cross-section of stock returns, and the predictability is concentrated among stocks with high growth opportunities, high financial constraint, low dividend payout, high leverage, high financial distress, low profitability, high unexpected earnings, low price, high turnover, high beta, high idiosyncratic volatility, young age, and small market cap. These results, consistent with Baker and Wurgler (2006), suggest that stocks that are difficult to value and costly to arbitrage are more sensitive to manager sentiment-driven mispricing. In contrast, while investor sentiment could significantly forecast stocks that are costly to arbitrage, it cannot forecast those that are difficult to value.

Our paper contributes to the literature on investor sentiment and its role in asset pricing. Baker and Wurgler (2006), Baker and Wurgler (2007), Yu and Yuan (2011), Baker et al. (2012), Stambaugh et al. (2012), Huang et al. (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 et al. (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 investor 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 textual 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 corporate textual 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 industries. Price et al. (2012) use the Henry (2008) word lists to gauge manager sentiment during earnings conference calls. The closest paper to ours is Loughran and McDonald (2011), who create a comprehensive list of sentiment words used in business context, and find a positive contemporaneous relationship between firm-level manager sentiment and the [0, 3] four-day event period return in the cross-section [see Loughran and McDonald (2016) for a recent literature review]. Complementary to their study, we find a negative predictive relationship between manager sentiment and future stock returns at both the aggregate level and at the firm level over longer horizons from one month to one year. Our results suggest that manager sentiment captures mispricing rather than fundamental information. We also find that incorporating positive words helps predict stock returns in the aggregate time series and the effect of manager sentiment is particularly important for firms that are difficult to value and costly 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 explains aggregate stock market returns. Kothari et al. (2006) find that aggregate earnings growth is negatively related to market returns. Anilowski et al. (2007) find that increases in upward managerial earnings guidance are positively associated with monthly market returns but find no evidence at the quarterly horizon. In contrast, we find that aggregate manager sentiment negatively predicts market returns from one month up to a year in the future. 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 surprises, 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 10-Ks, 10-Qs, and conference call transcripts 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. Although electronic 10-K and 10-Q filings are available on the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) beginning in 1995, SOX may have significantly altered their content. Hence, we construct a monthly manager sentiment index using 10-Ks, 10-Qs, and conference call transcripts 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 nonfinancial, 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 6715 firms. Using each firm's unique identifier, we then search Factiva's Fair Disclosure (FD) Wire for earnings conference calls made between 2003 and 2014 and find 113,570 total call transcripts for 5859 unique firms. The conference calls in our sample correspond to fiscal quarters from the fourth quarter of 2002 to the third quarter of 2014 due to the lag between fiscal quarter end and the date of the conference call.

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 held in each month. Price et al. (2012), among others, study 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 to remove seasonality and idiosyncratic jumps.

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 Management's Discussion and Analysis (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 code, 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 et al. (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, 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 manager 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.

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,

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

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 then captures the market-wide aggregate manager sentiment in any particular month.

Fig. 1 shows that the manager sentiment index S^{MS} reflects anecdotal accounts of time-series variation in

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

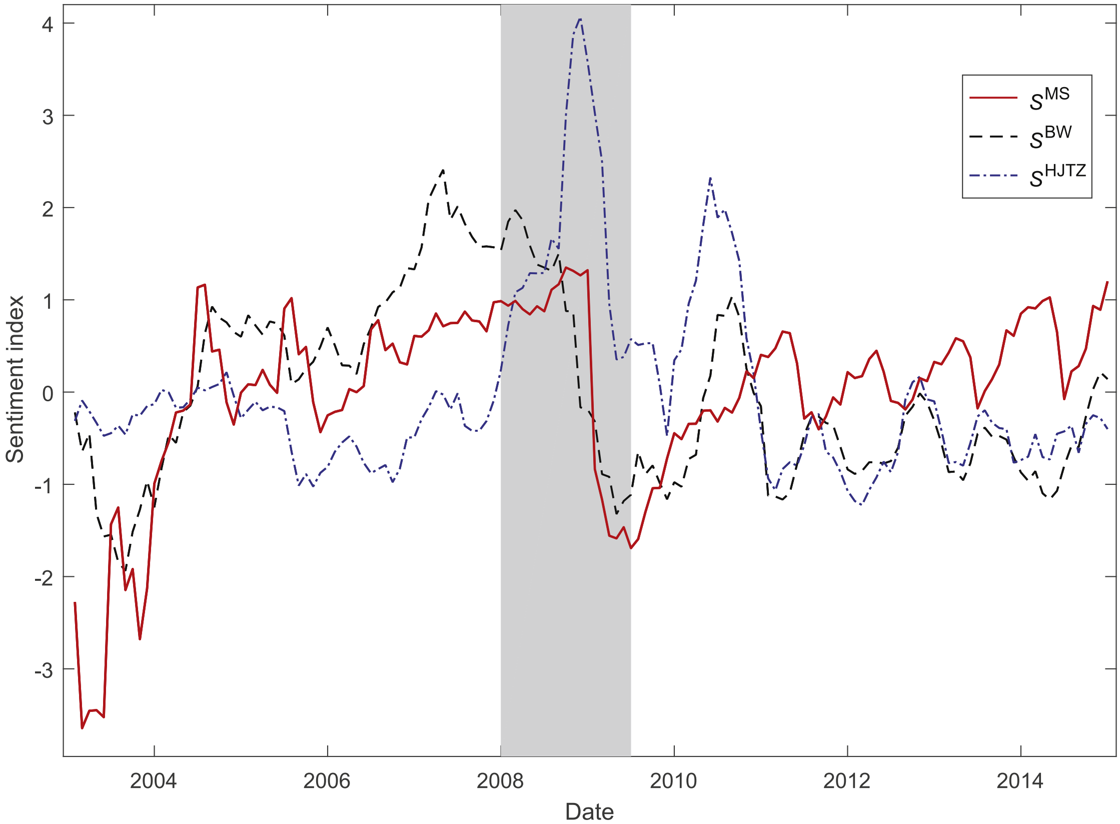

Fig. 1. The manager sentiment index. The solid line depicts the manager sentiment index S^{MS} which is the aggregate textual tone in 10-Ks, 10-Qs, and conference calls, filed in each month with a four-month moving average. The dashed and dotted lines depict the Baker and Wurgler (2006) investor sentiment index S^{BW} and the Huang et al. (2015) aligned investor sentiment index S^{HJTZ}, respectively, extracted from six stock market-based investor sentiment proxies. See Section 2 for detailed definitions of the sentiment indexes. All the sentiment measures are standardized to have zero mean and unit variance. The vertical bars correspond to NBER-dated recessions. The sample period is 2003:01– 2014:12.

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 2008–2009 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 Baker–Wurgler investor sentiment index, although they are constructed differently with different information sets.

The manager sentiment index has several appealing properties. First, it captures the common manager sentiment component in 10-Ks, 10-Qs, and conference calls and diversifies away the idiosyncratic noise in each individual component. 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. 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 et al. (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, $S^{RC} = 0.37S^{CC} + 0.63S^{FS}$, 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,

$$R^m_{t+1} = \alpha + \beta(\Upsilon^{CC}S^{CC}_t + \Upsilon^{FS}S^{FS}_t) + \varepsilon_{t+1}. \quad (2)$$

In the above specification (2), 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

Table 1
Sentiment indexes' correlations.
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}, conference call tone, S^{CC}, financial statement tone, S^{FS}, the Baker and Wurgler (2006) investor sentiment index, S^{BW}, the Huang et al. (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 et al. (2015) Financial and Economic Attitudes Revealed by Search (FEARS) investor sentiment index, S^{FEARS}. See Section 2 for detailed definitions of the sentiment indexes. The sample period is 2003:01–2014:12 (2004:07 – 2011:12 for S^{FEARS} due to data constraints).

	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}	0.10	0.15	−0.10	0.24	0.22	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

is equal to one, $\Upsilon^{CC} + \Upsilon^{FS} = 1$, such that the weights are uniquely determined by the data.

Second, we form value-weighted manager sentiment indexes. Generally, the equal-weighted index is preferred to the value-weighted. This is because equal-weighting represents breadth more fully. Huang et al. (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 manager 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 Standard and Poor's (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 the Center for Research in Security Prices (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 et al. (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 et al. (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 investor sentiment index S^{BW}, have been widely used in a number of studies such as Baker and Wurgler (2006), Baker and Wurgler (2007), Bergman and Roychowdhury (2008), Yu and Yuan (2011), Baker et al. (2012), Stambaugh et al. (2012), Brown et al. (2012), Hribar and McInnis (2012), Mian and Sankaraguruswamy (2012), Antoniou et al. (2016), 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

[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/.

for the influence of the business cycle, we use 14 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), and inflation rate (INFL). These variables are defined as follows:

- Dividend-price ratio (log), DP: log of a 12-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 the 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 12-month moving sums of net issues by NYSE-listed stocks to total end-of-year market capitalization of NYSE stocks.
- Treasury bill rate, TBL: interest rate on a 3-month Treasury bill (secondary market).
- Long-term yield, LTY: long-term government bond yield.
- Long-term return, LTR: return on long-term government bonds.
- Term spread, TMS: difference between the long-term yield and the Treasury bill rate.
- Default yield spread, DFY: difference between BAA- and AAA-rated corporate bond yields.
- Default return spread, DFR: difference between the long-term corporate bond return and the long-term government bond return.
- Inflation, INFL: calculated from the Consumer Price Index (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.

3. Predictive regression analysis

3.1. Market return predictability tests

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

$$R^m_{t\to t+h} = \alpha + \beta S^{\rm MS}_t + \varepsilon_{t\to t+h}, \tag{3}$$

where $R^m_{t\to t+h}$ is the h-month ahead cumulative 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 $S^{\rm MS}_t$ is the manager sentiment index. $S^{\rm MS}_t$ in the above regression is standardized to have zero mean and unit variance to facilitate comparison and interpretation across predictors. Our primary interest is to test the significance of β in Eq. (3). The null hypothesis is that manager sentiment has no predictive ability ($\beta = 0$). In this case, Eq. (3) reduces to the constant expected return model. As a more powerful test of return predictability, Inoue and Kilian (2004) recommend using a one-sided alternative hypothesis on β. Specifically, we test $H_0 : \beta = 0$ against H_A: $\beta < 0$, since finance theory suggests a negative sign on β.

It is well known that statistical inferences in Eq. (3) are complicated by several econometric issues. First, if a predictor is highly persistent, the ordinary least squares (OLS) regression may generate spurious results (Ferson et al., 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, following Huang et al. (2015), 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.[6]

Table 2 reports the in-sample OLS estimation results of the predictive regressions (3) for the manager sentiment index $S^{\rm MS}$ over each horizon. First, at the monthly horizon, the regression slope on $S^{\rm MS}$, 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, $S^{\rm MS}$ 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 $S^{\rm MS}$ as a sentiment index leads to market-wide over-valuation (under-valuation) when $S^{\rm MS}$ 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 $S^{\rm MS}$ 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

[5] The economic variables are reviewed in Goyal and Welch (2008), and the updated data are available from Amit Goyal's website, http://www.hec.unil.ch/agoyal/.

[6] The results of the wild bootstrap procedure are untabulated but available upon request. Amihud and Hurvich (2004), Lewellen (2004), Campbell and Yogo (2006), and Amihud et al. (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.

Table 2
Manager sentiment and aggregate market return.
This table reports the ordinary least squares estimation results for α, β, and R^2 statistics for the predictive regression model,

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

where $R^m_{t\to t+h}$ is the h-month ahead cumulative excess market return from month t to $t+h$ (in percentage) calculated from the monthly excess aggregate market return R^m, 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 aggregate manager tone extracted from 10-Ks, 10-Qs, and conference calls. 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.

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

(3) 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 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.

Second, we investigate the forecasting power of the manager sentiment index over longer horizons up to three years. 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 to 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 et al. (2012) find that global sentiment in year $t-1$ significantly predicts the following 12-month country-level market returns over 1980–2005. Huang et al. (2015) show that aligned investor sentiment S^{HJTZ} has significant forecasting power for up to a one-year forecasting horizon.

Table 2 shows that, at the quarterly, semi-annual, nine-month, annual, two-year, and three-year horizons, S^{MS} consistently and significantly predicts 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 year. Across horizons, the in-sample forecasting power in terms of R^2 increases as the horizon increases and then declines. Specifically, the in-sample R^2 of S^{MS} peaks at the nine-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. This evidence contributes to the existing market sentiment literature by showing that manager sentiment, similar to investor sentiment, peaks (troughs) in advance of weak (strong) stock market performance.

3.2. Firm-level return predictability tests

To better understand management sentiment at the aggregate level, in this subsection we investigate the relationship between manager sentiment and subsequent stock returns at the firm level.

Table 3 reports the regression estimation results of the relationship between firm-level manager sentiment and stock returns measured over various windows. Following Loughran and McDonald (2011), we control for firm size on the day before the event date (log(Size)), the book-to-market ratio based on the most recent Compustat and CRSP data no more than one year before the event date as specified in Fama and French (2001) (log(BM)), share turnover in days [−252, −6] prior to the event date (log(Turn)), the pre-event date Fama-French alpha using days [−252, −61] (Alpha), the percent of institutional ownership for the most recent quarter before the event date (Institute), and a dummy variable for Nasdaq listing (Nasdaq). Fama-French 48 industry dummies and a constant term are also included in each regression.

The first column of Table 3 shows a positive relationship between firm-level manager sentiment and four-day event period excess buy-and-hold returns using days [0, 3], consistent with Loughran and McDonald (2011). Complementary to Loughran and McDonald (2011) who focus on the contemporaneous event-window announcement returns, we also study the predictive relationship between firm-level manager sentiment and long-term excess buy-and-hold returns from one to 12 months after the filings. When we move to long-term excess returns cumulated over various horizons up to 12 months post event date, we find that manager sentiment has significantly negative predictive power for subsequent long-term stock returns, consistent with our findings at the aggregate market level.

In summary, we find a negative predictive relationship between manager sentiment and subsequent future stock returns at both the aggregate level and at the firm level over longer horizons. Combined with the positive contemporaneous association documented by Loughran and McDonald (2011), these results indicate that manager sentiment captures mispricing rather than fundamental information.

3.3. Alternative measures of manager sentiment

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

Table 3
Manager sentiment and cross-sectional stock return.
This table reports the estimation results for the OLS regressions on the relationship between firm-level manager sentiment and contemporaneous and subsequent long-term stock returns in the cross-section. The dependent variable in the first column is the four-day event period excess buy-and-hold return using days [0, 3], and the dependent variables in the second to the last columns are the long-term excess buy-and-hold returns from one to 12 months after the filings. S^{MS} is the firm-level manager sentiment extracted from the textual filings of 10-Ks, 10-Qs, and conference calls. Following Loughran and McDonald (2011), we also control for the firm size on the day before the event date (log(Size)), the book-to-market ratio based on the most recent Compustat and CRSP data no more than one year before the event date as specified in Fama and French (2001) (log(BM)), the share turnover in days [−252, −6] prior to the event date (log(Turn)), the pre-event date Fama-French alpha using days [−252, −61] (Alpha), the percent of institutional ownership for the most recent quarter before the event date (Institute), and a dummy variable for Nasdaq listing (Nasdaq). Fama-French 48 industry dummies and a constant term are also included in each regression. The regression coefficients, Newey–West heteroskedasticity- and autocorrelation-robust t-statistics clustered by firm, and R^2s are reported. The sample period is 2003:01−2014:12.

	(1) [0, 3]	(2) 1 Month	(3) 3 Months	(4) 6 Months	(5) 9 Months	(6) 12 Months
S^{MS}	0.004	−0.002	−0.004	−0.008	−0.010	−0.012
	(20.38)	(−8.16)	(−7.86)	(−9.41)	(−8.46)	(−7.60)
log(Size)	0.001	−0.002	−0.008	−0.018	−0.024	−0.031
	(6.17)	(−9.79)	(−15.14)	(−14.70)	(−13.30)	(−12.65)
log(BM)	0.002	0.002	0.007	0.013	0.017	0.021
	(7.95)	(5.39)	(8.47)	(8.18)	(7.26)	(6.71)
log(Turn)	−0.004	0.001	−0.004	−0.007	−0.014	−0.017
	(−14.05)	(3.41)	(−4.08)	(−3.69)	(−4.97)	(−4.41)
Alpha	0.693	0.751	0.844	−0.186	−2.779	−8.061
	(4.55)	(2.89)	(1.56)	(−0.17)	(−1.91)	(−4.26)
Institute	0.012	0.007	0.030	0.059	0.091	0.125
	(17.24)	(7.26)	(13.74)	(13.47)	(13.87)	(14.29)
Nasdaq	0.000	−0.001	−0.007	−0.019	−0.026	−0.035
	(0.42)	(−1.27)	(−4.53)	(−5.81)	(−5.23)	(−5.22)
R^2	0.006	0.003	0.007	0.010	0.012	0.014

Table 4
Robustness tests.
This table provides additional robustness tests 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 measure 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 word or negative word counts alone; S^{FSP} and S^{FSN}, the financial statement tone aggregated on positive word or negative word counts alone. See Section 2 for detailed definitions. 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 subsample 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.

Panel A: Alternative measures							
	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

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 4 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 et al. (2010) 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.

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 4 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 of the individual tone measures, consistent with the finding of (Baker and Wurgler, 2006; 2007) that a composite sentiment index is more powerful than the 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 4 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.

3.4. Subperiod analysis

From an economic point of view, while the overall R^2 is interesting, it is also important to analyze the predictability of the manager sentiment index during business-cycles to better understand the fundamental driving forces (e.g.,García, 2013). Following Rapach et al. (2010) and Henkel et al. (2011), we compute the R^2 statistics separately for economic recessions (R^2_{rec}) and expansions (R^2_{exp}),

$$R^2_c = 1 - \frac{\sum_{t=1}^{T} I_t^c (\hat{\varepsilon}_{i,t})^2}{\sum_{t=1}^{T} I_t^c (R_t^m - \bar{R}^m)^2}, \qquad c = \text{rec},\ \text{exp}, \tag{4}$$

where I_t^{rec} (I_t^{exp}) is an indicator that takes a value of one when month t is in a National Bureau of Economic Research (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 (3); $\bar{R}^m$ 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 4 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 et al. (2015) for investor sentiment indexes and Rapach et al. (2010) and Henkel et al. (2011) for other macroeconomic variables. Intuitively, managers tend to become highly optimistic (pessimistic) near business-cycle peaks (troughs) due to perhaps an over-extrapolation bias, which leads to misvaluation and a 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.

In Panel B of Table 4, 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 et al. (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 Eq. (4). Empirically, we find that the predictive power of S^{MS} is stronger during high sentiment periods. For example, over high sentiment periods, S^{MS} has an R^2_{high} of 12.9%. In contrast, over low sentiment periods, S^{MS} has a smaller R^2_{low} of 6.93% though still fairly large economically. In summary, these findings, largely consistent with Shen et al. (2017) and Huang et al. (2015), suggest that manager sentiment, similar to investor sentiment, has stronger forecasting power when sentiment is higher, during which mispricing is more likely due to limits to arbitrage and short-sale constraints.

3.5. Comparison with economic predictors

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

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

$$R_{t+1}^m = \alpha + \psi Z_t^k + \varepsilon_{t+1}, \qquad k = 1, \ldots, 15, \tag{5}$$

Table 5
Comparison with economic variables.

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_t^k,

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

where R_{t+1}^m is the monthly excess aggregate stock market return (in percentage), and Z_t^k is one of the 14 individual economic variables given in the first 14 rows of the first column or the ECON factor which is the first principal component factor extracted from the individual economic variables. See Section 2.2 for detailed definitions for economic variables. Panel B reports the in-sample estimation results for the bivariate predictive regressions on both the lagged manager sentiment index S_t^{MS} and Z_t^k,

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

We report the regression coefficients, Newey–West t-statistics, and R^2s. The sample period is 2003:01–2014:12.

	Panel A: Univariate regressions $R_{t+1}^m = \alpha + \psi Z_t^k + \varepsilon_{t+1}$			Panel B: Bivariate regressions $R_{t+1}^m = \alpha + \beta S_t^{MS} + \psi Z_t^k + \varepsilon_{t+1}$				
	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
ECON	0.13	0.29	0.12	−1.30	−3.64	0.30	0.69	10.4

where Z_t^k is one of the 14 individual economic variables described in Section 2.2 or the ECON factor which is the first principal component (PC) extracted from these economic variables.

Panel A of Table 5 reports the estimation results for Eq. (5). Out of the 14 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 is insignificant in forecasting the excess market return, with an R^2 of only 0.12%. Hence, S^{MS} outperforms all the individual economic predictors and the PC common factor, ECON, in forecasting the monthly excess market returns in-sample.

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

$$R_{t+1}^m = \alpha + \beta S_t^{MS} + \psi Z_t^k + \varepsilon_{t+1}, \qquad k = 1, ..., 15. \tag{6}$$

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 (6) range from −1.10 to −1.42, all of which are negative and economically large, in line with the results in the earlier predictive regression (3) 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 (6) range from 9.83% to 14.2%, 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.

3.6. 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. The current return predictability literature almost exclusively focuses on investor sentiment in forecasting stock returns. Given that managers are better informed about their firms and yet are also subject to cognitive biases and emotion, it is of interest to examine the predictive power of manager sentiment in relation to that of investor sentiment.

We run the following predictive regressions of the monthly excess market return (R_{t+1}^m) on the lagged

Table 6
Comparison with existing investor sentiment indexes.
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,

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

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 et al. (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 et al. (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.

	(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

manager sentiment index, S^{MS}, with controls for alternative sentiment indexes, S^k_t,

$$R^m_{t+1} = \alpha + \beta S^{MS}_t + \delta S^k_t + \varepsilon_{t+1},$$
$$k = \text{BW, HJTZ, MCS, CBC, FEARS}, \quad (7)$$

where S^{BW} denotes the Baker and Wurgler (2006) investor sentiment index, S^{HJTZ} denotes the Huang et al. (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 et al. (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 investor sentiment indexes are provided in Section 2.2.

As a benchmark, the first column of Table 6 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 6 shows that the Huang et al. (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 question of interest is whether manager sentiment dominates 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 6 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 et al. (2015) FEARS investor sentiment index (S^{FEARS}) are smaller than that of S^{MS}, whose R^2 values range from 0.26% to 2.71%. Most importantly, each index becomes statistically insignificant when controlling for S^{MS} in the bivariate regressions, while S^{MS} remains consistently negative and significant. 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.

3.7. 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} simply reacts to lagged information contained in existing investor sentiment measures (i.e., investor sentiment leads manager sentiment), or that lagged S^{MS} simply drives existing investor sentiment measures (i.e., manager sentiment leads investor sentiment), or, most likely, that 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,

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

and

$$S_t^{k} = \alpha + \sum_{i=1}^{s} \delta_i S_{t-i}^{k} + \sum_{i=1}^{s} \beta_i S_{t-i}^{MS} + \varepsilon_t, \qquad k = \text{BW, HJTZ}, \tag{9}$$

where S^{MS} denotes the manager sentiment index, S^{BW} denotes the Baker and Wurgler (2006) investor sentiment index, and S^{HJTZ} denotes the Huang et al. (2015) aligned investor sentiment index.[7] We set $s = 5$ for our lag choice, although alternative choices do not affect the conclusions. The regressions in (8) and (9) 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.

Panel A of Table 7 presents the estimated coefficients for Eq. (8), which measures the feedback effect from each investor sentiment measure to manager sentiment. Panel B from Table 7 presents the estimated coefficients for Eq. (9), which measures the feedback effect from manager sentiment to investor sentiment.

Table 7 shows that the simple models in (8) and (9) could largely explain the time-series dynamics of manager sentiment and investor sentiment, with adjusted R^2s of 83–94%. Most importantly, Table 7 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.

3.8. Forecast encompassing test

To further assess the information content of the manager sentiment index S^{MS} relative to the five alternative sentiment indexes, we conduct a forecast encompassing test. Harvey et al. (1998) develop a statistic for testing the null hypothesis that a given forecast contains all of the relevant information found in a competing forecast (i.e., the given forecast encompasses the competitor) against the alternative that the competing forecast contains relevant information beyond that in the given forecast.

Table 8 reports p-values for the Harvey et al. (1998) forecast encompassing test. The first row of Table 8 shows that the manager sentiment index S^{MS} encompasses the two individual tone measures as well as four of the 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 4. In addition, the fourth to eighth rows of Table 8 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, 2013). 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

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

Table 7
Feedback between manager sentiment and investor sentiment.

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

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

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

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

where the choice of lag s is equal to 5, S^{MS} denotes the manager sentiment index, S^{BW} denotes the Baker and Wurgler (2006) investor sentiment index, and S^{HJTZ} denotes the Huang et al. (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.

	Panel A: IS ⇒ MS				*Panel B: MS ⇒ IS*			
	$S^{\mathrm{BW}} \Rightarrow S^{\mathrm{MS}}$		$S^{\mathrm{HJTZ}} \Rightarrow S^{\mathrm{MS}}$		$S^{\mathrm{BW}} \Rightarrow S^{\mathrm{MS}}$		$S^{\mathrm{HJTZ}} \Rightarrow S^{\mathrm{MS}}$	
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	

Table 8
Forecast encompassing tests.

This table reports the p-values for the Harvey et al. (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}, conference call tone, S^{CC}, financial statement tone, S^{FS}, the Baker and Wurgler (2006) investor sentiment index, S^{BW}, the Huang et al. (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 et al. (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).

	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	

predictive regressions recursively on each lagged manager sentiment measure,

$$\hat{R}_{t+1}^m = \hat{\alpha}_t + \hat{\beta}_t S_{1:t;t}^k, \tag{10}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates from regressing $\{R_{s+1}^m\}_{s=1}^{t-1}$ on a constant and a recursively estimated sentiment measure $\{S_{1:t;s}^k\}_{s=1}^{t-1}$. 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 a combination forecast, S^{C}, combined from S^{CC} and S^{FS}, since Timmermann (2006) and Rapach et al. (2010) find that the simple combination forecast often beats forecasts with sophisticated optimally estimated parameters in a more realistic out-of-sample setting with a complex and constantly evolving data-generating process. For comparison purposes, we also examine the out-of-sample forecasting performance of the five alternative investor sentiment indexes.

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: $\{\hat{R}_{t+1}^m\}_{t=p}^{T-1}$. 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.[8]

[8] Hansen and Timmermann (2012) and Inoue and Rossi (2012) show that out-of-sample tests of predictive ability have better size properties

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,

$$R^2_{\rm OS} = 1 - \frac{\sum_{t=p}^{T-1}(R^m_{t+1} - \hat{R}^m_{t+1})^2}{\sum_{t=p}^{T-1}(R^m_{t+1} - \bar{R}^m_{t+1})^2}, \quad (11)$$

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

$$\bar{R}^m_{t+1} = \frac{1}{t}\sum_{s=1}^{t} R^m_s. \quad (12)$$

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: $R^2_{OS} \le 0$ 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 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.

The first row of Table 9 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 9, in particular, all the five existing investor sentiment indexes. In addition, the fourth and fifth columns of Table 9 show that the predictability of the manager sentiment index S^{MS} is concentrated during recessions, confirming our earlier in-sample findings in Table 4.

when the forecast evaluation period is a relatively large proportion of the available sample, as in our case.

Table 9
Out-of-sample forecasting results.
This table reports the out-of-sample performance in predicting the monthly excess market return using the manager sentiment index, S^{MS}, the combination forecast of manager sentiment proxies S^{CC} and S^{FS}, S^{C}, and the Baker and Wurgler (2006) investor sentiment index, S^{BW}, the Huang et al. (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 et al. (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. $R^2_{OS,rec}$ ($R^2_{OS,exp}$) 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 constraints).

	R^2_{OS} (%)	MSFE-*adj*	$R^2_{OS,rec}$ (%)	$R^2_{OS,exp}$ (%)
S^{MS}	8.38***	2.55	18.8	−1.20
S^{C}	7.94**	2.07	12.8	−7.27
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

The second row of Table 9 shows that 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) and Rapach et al. (2010) that while sophisticated models may have good in-sample fit, their out-of-sample performance tends to be worse due to large estimation error.

Table 9 also reports the out-of-sample performance of the five existing investor 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 the 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 investor sentiment indexes documented in the literature in an out-of-sample forecasting 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) and Campbell and Thompson (2008), 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

$$w_t = \frac{1}{\gamma}\frac{\hat{R}^m_{t+1}}{\hat{\sigma}^2_{t+1}} \tag{13}$$

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

$$R^p_{t+1} = w_t R^m_{t+1} + R^f_{t+1}, \tag{14}$$

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 zero and 1.5 to exclude short sales and to allow for at most 50% leverage.

The CER of the portfolio is

$$\text{CER}_p = \hat{\mu}_p - 0.5\gamma\hat{\sigma}^2_p, \tag{15}$$

where $\hat{\mu}_n$ and $\hat{\sigma}^2_n$ are the sample mean and variance, respectively, for the investor's portfolio over the q forecasting evaluation periods. The CER gain is the difference between the CER for the investor who uses a predictive regression forecast of market return generated by (10) and the CER for an investor who uses the historical average forecast (12). 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 50 basis points (bps) transaction costs, which is generally considered a relatively high number.

The first row of Table 10 shows that the manager sentiment index S^{MS} generates large economic gains for the mean–variance investor, consistent with its large R^2_{OS} statistic in Table 9. 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 second row shows that the combination forecast of manager sentiment proxies, S^{C}, also generates large economic gains for the investor.

The rest of Table 10 shows that, out of the five alternative investor sentiment indexes, 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} 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^{CBC} only generates a small CER gain of 0.62% and a negative Sharpe ratio of −0.03.

Overall, Table 10 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 and earnings surprises

In this section, we investigate the relationship between the manager sentiment index S^{MS} and future aggregate earnings and earnings surprises to explore the cash flow expectation error 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 (Huang et al., 2015).

Specifically, manager sentiment might be high when past realized aggregate earnings are high, and managers may extrapolate the recent earnings trend and optimistically expect that future earnings will be high as well, leading to overvaluation. In reality, earnings tend to mean revert, resulting in realized earnings being lower than expected and leading to negative earnings surprises and low stock returns (e.g., Greenwood and Shleifer, 2014; Hirshleifer et al., 2015).

Panel A1 of Table 11 reports the estimation results of predicting the future aggregate earnings surprises using the lagged manager sentiment index at different horizons. We employ the following standard predictive regressions (Campbell and Shiller, 1988; Fama and French, 2000; Menzly et al., 2004; Cochrane, 2008; 2011; Huang et al., 2015),

$$\text{SUE}_{t+h} = \alpha + \beta S^{MS}_t + \upsilon_{t+h}, \tag{16}$$

where the dependent variable, SUE_{t+h}, is the h-month ahead aggregate earnings surprise (in percentage) calculated as the value-weighted seasonally adjusted firm-level earnings surprises (i.e., earnings relative to earnings in the same quarter of the previous year) standardized by stock price. The forecast horizon h spans from zero to 36 months, where zero refers to the contemporaneous relationship. The coefficient of interest is the slope β on S^{MS}_t. If the time-varying risk premium is the primary channel through which manager sentiment predicts future market

Table 10
Asset allocation results.

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 forecasts of the excess market returns based on the manager sentiment index, S^{MS}, the combination forecast of manager sentiment proxies S^{CC} and S^{FS}, S^{C}, and the Baker and Wurgler (2006) investor sentiment index, S^{BW}, the Huang et al. (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 et al. (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).

	No transaction cost		50bps transaction cost	
Predictor	CER gain (%)	Sharpe ratio	CER gain (%)	Sharpe ratio
S^{MS}	7.92	0.17	7.86	0.17
S^{C}	8.11	0.16	8.06	0.16
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

Table 11
Manager sentiment and aggregate earnings and earnings surprises.

Panels A1 and A2 report the estimation results for the univariate and bivariate predictive regressions of the h-month ahead aggregate earnings surprises (SUE_{t+h}, in percentage) on the lagged manager sentiment index (S^{MS}) as well as the Baker and Wurgler (2006) investor sentiment index (S^{BW}). Forecasting horizon h spans from zero to 36 months, where zero refers to the contemporaneous relationship. The aggregate earnings surprises are calculated as the value-weighted changes in firm-level earnings from their values four quarters ago standardized with stock prices. Panels B1 and B2 report the estimation results for the univariate and bivariate predictive regressions of the h-month ahead aggregate earnings (ROA_{t+h}, in percentage), calculated as the value-weighted average firm-level ROA from the Compustat database, on the lagged S^{MS} and S^{BW}. Panel C reports the estimation results for the annual predictive regressions of the one-year ahead cumulative excess market return (R^m, in percentage) on the lagged S^{MS}, S^{BW}, and the one-year ahead realized aggregate earnings surprises (SUE). The regression coefficients, Newey-West heteroskedasticity- and autocorrelation-robust t-statistics, and R^2s are reported. The sample period is 2003:01–2014:12.

Panel A: Predicting aggregate earnings surprises (SUE)								
Horizon	β (%)	t-stat	R^2 (%)	β (%)	t-stat	γ (%)	t-stat	R^2 (%)
	Panel A1: Manager sentiment $\text{SUE}_{t+h} = \alpha + \beta S_t^{MS} + \upsilon_{t+h}$			*Panel A2: Investor sentiment* $\text{SUE}_{t+h} = \alpha + \beta S_t^{MS} + \gamma S_t^{BW} + \upsilon_{t+h}$				
0	0.06	0.37	0.53	0.05	0.36	0.02	0.26	0.56
3	−0.23	−2.42	6.84	−0.24	−1.98	0.01	0.08	6.85
6	−0.41	−2.37	21.33	−0.36	−1.98	−0.09	−1.11	22.06
9	−0.48	−2.33	29.04	−0.37	−1.92	−0.20	−1.61	31.49
12	−0.49	−2.45	31.03	−0.35	−2.12	−0.25	−1.59	35.17
24	−0.08	−0.46	0.74	0.12	0.75	−0.31	−1.25	5.84
36	0.08	0.65	0.74	−0.08	−0.72	0.23	1.20	2.23
Panel B: Predicting aggregate earnings (ROA)								
	Panel B1: Manager sentiment $\text{ROA}_{t+h} = \alpha + \beta S_t^{MS} + \upsilon_{t+h}$			*Panel B2: Investor sentiment* $\text{ROA}_{t+h} = \alpha + \beta S_t^{MS} + \gamma S_t^{BW} + \upsilon_{t+h}$				
0	0.21	5.55	20.21	0.24	5.28	−0.07	−1.29	22.06
3	0.12	2.97	7.54	0.15	2.58	−0.05	−0.71	8.34
6	0.09	1.47	4.23	0.13	1.71	−0.08	−1.21	5.36
9	0.05	0.67	1.32	0.09	1.38	−0.08	−1.65	2.43
12	0.01	0.21	0.16	0.06	0.95	−0.08	−1.54	0.66
24	−0.08	−1.66	2.66	0.03	0.29	−0.15	−1.42	8.78
36	0.04	0.66	0.97	0.07	1.10	−0.04	−0.75	1.51

Panel C: Market return annual predictive regressions

$\text{R}^m_{t+1} = \alpha + \beta S_t^{MS} + \gamma S_t^{BW} + \psi \text{SUE}_{t+1} + \upsilon_{t+1}$

	β (%)	t-stat	γ (%)	t-stat	ψ (%)	t-stat	R^2 (%)
(1)	−2.41	−1.22			12.37	13.36	54.53
(2)	0.59	0.31	−6.85	−2.75	10.34	9.91	64.24

returns, manager sentiment should not be systematically associated with future earnings surprises. In contrast, if manager sentiment predicts future stock returns because it captures mispricing driven by cash flow expectation error, we would expect to see negative earnings surprises following periods of high manager sentiment.

Panel A1 of Table 11 shows that manager sentiment negatively predicts future aggregate earnings surprises from the next quarter to the next year. For example, at the annual forecasting horizon, the regression coefficient β on S_t^{MS} is significantly negative at -0.49 with a t-statistic of -2.45. The predictive power is economically large with an R^2 of 31% for the univariate predictive regression. Thus, high manager sentiment reflects overly optimistic expectation errors for future cash flows, leading to negative earnings surprises.

For comparison, in Panel B1, we also study manager sentiment's predictive power for future aggregate earnings (ROA) at different horizons,

$$\text{ROA}_{t+h} = \alpha + \beta S_t^{\text{MS}} + \upsilon_{t+h}. \tag{17}$$

We find that manager sentiment is positively related to concurrent aggregate earnings. The positive relationship remains significant for aggregate earnings over the subsequent six months, then turns insignificant, and even marginally negative within two years, indicating that aggregate earnings is persistent and reverts to the mean gradually.

Taken together, Panels A1 and B1 show that high manager sentiment predicts high concurrent aggregate earnings but low subsequent earnings surprises in the next year, and the dynamics of earnings surprises following periods of high manager sentiment display a U-shaped predictive pattern. Our findings are largely consistent with the extrapolative expectations models in Greenwood and Shleifer (2014) and Hirshleifer et al. (2015). In year t, when manager sentiment is high, realized aggregate earnings is also high. The aggregate earnings surprise may also be high or insignificant. Managers overly extrapolate the recent earnings trend and expect that future earnings in year $t+1$ will be high as well. In year $t+1$, realized earnings reverts to the mean and is lower than expected, leading to a negative earnings surprise. Managers learn from the realized earnings disappointment and revise their earnings expectation downward for year $t+2$. Thus, in year $t+2$ and onward, there is no longer a significant earnings surprise.

In Panel C of Table 11, we perform one additional market return annual prediction test to further illustrate the underlying channel of our results that stems from errors in predicting future earnings. Specifically, we examine whether manager sentiment continues to predict future stock returns after controlling for future information about earnings surprises,

$$\text{R}_{t+1}^m = \alpha + \beta S_t^{\text{MS}} + \psi\,\text{SUE}_{t+1} + \upsilon_{t+1}. \tag{18}$$

If the return predictive power of manager sentiment originates from the expectation errors about fundamentals, manager sentiment would be subsumed by these subsequent shocks to fundamentals. The results in Panel C indicate that, at the annual predictive horizon, manager sentiment is no longer associated with one-year ahead cumulative excess aggregate market returns when we control for one-year ahead realized aggregate earnings surprises. Therefore, expectation errors for future cash flows are likely the primary driver for the predictive power of manager sentiment for future stock returns.

At the firm level, Loughran and McDonald (2011) find that firm-level manager sentiment negatively forecasts subsequent quarterly earnings surprises after the filing date, and they claim that managers are strategically lowering investor expectations. In unreported results, we further show that firm-level manager sentiment relates positively to contemporaneous earnings and earnings surprises but negatively forecasts subsequent quarterly earnings surprises, similar to our aggregate-level evidence in Table 11. We argue that the strategic view might not fully explain our results, which seem more consistent with the sentiment explanation that managers become overly optimistic at the end of expansions as earnings peak and become overly pessimistic at the end of recessions as earnings start to rebound. As shown in Table 4, we observe that manager sentiment's predictability comes from both the high-sentiment and low-sentiment periods, and the predictability is stronger in the high-sentiment periods. The strategic explanation may explain our results for the low-sentiment periods, but might be inconsistent with the results for high-sentiment periods. Specifically, it is plausible that when manager sentiment is low, managers strategically lower investor expectations to generate positive SUE in the future. However, it is less clear why managers would strategically increase investor expectations with high sentiment, if high sentiment generates negative future SUE. In addition, the strategic explanation is unable to explain why high manager sentiment would lead to overinvestment as shown in Table 12 and Section 5.2.

Lastly, in Table 11, we further control for investor sentiment and re-run all of the above tests to see whether manager sentiment continues to have predictive power. Panels A2 and B2 show that manager sentiment's predictive power for aggregate earnings surprises and aggregate earnings remains significant and largely unchanged after controlling for investor sentiment. However, investor sentiment generally has insignificant and small incremental predictive power for future aggregate earnings and earnings surprises beyond manager sentiment. Panel C further shows that investor sentiment's return predictability has a weak link to future realized aggregate earnings surprises. In summary, our findings indicate that manager sentiment is distinct from investor sentiment. While manager sentiment captures expectation errors about future cash flows, investor sentiment may contain information about expectation errors for future expected returns or discount rates.

5.2. Manager sentiment and aggregate investment growth

In this subsection, we examine the relationship between manager sentiment and future aggregate investment growth to identify a potential source for the negative predictability. The existing literature shows that managerial investment decisions may be influenced by sentiment (Arif and Lee, 2014; Gennaioli et al., 2016). Therefore, when manager sentiment is high, managers may overinvest in

Table 12
Manager sentiment and aggregate investment growth.
Panel A reports the estimation results for the univariate predictive regressions of the aggregate investment growth (IG_{t+h}) on the lagged manager sentiment index (S^{MS}),

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

where IG_{t+h} is the h-month ahead year-to-year growth rate of the aggregate capital expenditures (in percentage) calculated from the Compustat database. Forecasting horizon h spans from zero to 36 months, where zero refers to the contemporaneous relationship. S_t^{MS} is the manager sentiment index defined as the aggregated textual tone extracted from 10-Ks, 10-Qs, and conference calls. Panel B reports the estimation results for the bivariate predictive regressions on both the lagged manager sentiment index (S^{MS}) and the Baker and Wurgler (2006) investor sentiment index (S^{BW}),

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

The regression coefficients, Newey-West heteroskedasticity- and autocorrelation-robust t-statistics, and R^2s are reported. The sample period is 2003:01–2014:12.

	Panel A: Manager sentiment $\mathrm{IG}_{t+h} = \alpha + \beta S_t^{\mathrm{MS}} + \upsilon_{t+h}$			Panel B: Investor sentiment $\mathrm{IG}_{t+h} = \alpha + \beta S_t^{\mathrm{MS}} + \gamma S_t^{\mathrm{BW}} + \upsilon_{t+h}$				
Horizon	β (%)	t-stat	R^2 (%)	β (%)	t-stat	γ (%)	t-stat	R^2 (%)
0	7.79	6.06	37.88	5.99	4.71	3.43	1.79	43.19
3	7.79	4.65	40.28	5.98	3.70	3.39	1.62	45.83
6	6.34	3.82	28.49	4.68	3.01	3.12	1.61	33.44
9	4.52	2.75	14.97	2.80	1.96	3.10	1.95	19.82
12	1.65	0.85	2.05	0.29	0.15	2.32	1.94	4.66
24	−6.13	−2.79	29.26	−3.75	−2.22	−3.74	−1.21	35.32
36	−2.15	−0.92	3.85	1.15	0.55	−5.02	−1.56	13.99

capital expenditures because they overestimate future cash flows from investments, resulting in firm value destruction and low future stock returns.

Panel A of Table 12 reports the estimation results of predicting future aggregate investment growth using the lagged manager sentiment index at different horizons. We employ the following predictive regressions,

$$\mathrm{IG}_{t+h} = \alpha + \beta S_t^{\mathrm{MS}} + \upsilon_{t+h}, \tag{19}$$

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

The first row of Panel A of Table 12 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 12 shows that the dynamics of aggregate investment growth following periods of high manager sentiment display a hump-shaped pattern. Specifically, in the short run up to three quarters, high manager sentiment is associated with high aggregate investment growth.[9] The predictive relationship between manager sentiment and aggregate investment growth becomes statistically insignificant in one year. However, over longer horizons of up to two years, high manager sentiment predicts a sharp decline in aggregate investment. In summary, manager sentiment appears to peak at the end of expansions and trough at the end of recessions, and high manager sentiment forecasts high investment growth in the short run, but low investment growth in the longer run.

Economically, our results are generally consistent with the extrapolative expectations models for investment of Gennaioli et al. (2016) and the frictions of investment lags in Lamont (2000). When manager sentiment is high, aggregate earnings may also be high and the stock market may be overvalued. Extrapolating the recent performance in earnings and stock prices, managers are optimistic and hence decide to invest more. When the fundamentals are subsequently revealed, the stock market quickly responds by correcting the sentiment-driven overvaluation resulting in low stock returns. However, as stock prices drop, managers respond slowly and continue overinvesting in the short run up to three quarters, likely because the actual investment expenditure lags the decision to invest by some period of time. Investment lags and the cost of adjusting investments prevent firms from immediately changing investment which might cause actual investment to be negatively correlated with returns (Lamont, 2000; Li et al., 2017). In addition, Gennaioli et al. (2016) and Kothari et al. (2016) show that managers are extrapolative and slow in updating their expectations with regard to the past year's earnings and returns, which would also slow down managers' responses. Within one year, managers may begin to respond by making plans to cut investments after observing the past year's negative earnings surprises and low stock returns, but the actual decline in investment occurs in two years due to the investment lags.

[9] In untabulated analyses, we find evidence of overinvestment following high manager sentiment at the firm level as well.

Arif and Lee (2014) show that high investor sentiment is associated with increases in aggregate investment. Therefore, we further control for investor sentiment to test whether manager sentiment continues to have incremental predictive power or whether its predictive power is due to its positive correlation with investor sentiment. We run the following bivariate predictive regressions on the manager sentiment index S_t^{MS} and the Baker and Wurgler (2006) investor sentiment index (S^{BW}),

$$\mathrm{IG}_{t+h} = \alpha + \beta S_t^{\mathrm{MS}} + \gamma S_t^{\mathrm{BW}} + \upsilon_{t+h}. \tag{20}$$

We report the findings in Panel B of Table 12.

Panel B of Table 12 shows that manager sentiment's predictive power for future aggregate investment growth remains significant and largely unchanged after controlling for investor sentiment. In sharp contrast, investor sentiment generally has insignificant and small incremental predictive power for aggregate investment when controlling for manager sentiment. Therefore, the results indicate that manager sentiment is distinct from existing investor sentiment. High manager sentiment is strongly tied to overinvestment, but the link between investor sentiment and overinvestment is weak.

In summary, Table 12 shows that periods with high (low) manager sentiment are accompanied by high (low) 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 returns to investment which leads to overinvestment. In contrast, investor sentiment has insignificant predictive power for overinvesting beyond manager sentiment.

5.3. Manager sentiment and characteristic-sorted portfolios

In this section, we explore cross-sectional variation in manager sentiment's effects on stock returns. According to Baker and Wurgler (2006), Stambaugh et al. (2012), and Huang et al. (2015), among others, if the manager sentiment index indeed reflects market sentiment, its forecasting power should be stronger among stocks that are more speculative, difficult to value, and costly to arbitrage. These cross-sectional tests not only strengthen our previous findings for aggregate stock market predictability, but also enhance our understanding of the economic channels through which manager sentiment impacts asset prices.

We consider 15 well-documented cross-sectional anomalies formed by single sorting on firm characteristics, including capital investment, the SA financial constraint measure index, dividend payout, the leverage ratio, the O-score bankruptcy probability measure, ROE, the earnings surprise (SUE), the book-to-market ratio (B/M), stock price, share turnover, idiosyncratic volatility, market beta, sentiment beta, firm age, and firm size, which are related to the subjectivity of valuation and limits to arbitrage. These variables are defined as follows:

- Investment, the year-to-year change in total assets divided by lagged total assets. High-investment firms are high growth stocks, while low-investment firms are distressed.
- SA Index, the financial constraint measure is calculated as $-0.737 \times \mathrm{Size} + 0.043 \times \mathrm{Size}^2 - 0.040 \times \mathrm{Age}$, where size equals the log of inflation-adjusted book assets, and age is the number of years the firm is listed with a non-missing stock price on Compustat. Financially constrained firms tend to be difficult to value and hard to arbitrage.
- Dividend payout, total dividends divided by book equity. Low dividend paying stocks are difficult to value and arbitrage.
- Leverage, the ratio of net debt to market equity. High leverage firms are speculative and distressed.
- O-Score, the Ohlson (1980) measure of financial distress is the probability of bankruptcy estimated in a static model using accounting variables. Distressed firms are hard to arbitrage.
- ROE, income before extraordinary items divided by lagged book equity. Unprofitable firms are difficult to value and they have higher limits to arbitrage.
- SUE, the year-to-year change in quarterly earnings relative to earnings in the same quarter of the prior year standardized by stock price. Firms with nonzero earnings surprises are difficult to value.
- B/M, the book-to-market equity ratio. 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 and distressed firms are difficult to value and costly to arbitrage.
- Price, the stock price per share from CRSP. Low price stocks are illiquid and hard to arbitrage.
- Share turnover, the average number of shares traded divided by the number of shares outstanding over the past six months. Stocks with high turnover are uncertain and difficult to value, while stocks with low turnover are illiquid and hard to arbitrage.
- Idiosyncratic volatility, the standard deviation of the residuals from regressing daily stock returns on market returns over a year. High-volatility stocks are more speculative and hard to arbitrage.
- Beta, the Scholes–Williams beta for daily common stock returns over a year available from CRSP. High-beta stocks are more prone to speculate and are more difficult to arbitrage.
- Sentiment beta, the beta for monthly portfolio returns on monthly changes in the manager sentiment index, which is a measure of sensitivity to manager sentiment influences.
- Age, the number of years the firm is listed in Compustat. Young firms are more difficult to value and to arbitrage.
- Size, the price per share multiplied by the number of shares outstanding in CRSP. Small firms are difficult to arbitrage.

We form monthly decile portfolios based on the above 15 firm characteristics. Decile 1 refers to firms in the lowest decile, 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

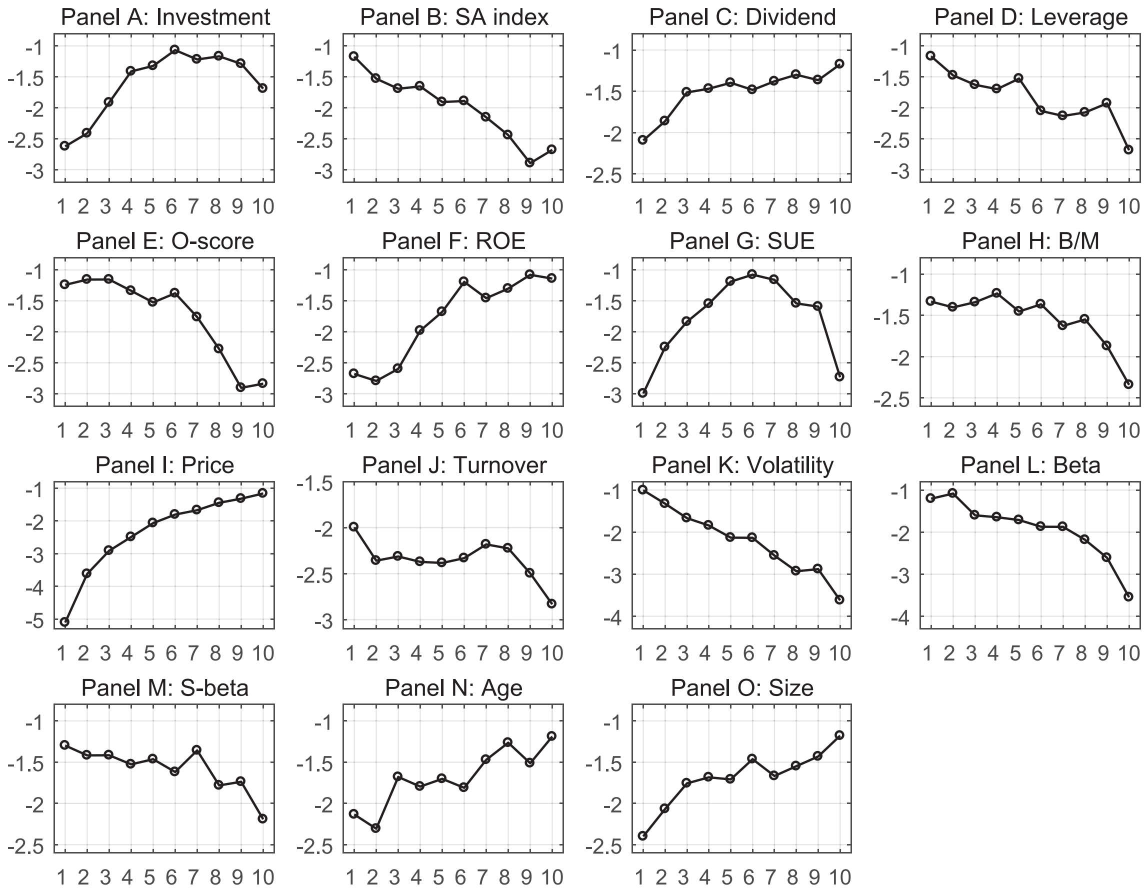

Fig. 2. Return predictability across characteristic portfolios. Panels A to O plot the regression coefficients (β, in percentages) for the univariate predictive regressions of the monthly excess returns (R^j_{t+1}) of 15 characteristics-based decile portfolios on the lagged manager sentiment index (S^{MS}), $R^j_{t+1} = \alpha + \beta S^{MS}_t + \varepsilon^j_{t+1}$. Decile 1 refers to firms in the lowest decile, and decile 10 refers to firms in the highest decile. The decile portfolio returns are formed by single sorting based on the following firm characteristics: capital investment, the SA financial constraint index, dividend payout, the leverage ratio, the O-score bankruptcy probability measure, ROE, earnings surprise (SUE), the book-to-market ratio (B/M), stock price, share turnover, idiosyncratic volatility, market beta, sentiment beta (S-beta), firm age, and firm size, which are related to the propensity to speculate or limits to arbitrage. See Section 5.3 for detailed definitions of the firm characteristics. The sample period is 2003:01–2014:12.

expect that, as in Baker and Wurgler (2006), manager sentiment should present stronger forecasting power for stocks that are speculative and with difficult-to-value future cash flows (i.e., high investment, low dividend payout, low profitability, high unexpected earnings, high growth opportunities, high turnover, high volatility, high beta, young age, small size) and/or costly to arbitrage (i.e., low investment, high financial constraints, high leverage, high distress, low profitability, high growth opportunities, low price, high volatility, high beta, young age, small size).

Fig. 2 plots the regression coefficients (β) of the univariate predictive regressions for characteristic decile portfolios over the sample period 2003:01–2014:12,

$$R^j_{t+1} = \alpha + \beta S^{MS}_t + \varepsilon^j_{t+1}, \tag{21}$$

where R^j_{t+1} is the monthly excess returns of the 15 characteristics-based decile portfolios, and S^{MS} is the lagged manager sentiment index. The results in Fig. 2 show that all of the regression slope estimates for S^{MS} are negative and economically large; thus the negative predictability of manager sentiment for subsequent stock returns is pervasive in the cross-section as well, consistent with our findings at the aggregate market level. More importantly, we detect large cross-sectional variation in the regression slope estimates. The slope is more negative for firms with high investment and high growth, a high SA financial constraint index, low dividend payout, high leverage, high financial distress (high O-score, high B/M, low investment), low ROE, high absolute earning surprises, low price, high turnover, high volatility, high beta, high sentiment beta, young age, and small market cap. These results indicate that manager sentiment's effect is stronger among stocks that are speculative, hard to value, or costly to arbitrage, consistent with our hypothesis.

Table 13 reports the regression coefficients and Newey–West t-statistics for the univariate predictive regressions of the monthly long-short returns of the 15 characteristics-based decile portfolios on the lagged manager sentiment index (S^{MS}) and the corresponding estimation results for bivariate regressions on both the lagged manager sentiment index (S^{MS}) and the Baker and Wurgler (2006) investor sentiment index (S^{BW}). The long-short portfolio

Table 13

Manager sentiment and characteristic portfolio returns.

Panels A and B report the regression coefficients (in percentages) and Newey–West *t*-statistics (in brackets) for the univariate and bivariate predictive regressions of the monthly long-short returns of 15 characteristics-based decile portfolios on the lagged manager sentiment index (S^{MS}) and the Baker and Wurgler (2006) investor sentiment index (S^{BW}). The long-short portfolio returns 10−1, 10−5, and 5−1 (R^j_{t+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, and decile 10 refers to firms in the highest decile. The decile portfolio returns are formed on the following firm characteristics: capital investment, the SA financial constraint measure index, dividend payout, the leverage ratio, the O-score bankruptcy probability measure, ROE, earnings surprise (SUE), the book-to-market ratio (B/M), stock price, share turnover, idiosyncratic volatility, market beta, sentiment beta (S-beta), firm age, and firm size. See Section 5.3 for detailed definitions of the firm characteristics. The sample period is 2003:01–2014:12.

	Panel A: Manager sentiment $R^j_{t+1} = \alpha + \beta S^{MS}_t + \varepsilon^j_{t+1}$			Panel B: Investor sentiment $R^j_{t+1} = \alpha + \beta S^{MS}_t + \gamma S^{BW}_t + \varepsilon^j_{t+1}$					
				10 − 1		10 − 5		5 − 1	
	10 − 1	10 − 5	5 − 1	S^{MS}_t	S^{BW}_t	S^{MS}_t	S^{BW}_t	S^{MS}_t	S^{BW}_t
Investment	0.93	−0.37	1.30	0.79	0.27	−0.40	0.05	1.19	0.22
	[2.80]	[−1.68]	[4.85]	[2.24]	[0.94]	[v1.80]	[0.20]	[4.16]	[1.01]
SA index	−1.51	−0.77	−0.73	−1.21	−0.56	−0.47	−0.59	−0.75	0.03
	[−5.20]	[−3.35]	[−5.20]	[−3.18]	[−1.34]	[−1.52]	[−1.77]	[−4.21]	[0.15]
Dividend	0.92	0.22	0.70	0.92	0.01	0.28	−0.10	0.64	0.11
	[4.36]	[1.77]	[4.03]	[4.14]	[0.03]	[1.96]	[−0.63]	[3.59]	[0.63]
Leverage	−1.52	−1.16	−0.36	−1.44	−0.15	−0.89	−0.52	−0.55	0.37
	[−3.93]	[−4.04]	[−1.60]	[−3.30]	[−0.41]	[−2.61]	[−1.73]	[−2.20]	[1.27]
O-score	−1.60	−1.31	−0.28	−1.02	−1.09	−0.78	−1.01	−0.24	−0.08
	[−4.62]	[−4.39]	[−1.93]	[−2.69]	[−2.98]	[−2.15]	[−2.80]	[−1.36]	[−0.48]
ROE	1.54	0.54	1.00	1.03	0.96	0.43	0.21	0.61	0.75
	[4.32]	[2.69]	[3.03]	[2.67]	[3.02]	[1.94]	[1.46]	[1.52]	[2.71]
SUE	0.26	−1.54	1.81	0.26	0.01	−1.44	−0.20	1.70	0.21
	[0.70]	[−4.49]	[4.72]	[0.56]	[0.03]	[−3.43]	[−0.70]	[3.87]	[0.63]
B/M	−1.01	−0.89	−0.12	−0.95	−0.10	−0.70	−0.35	−0.25	0.25
	[−2.23]	[−2.31]	[−0.72]	[−1.83]	[−0.23]	[−1.71]	[−0.93]	[−1.23]	[1.23]
Price	3.94	0.90	3.04	3.29	1.25	0.68	0.42	2.60	0.83
	[5.62]	[4.05]	[5.47]	[4.10]	[1.85]	[3.14]	[2.22]	[3.80]	[1.38]
Turnover	−0.84	−0.45	−0.39	−1.24	0.76	−0.67	0.42	−0.56	0.33
	[−2.48]	[−1.83]	[−1.51]	[−3.49]	[2.45]	[−2.56]	[1.99]	[−2.18]	[1.44]
Volatility	−2.62	−1.49	−1.13	−2.14	−0.90	−0.84	−1.23	−1.30	0.33
	[−4.81]	[−3.45]	[−3.31]	[−3.73]	[−1.88]	[−2.01]	[−3.21]	[−4.09]	[1.07]
Beta	−2.34	−1.84	−0.51	−2.52	0.34	−2.07	0.45	−0.45	−0.11
	[−2.84]	[−3.15]	[−1.21]	[−2.94]	[0.65]	[−3.71]	[1.22]	[−0.92]	[−0.39]
S-beta	−0.89	−0.73	−0.17	−0.94	0.09	−0.76	0.07	−0.18	0.02
	[−2.72]	[−2.65]	[−1.86]	[−2.32]	[0.38]	[−2.49]	[0.42]	[−1.32]	[0.19]
Age	0.94	0.51	0.43	0.80	0.28	0.61	−0.19	0.18	0.47
	[3.37]	[3.00]	[2.61]	[3.14]	[1.26]	[3.44]	[−0.99]	[1.09]	[2.55]
Size	1.22	0.53	0.69	1.06	0.30	0.61	−0.15	0.46	0.45
	[5.47]	[3.00]	[4.34]	[4.22]	[1.01]	[3.15]	[−0.72]	[2.65]	[2.46]

returns 10−1, 10−5, and 5−1 (R^j_{t+1}) are computed as the return differences between deciles 10 and 1, deciles 10 and 5, and deciles 5 and 1, respectively. The predictive regression analysis in Table 13 allows us to conduct formal statistical tests on the cross-sectional effects of manager sentiment on stock returns.

Panel A of Table 13 confirms our hypothesis that manager sentiment generally has a significantly stronger impact for portfolios with cash flows that are difficult to value (i.e., high investment, low dividend payout, low profitability, high unexpected earnings, high growth opportunities, high turnover, high volatility, high beta, young age, small size) and/or costly to arbitrage (i.e., low investment, high financial constraint, high leverage, high distress, low profitability, high growth opportunities, low price, high volatility, high beta, young age, small size), consistent with Baker and Wurgler (2006). The cross-sectional differences are statistically significant and economically large. 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.

Panel B of Table 13 further shows that manager sentiment's predictive ability remains significant, when controlling for investor sentiment. Moreover, Panel B shows that investor sentiment contains significant incremental forecasting power for stocks with a high SA index, high leverage, high O-score, low ROE, low price, low turnover, high volatility, young age, and small size, all of which belong to firms that are costly to arbitrage. However, investor sentiment generally has insignificant incremental predictive power for firms that are difficult to value beyond manager sentiment. Intuitively, hard-to-value stocks are likely more opaque and have higher valuation uncertainty, and hence managers are more likely to make mistakes and manager sentiment has stronger predictive power. Difficult-to-arbitrage stocks are perhaps more related to illiquidity, and hence both manager sentiment and investor sentiment are important.

In summary, our findings indicate that manager sentiment has strong negative predictive power that varies with cross-sectional attributes of the firm, particularly for firms that are difficult to value and costly to arbitrage. In contrast, investor sentiment forecasts stocks that are costly to arbitrage but does not forecast those that are difficult to value after controlling for manager sentiment.

6. Conclusion

In this paper, we propose a manager sentiment index constructed based on the aggregate textual tone in 10-Ks, 10-Qs, and conference calls. We find that manager sentiment negatively predicts stock returns with lower future market returns following high manager sentiment periods. Manager sentiment's predictive power is far greater than commonly used macroeconomic variables, and it outperforms existing investor sentiment measures. Manager sentiment is complementary to investor sentiment in forecasting stock returns, implying that manager sentiment has a different impact on valuation relative to investor sentiment. Moreover, higher manager sentiment precedes lower aggregate earnings surprises and greater aggregate investment growth, implying that managers' biased beliefs about future cash flows and overinvestment helps to explain the predictability of manager sentiment. Finally, manager sentiment also strongly forecasts the cross-section of stock returns, particularly for stocks that are difficult to value or costly to arbitrage.

Overall, our empirical results suggest that manager sentiment has 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 investors from asset allocation. 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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