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# Measuring Investor Sentiment

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## Abstract

Investor sentiment indicates how far an asset value deviates from its economic fundamentals. In this article, we review various measures of investor sentiment based on market, survey, and text and media data. There is ample evidence that sentiment can explain returns on stocks that are difficult to value and costly to arbitrage, such as unprofitable stocks, nondividend-paying stocks, extreme growth stocks, and distressed stocks. However, much remains to be done. We discuss three issues for future research: aggregating measures over various sources and various time horizons, linking investor sentiment to technical analysis, and statistically modeling the evolution of investor sentiment.

## 1. INTRODUCTION

In the history of financial markets, there have been many manias, panics, and crashes (e.g., Aliber & Kindleberger 2015), which are difficult to justify by using fundamentals alone. Academically, Keynes (1936) provides an early analysis of speculative markets and investor sentiment. Practitioners, too, recognize the importance of investor emotions and developed intuitive measures of extreme optimism and pessimism long before any modern academic studies (e.g., Lefèvre 1923, Murphy 1986).

Theoretically, De Long et al. (1990) show that noisy trader risk—the unpredictability of noise traders' beliefs—can make asset prices diverge significantly from their fundamental values even in the absence of fundamental risk. Various models have subsequently been developed to understand how investor sentiment may form and impact markets. Empirically, however, investor sentiment is not observable and has to be estimated. Among existing measures, the closed-end fund discount, analyzed by Zweig (1973) and explained by Lee, Shleifer & Thaler (1991), is perhaps the oldest. Combining it with five other measures, Baker & Wurgler (2006) form an investor sentiment index. As it turns out, this index captures sentiment much better than any of the components alone in explaining the cross section of stock returns, and it has become the most widely used measure of investor sentiment in various applications.

We review the sentiment index of Baker & Wurgler (2006), as well as various other measures based on survey, text, and media data. Since Baker & Wurgler's seminal work, it has been well established that investor sentiment plays an important role in explaining returns on stocks that are difficult to value and costly to arbitrage, such as small stocks, young stocks, high-volatility stocks, unprofitable stocks, nondividend-paying stocks, extreme growth stocks, and distressed stocks. However, traditional measures of investor sentiment have insignificant predictive power on the aggregate stock market. Emphasizing the importance of aligning an index with its purpose, Huang et al. (2015) show that an alternative index with the same proxies used by Baker & Wurgler (2006) can negatively predict the stock market: Higher sentiment today predicts lower future market returns. The predictive power is both economically and statistically significant.

Nevertheless, much remains to be done in measuring investor sentiment well, and there are several open issues. We focus on three here. The first is to develop efficient methods that pool all information across various variables and time horizons. Whereas existing studies focus on monthly data, practitioners have developed measures at daily and even hourly frequencies. Aggregating measures over firms and time horizons is likely to generate a more universal and more accurate investor sentiment that can potentially lead to a sentiment factor explaining the entire cross section of stock returns, similar to those nonmarket factors of Fama & French (2015) and Hou, Xue & Zhang (2015). The second is to make connections with technical analysis, which is widely used in making trading decisions that impact markets. Such connections may shed light on why and how sentiment affects asset prices. The final issue is how to use sentiment information optimally, either to better predict the stock market or to better manage a portfolio. To this end, we need to understand more about what stochastic processes investor sentiment follows.

## 2. DEFINITIONS

Consider first an investor's exaggerated belief. In general, investor sentiment may indicate either an exaggerated belief or simply a view being expressed. Historically, however, investor sentiment primarily refers to an exaggerated belief related to speculative stock prices when they diverge from fundamental values. A typical question is whether an asset is over- or undervalued. In this case, we can measure investor sentiment by

$$S_t = P_t - P_t^*, \tag{1.}$$

where $P_t$ is the observed price from the market and $P_t^*$ is the fundamental price estimated from a rational benchmark asset pricing model. For example, the present value of cash flows from an asset can serve as the fundamental price. With the above definition, $S_t = 0$ implies that the market price agrees with the fundamental value. In practice, however, $S_t$ is rarely zero. The greater the $S_t$, the more optimistic investors are about the asset value. $S_t$ can of course be negative, representing pessimism about the asset value.

It should be noted that, in order to determine an exaggerated belief, the so-called true model price has to be provided. Otherwise, one cannot compute $S_t$. As a practical matter, however, it is always difficult to provide the true fundamental value of an asset, and there is always debate on what the true value is. Moreover, for any given model, there are likely missing factors and questionable assumptions. Hence, investor sentiment is inherently measured with errors, even though there is assumed to be a true investor sentiment. In fact, the true investor sentiment is almost always unobservable, and all computed measures are proxies. Different investors or researchers may use different fundamental models, leading to multiple measures of investor sentiment. The important question is how well they behave and what gains they make in an application of interest.

$S_t$ above is defined by using prices. This definition is intuitive and widely used. However, it is difficult to compare $S_t$ between two assets when investor sentiment is measured with prices. This is because a $2 sentiment on an asset worth $100 is in fact less sentimental than a $1 sentiment on an asset worth $1. To resolve this issue, one typically uses

$$S_t^{\mathrm{n}} = (P_t - P_t^*)/P_t^*, \tag{2.}$$

which is simply a normalization of the original sentiment by the fundamental price. In fact, focusing on returns, we can define an alternative investor sentiment,

$$s_t = r_t - r_t^*, \tag{3.}$$

where $r_t$ is the observed or expected return and $r_t^*$ is the fundamental return from a rational benchmark asset pricing model. Since most models are cast in terms of returns, the return-based sentiment conveniently links data to models.

In general, we can define sentiment in terms of any characteristic,

$$S_t^{\mathrm{c}} = \mathrm{CH}_t - \mathrm{CH}_t^*, \tag{4.}$$

where $\mathrm{CH}_t$ is the observed or expected asset characteristic and $\mathrm{CH}_t^*$ is the same characteristic implied by a benchmark model. For example, $\mathrm{CH}_t$ can be the realized volatility or expected volatility, with $\mathrm{CH}_t^*$ being the model volatility. It is well known that the stock market is more volatile than can be justified by the variation of fundamentals (e.g., Shiller 1981, Giglio & Kelly 2017). Existing sentiment studies largely rely on prices, returns, and expected probabilities; much work remains to be done on volatility sentiment, tail sentiment, and sentiment of other characteristics of asset returns.

The above definitions reveal investors' false beliefs about an asset value. By using a suitable model, they can also reveal a false belief about any economic variable, such as the surveyed probability of a market crash versus the model probability. Again, it is important to have a benchmark model for this. Without it, it is impossible to know whether a belief is exaggerated. Hence, we refer to the above definitions as model-based investor sentiment. The greater the sentiment, the greater the deviation from theoretically predicted behavior.

However, most proxies of investor sentiment, such as five of Baker & Wurgler's (2006) proxies, are simply measures of various beliefs without benchmark models. In this case, it is difficult to distinguish rational and irrational behaviors of investors because the measured beliefs may match rational models.

Generally speaking, measures of investor sentiment can be grouped into three categories according to the data they use. The first category is market-based, where observed market data, such as prices and trading activities, are used to measure sentiment. The second is survey-based, where polls are gathered from market participants to infer their views. The third is text- and media-based, where opinions are extracted from texts, publications, recordings, events, and various Internet activities.

## 3. BAKER–WURGLER MEASURE

In this section, we discuss Baker & Wurgler's (2006) sentiment index and review some of its major applications, with a focus on its predictive power on the entire stock market.

The Baker–Wurgler index is based on the first component of a principal component analysis (PCA) with the following six proxies from market data:

- Trading volume: TURN is defined as the natural logarithm of the turnover ratio of trading volume to the number of shares listed on the New York Stock Exchange (NYSE), detrended by the 5-year moving average.
- Closed-end fund discount: CEFD is defined as the average difference between the net asset values of closed-end stock fund shares and their market prices.
- Initial public offering (IPO) activity: NIPO is defined as the number of IPOs.
- First-day returns: RIPO is defined as the average of first-day returns on IPOs.
- Equity issues: EIT is defined as the ratio of equity issues to total equity and debt issues by all corporations.
- Dividend premium: DP is defined as the difference between the average market-to-book ratios of dividend payers and nonpayers.

The index data are monthly and are available from July 1965 to September 2015 at Wurgler's website (**http://people.stern.nyu.edu/jwurgler**). Note that TURN is discarded in the latest data, for the reason that it "does not mean what it once did, given the explosion of institutional high-frequency trading and the migration of trading to a variety of venues." Although most existing studies are based on the original index that contains TURN, the omission does not seem to affect the conclusions.

### 3.1. Applications

It is important for any stock-based measure of investor sentiment to capture the major ups and downs of the stock market (or, for a housing-based measure, the housing market). Baker & Wurgler (2006, 2007) provide a detailed anecdotal history of the relation between major stock market episodes and their index over the period 1961–2005. They find that their index rises from 1961, when there was high demand for small and growth stocks, and reaches a peak coincident with the bubble developed in 1967 and 1968. Subsequently, it reaches its bottom in the bear market of the 1970s. The late 1970s and 1990s are high-sentiment periods corresponding to the biotechnology boom and the Internet bubble, respectively. Overall, the major ups and downs of their index echo well the manias and crashes of the stock market.

Baker & Wurgler (2007) also show that their index is related to mutual fund flows, which are measures of investor over- and underreactions. After controlling for the general demand of mutual funds, they find that fund flows to more speculative categories, such as growth funds, are more sensitive to the sentiment index than are flows to less speculative categories, such as income funds.

After establishing that their index measures sentiment, Baker & Wurgler (2006, 2007) find several implications on the cross section of stock returns. They show that their index can explain returns on stocks that are difficult to value and costly to arbitrage, such as unprofitable stocks, nondividend-paying stocks, extreme growth stocks, and distressed stocks. Moreover, they find that, when sentiment is high, the future returns of speculative stocks are on average lower than the returns of bond-like stocks. This highlights the role of investor sentiment in asset pricing, which is in support of a potential sentiment factor discussed in Section 6.1.

Many studies examine the role that investor sentiment plays by dividing time into high- and low-sentiment periods on the basis of the Baker–Wurgler index. For example, Yu & Yuan (2011) show that the significant positive relation between the aggregate market's expected return and its conditional volatility breaks down following high-sentiment periods. Stambaugh, Yu & Yuan (2012) show that high-sentiment periods are associated with overpricing due to short-sale impediments. Baker, Wurgler & Yuan (2012) extend US sentiment to six other countries. Yu (2013) documents that sentiment plays a significant role in foreign exchange markets. In recent work, Antoniou, Doukas & Subrahmanyam (2016) examine the relation between sentiment and beta risk, and Pástor, Stambaugh & Taylor (2017) show that active funds trade more when sentiment is high (i.e., when there is more mispricing). Jiang et al. (2017) and Jiang, Wu & Zhou (2017) find that many asymmetric risk measures are sensitive to investor sentiment as well. Shen, Yu & Zhao (2017) find that macrorelated factors cannot explain the asset risk–return relation during high-sentiment periods. Chu et al. (2017) show that both the predictive power of various economic predictors and the predictability of the market are sentiment dependent.



## 3.2. Market Predictability

We now examine the predictive power of investor sentiment on the entire stock market. As emphasized by Cochrane (2008), the market risk premium has important implications in all areas of finance. Hence, it is important to find out whether investor sentiment explains the time-varying broad-market risk premium beyond its role in predicting the cross section of stock returns.

For continuity, we keep TURN in the Baker–Wurgler index. In what follows, we use data up to December 2016 (available online at **http://apps.olin.wustl.edu/faculty/zhou**). Note that Baker & Wurgler (2006, 2007) use TURN, RIPO, and DP with values lagged by 1 year to capture lagged reactions. To be consistent, we do the same here.[1] However, a more systematic approach is to use both current and lagged values for all the variables. Then an information aggregation method, such as the partial least squares (PLS) regression described below, can provide weights for the predictors that are completely data-driven without removing any one of them. In this case, the $R^2$ of the PLS regression of the 12 predictors is 1.80%.

To adjust for effects of the macroeconomy, Baker & Wurgler (2006) also run regressions of the above proxies on various economic variables and use the residuals to form an alternative index (for the effects of macroeconomic variables, see Sibley et al. 2016; Chu, Du & Tu 2017). Note that there are reasons for and against the adjustment. To see this, assume for simplicity that the true value of a proxy is

$$\mathrm{CH}^* = \beta_1 x_t + \beta_2 E[x_{t+1}] + v_t, \tag{5.}$$

[1]Without TURN or without the lag, the $R^2$ of the partial least squares (PLS) regression in **Table 1** changes from 1.86% to 2.06% or 1.18%, respectively.

**Table 1 Baker–Wurgler sentiment measures**

| Measure | $\beta$ | $t$-Statistic | $R^2$ | Mean | Standard deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| TURN | −0.23 | −1.44 | 0.27 | 0.00 | 1.00 | −0.62 | 2.97 |
| CEFD | 0.10 | 0.52 | 0.05 | 0.00 | 1.00 | −0.06 | 2.58 |
| NIPO | −0.03 | −0.15 | 0.00 | 0.00 | 1.00 | 0.82 | 2.76 |
| RIPO | −0.50 | −3.87 | 1.31 | 0.00 | 1.00 | 2.16 | 8.27 |
| EIT | −0.43 | −2.31 | 1.00 | 0.00 | 1.00 | 1.04 | 3.59 |
| DP | −0.04 | −0.19 | 0.01 | 0.00 | 1.00 | 0.46 | 3.09 |
| EW | −0.34 | −1.86 | 0.58 | 0.00 | 1.00 | 0.80 | 2.92 |
| PCA | −0.25 | −1.21 | 0.33 | 0.00 | 1.00 | 0.40 | 3.14 |
| PLS | −0.59 | −4.09 | 1.86 | 0.00 | 1.00 | 1.28 | 3.97 |

This table reports predictive regression results of the S&P 500 excess return on the sentiment measures of Baker & Wurgler (2006). TURN, CEFD, NIPO, RIPO, EIT, and DP are defined above in Section 3. All the variables are standardized, and $R^2$ is in percentage points; $\beta$ is the regression slope. Equal weighting (EW), principal component analysis (PCA), and partial least squares (PLS) are three pooling procedures that combine information from the proxies. Data are from July 1965 to December 2016.

where $x_t$ is a state variable, $\beta_1$ and $\beta_2$ are constant, $E$ is the expectation operator, and $v_t$ denotes other valuation factors. The sentiment should be CH − CH*, where CH is the observed proxy. If $\beta_2 = 0$ and $v_t = 0$, it is clear that the residual is the perfect sentiment measure. However, valuation is usually more about future outlooks of $x_t$, so typical regressions can be misspecified to generate noise in the proxy that can be exacerbated by measurement errors and updates of macroeconomic variables. Moreover, $x_t$, of central interest at time $t$, may not be any of the economic regressors, such as the market's recent focus on a possible corporate tax cut. In this case, economic variables (say GDP) and market frictions (say liquidity) may be stable, and their effects roughly constant. They then, while affecting levels of sentiment, have no impact on innovations, which can capture investors' overreaction or underreaction to $x_t$. In general, the intended application should dictate whether, when, and how an adjustment should be made. We do not make adjustments below since they matter little for our purpose here.

**Table 1** reports the results of predictive regressions of the S&P 500 on sentiment,

$$r_t = \alpha + \beta x_{t-1} + \epsilon_t, \qquad 6.$$

where $r_t$ is the index return in excess of the risk-free rate and $x_t$ is one of the proxies or the sentiment index. Interestingly, the $R^2$ values for the individual proxies vary substantially, from 0% to 1.31%, and only two of them are significant at the 5% level. (For brevity, we consider only in-sample analysis.) This indicates the importance of using an aggregated index to obtain meaningful results, as ex ante it is difficult to know which of the proxies will be the best predictor. For the Baker–Wurgler index, $R^2$ is 0.33% (this value is still greater than that for common macroeconomic predictors, as shown in Huang et al. 2015, table 4). Although the slope is negative, it is not statistically significant. The results are consistent with the literature. Hirshleifer (2001) provides an early survey on studies of sentiment and asset prices. Baker & Wurgler (2007), among others, find that sentiment has only small predictability on the aggregate stock market (for more of the large literature on predictability, see, e.g., Fama & Schwert 1977; French, Schwert & Stambaugh 1987; Kandel & Stambaugh 1996; Ang & Bekaert 2007; Campbell & Thompson 2008; Cochrane 2008, 2011; Spiegel 2008; Welch & Goyal 2008; Rapach & Zhou 2013; Lie et al. 2017). Note that sentiment is multidimensional in the sense that sometimes there is investor enthusiasm for particular themes, even if not for the entire market; Greenwood & Hanson (2012) make a similar point about multidimensionality with respect to firm characteristics. Hence, although the Baker–Wurgler index captures cross-sectional differences among difficult-to-value stocks, it does not necessarily predict the market well.

To improve the predictability on the market, a new index is needed. Note that PCA captures the variation of all six proxies, but it can contain common errors that are not relevant for forecasting market returns, and these errors tend to worsen the predictive regression. Hence, we consider two alternative approaches for extracting information from the six proxies (for details, see Section 6.1). The first, equal weighting (EW), is a naive approach that simply places equal weights on the six standardized proxies to obtain a new predictor. As reported in **Table 1**, EW improves $R^2$ from 0.33% to 0.58%. The second is the PLS method. Huang et al. (2015) propose using it to construct a new index out of the six proxies to minimize the common errors. They align the method of formation of the index with the objective of predicting the market, so it should, in general, perform better than the original PCA index. Indeed, they find that the PLS sentiment index improves the value of $R^2$ (relative to PCA) from 0.30% to 1.70% with data up to 2010, and here we see that PLS further raises $R^2$ from 0.33% to 1.86% with data up to 2016. Overall, Huang et al. (2015) show that investor sentiment can predict the stock market, and the predictability is both economically and statistically significant.

## 4. OTHER MEASURES

In this section, we examine alternative measures of investor sentiment based on market data, survey data, and text and media information.

### 4.1. Market Data

When investor sentiment is high, investors are likely to trade with less attention to price advances. Consider the quantities

$$S_t^{\mathrm{b}} = \log(\mathrm{ADVIS}_t/\mathrm{TOLIS}_t) \qquad 7.$$

and

$$S_t^{\mathrm{h}} = \log(\mathrm{HIGHS}_t/\mathrm{TOLIS}_t), \qquad 8.$$

where, at time $t$, $\mathrm{ADVIS}_t$ is the number of advancing issues, $\mathrm{TOLIS}_t$ is the total number of issues in the market, and $\mathrm{HIGHS}_t$ is the number of stocks that make new highs. (These and the survey data below are readily available from Pinnacle Data.) $S_t^{\mathrm{b}}$ and $S_t^{\mathrm{h}}$ capture buying pressure from the perspective of market breadth. Since our objective here is forecasting market returns, for which standard regression controls of macroeconomic variables make little difference, we use the above quantities directly as investor sentiment proxies, as we do for the Baker–Wurgler proxies. Of course, although this is perhaps adequate for an exploratory analysis, further research is called for to improve the use of these proxies and to utilize other trading activity variables such as fund flows.

In addition to not controlling for macroeconomic effects, we also do not control for the effects of other fundamentals, as that would require a choice of models to use and a choice of estimation techniques. Ross (2005), Zhou (2010), and Huang & Zhou (2017) show that existing rational asset pricing models allow extremely low predictability. Thus, quantifying the model rational prices would have little effect on the predictability of the proxies. Indeed, if sizeable predictability were found, it would be likely be thanks to the impact of investor sentiment, rather than fundamental valuation. Therefore, as a preliminary study, below we use the raw sentiment proxies directly

**Table 2 Breadth-based sentiment measures**

| Measure | Start period | $\beta$ | *t*-Statistic | $R^2$ | Mean | Standard deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|
| NY-ADVIS | January 1940 | −0.37 | −1.95 | 0.73 | 45.98 | 13.04 | 0.20 | 3.49 |
| NY-DECIS | January 1940 | 0.33 | 2.06 | 0.59 | 38.85 | 12.90 | 0.81 | 3.96 |
| NY-HIGHS | March 1965 | −0.16 | −0.95 | 0.13 | 3.46 | 3.03 | 1.54 | 6.31 |
| ND-ADVIS | January 1978 | −0.31 | −1.45 | 0.52 | 36.60 | 14.79 | 0.45 | 2.70 |
| ND-DECIS | January 1978 | 0.12 | 0.66 | 0.08 | 33.25 | 16.10 | 0.62 | 2.60 |
| ND-HIGHS | January 1978 | −0.17 | −0.88 | 0.16 | 2.75 | 1.90 | 1.17 | 5.00 |
| EW | January 1978 | −0.47 | −2.58 | 1.18 | 0.00 | 1.00 | −0.50 | 4.44 |
| PCA | January 1978 | −0.50 | −2.97 | 1.34 | 0.00 | 1.00 | −0.26 | 3.86 |
| PLS | January 1978 | −0.52 | −2.91 | 1.43 | 0.00 | 1.00 | −0.21 | 3.82 |

This table reports the predictive regression results of the S&P 500 excess return on breadth-based sentiment measures: NY-ADVIS, NY-DECIS, and NY-HIGHS are the number advancing issues, number of declining issues, and number of stocks making new highs, respectively, on the New York Stock Exchange, and ND-ADVIS, ND-DECIS, and ND-HIGHS are the same for the NASDAQ market. $R^2$ is in percentage points. Equal weighting (EW), principal component analysis (PCA), and partial least squares (PLS) are three pooling procedures that combine information from the proxies, and the pooled predictors are standardized. Data begin in the months shown and end in December 2016.



and leave the use of proper and perhaps new rational asset pricing benchmark models for future research.

Another important issue is that activity-based measures may not fully capture the sentiment $S_t$. To see this, we project $S_t^{\mathrm{b}}$ on $S_t$:

$$S_t^{\mathrm{b}} = \alpha + \beta S_t + u_t. \qquad 9.$$

Note that changes in $S_t^{\mathrm{b}}$ can be caused by changes in $\beta$. Given the same level of sentiment, variation in $\beta$ can cause more or less activity. This is true not only for $S_t^{\mathrm{b}}$, but for any nonprice variable, implying that more elaborate econometric procedures may be needed to identify $S_t$ in general. For simplicity, here we use $S_t^{\mathrm{b}}$ and $S_t^{\mathrm{h}}$ as sentiment proxies without further filtering.

**Table 2** provides the predictive regression results. Given the well-known difficulty of predicting the market, the individual breadth variables seem to perform reasonably well. The first two are are statistically significant, although the third is not. The next three are less important, indicating that NASDAQ trading activity is less relevant than NYSE trading activity in forecasting the broad market.

Interestingly, all the aggregated indices predict the market significantly. The PCA index has a significant $R^2$ of 1.34%, much larger than 0.33%, the corresponding PCA $R^2$ of the Baker–Wurgler proxies. Moreover, the PLS index performs almost as well as the PLS index of the Baker–Wurgler proxies. This is surprising, as the breadth variables cover only one aspect of trading and are much less diverse than the Baker–Wurgler proxies.

Since investor sentiment is largely about over- or undervaluation of assets, it is a straightforward idea to use valuation factors to assess sentiment. Of the hundreds of factors that are shown to affect the cross section of stock returns (see, e.g., Harvey, Liu & Zhu 2016), most are fundamental. Let $f_t$ be such a fundamental factor and $\mu_f$ its long-run return. The greater the difference $f_t - \mu_f$, the greater the overvaluation. Hence, $f_t - \mu_f$ can be regarded as a sentiment proxy. For the purpose of forecasting, the constant $\mu_f$ plays no role, and it is ignored in what follows. (For an examination of the predictive power of financial ratios, for which sentiment is a new motivation, see Lewellen 2004.)

**Table 3 Factor-based sentiment measures**

| | Start period | $\beta$ | *t*-Statistic | $R^2$ | Mean | Standard deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|
| HML | July 1963 | −0.19 | −1.26 | 0.20 | 0.37 | 2.82 | 0.05 | 5.18 |
| RMW | July 1963 | −0.24 | −1.68 | 0.32 | 0.24 | 2.23 | −0.35 | 16.21 |
| CMA | July 1963 | −0.31 | −1.84 | 0.52 | 0.31 | 2.01 | 0.28 | 4.64 |
| IA | January 1967 | −0.37 | −2.03 | 0.70 | 0.41 | 1.88 | 0.11 | 4.44 |
| ROE | January 1967 | −0.16 | −0.87 | 0.13 | 0.55 | 2.55 | −0.69 | 7.65 |
| EW | January 1967 | −0.39 | −2.26 | 0.78 | 0.00 | 1.00 | 0.42 | 12.43 |
| PCA | January 1967 | −0.33 | −1.95 | 0.57 | 0.00 | 1.00 | −0.28 | 4.63 |
| PLS | January 1967 | −0.41 | −2.30 | 0.86 | 0.00 | 1.00 | 0.45 | 9.67 |

This table reports predictive regression results of the S&P 500 excess return on factor-based sentiment measures. High minus low (HML), robust minus weak (RMW), and conservative minus aggressive (CMA) are the value, profitability, and investment factors of Fama & French (2015), and the investment-to-asset (IA) ratio and return on equity (ROE) are the investment and profitability factors of Hou, Xue & Zhang (2015). $R^2$ is in percentage points. Equal weighting (EW), principal component analysis (PCA), and partial least squares (PLS) are three pooling procedures that combine information from the proxies, and the pooled predictors are standardized. Data begin in the months shown and end in December 2016.

**Table 3** provides predictive regression results for five fundamental factors from the work of Fama & French (2015) and Hou, Xue & Zhang (2015). It is interesting that all of them negatively predict the market return, as this is a typical sign of a sentiment measure. Moreover, the EW and PLS indices have significant predictive power, although the magnitudes of the $R^2$ values are small. Clearly, the $R^2$ values are likely to increase if more valuation factors are added into the analysis; this subject is worthy of further research.

Although fundamental factors can be viewed as valuations, they focus only on the aspects they capture. In contrast, the capital asset pricing model (CAPM) and related systematic factor models provide an overall assessment of the asset value, yielding its unique expected return at any given time. Clearly, one can compute investor expected return versus model expected return to determine the degree of over- or undervaluation.

He, Huang & Zhou (2018) appear to be the first to investigate in this direction. An investor sentiment for every stock is defined by

$$s_t = E[r_{t+1}] - E^*[r_{t+1}], \quad 10.$$

where is $E^*[r_{t+1}]$ is the expected return from a factor model, say the CAPM, and $E[r_{t+1}]$ is the expected return of investors, who form their expectations by extrapolating from past returns. This is supported by survey evidence and is consistent with the extrapolative expectations models of Greenwood & Shleifer (2014) and Hirshleifer, Li & Yu (2015). He, Huang & Zhou (2018) show that this sentiment, or pricing error, can be used as a diagnostic test for asset pricing models in addition to being a predictor of market returns.

Among economic fields, finance has the most extensive, highest-quality data. Trading happens almost 24 hours a day, with all transactions being recorded, so that investor sentiment is reflected daily or hourly. Thomson Reuters, for example, provides a variety of sentiment measures that account for this. Yet, existing studies primarily use the index of Baker & Wurgler (2006), which is based on 6-month time series. It seems that much research is needed to go beyond this. Huang et al. (2018) appear to be the first to study proxies from Thomson Reuters.

## 4.2. Survey Data

Survey data provide a unique perspective on how investors form their beliefs. This is important because such data allow for an examination of whether certain sentiment measures based on market data are consistent with investors' beliefs. Surveys have limitations, however. The available data are very limited in terms of both scope and time frequency. They are also usually based on small groups of investors, from as few as about 20 to as many as a few hundred, and the answers are rough estimates and depend heavily on how the survey is designed (including how it is written and interpreted). Most importantly, those who are informed may not respond, and those who respond may not have an incentive to tell the truth.

Nevertheless, survey data do seem to contain some important information. Greenwood & Shleifer (2014) analyze six survey-based measures of expectations between 1963 and 2011 (for the literature on studies with survey data, see the references contained in their work). They find that the measures are highly positively correlated with one another, as well as with past stock returns and the level of the stock market. However, the survey-based expectations are strongly negatively correlated with model-based expected returns.

There are two practical issues with survey data. The first is interpreting them. They measure beliefs, but not necessarily over- or underreactions. This is because there is no rational benchmark model provided to the investors being surveyed. For example, consider the probability of the market being up in the next 6 months. Ideally, we are interested in

$$S_t^{\mathrm{u}} = E[\mathrm{up}] - E^*[\mathrm{up}], \tag{11.}$$

where $E[\mathrm{up}]$ is the probability expected by investors and $E^*[\mathrm{up}]$ is the true or rational expectation. In practice, however, only $E[\mathrm{up}]$ is available. The second issue is the accuracy of the survey. Since there are multiple observations of $E[\mathrm{up}]$, the volatility (disagreement) should have an important impact on the quality of a survey. Unfortunately, this does not seem to have received much attention in the literature.

As an example, consider three surveys. The first is from the American Association of Individual Investors. The data are the percentage of investors who are bullish or bearish on the stock market for the next 6 months. The second is a similar survey of investment advisors, run by Chartcraft Inc. The last is from Market Vane Corporation and focuses on bullish futures traders.

**Table 4** shows that the predictive power is small and insignificant when each of the survey variables is used alone. (The bullish surveys are positively related to each other, as are the bearish ones, in consistency with the work of Greenwood & Shleifer 2014.) However, the surveys may have greater predictive power over longer horizons, as found by Brown & Cliff (2005) for horizons over 1 year. Pooling information across the surveys, the PLS index predicts the market significantly, with an $R^2$ of 2.60%, greater than that of the PLS index of the Baker–Wurgler proxies. This contrasts with earlier insignificant results of Fisher & Statman (2000). A related open question is how bullish/bearish sentiment interacts with insiders buying/selling and with short-selling activities, which Rapach, Ringgenberg & Zhou (2016) and Lie et al. (2017) find to have strong predictive power on the market.

It is interesting that, despite of the limitations of survey data, they can contain substantial information on future stock returns. With increasingly advanced survey tools available over the Internet and smartphones, high-quality surveys from more investors at higher frequency are possible. It will be interesting to find out what new information they can provide beyond market data.

**Table 4 Survey-based sentiment measures**

| | Start period | $\beta$ | $t$-Statistic | $R^2$ | Mean | Standard deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|
| AAIIBULL | July 1987 | −0.37 | −1.29 | 0.71 | 38.69 | 10.33 | 0.43 | 2.77 |
| AAIIBEAR | July 1987 | −0.05 | −0.19 | 0.02 | 30.23 | 9.63 | 0.51 | 2.91 |
| INVIBULL | December 1969 | −0.04 | −0.21 | 0.01 | 45.20 | 10.07 | 0.12 | 3.07 |
| INVIBEAR | December 1969 | 0.00 | 0.02 | 0.00 | 30.94 | 11.39 | 0.45 | 2.75 |
| MKTVBULL | April 1982 | 0.25 | 1.04 | 0.32 | 52.31 | 13.12 | −0.29 | 2.57 |
| EW | July 1987 | −0.17 | −0.67 | 0.16 | 0.00 | 1.00 | −0.19 | 2.49 |
| PCA | July 1987 | −0.27 | −1.03 | 0.38 | 0.00 | 1.00 | −0.23 | 2.56 |
| PLS | July 1987 | −0.70 | −2.46 | 2.60 | 0.00 | 1.00 | −0.26 | 2.75 |

This table reports predictive regression results of the S&P 500 excess return on survey-based sentiment measures: AAIIBULL and AAIIBEAR represent the percentage of investors who are bullish or bearish, as surveyed by the Association of American Individual Investors; INVIBULL and INVIBEAR represent the same percentage but for investment advisors, as surveyed by Chartcraft Inc.; and MKTVBULL represents the percentage of bullish investors, as surveyed by Market Vane Corporation. $R^2$ is in percentage points. Equal weighting (EW), principal component analysis (PCA), and partial least squares (PLS) are three pooling procedures that combine information from the proxies, and the pooled predictors are standardized. Data begin in the months shown and end in December 2016.

## 4.3. Text and Media Data

With the current fast advancement in computer technology, learning algorithms, and dictionaries, it it becoming increasingly popular to obtain sentiment measures from textual analysis and media sources.

On the basis of more than 1.5 million observations, Antweiler & Frank (2004) find that Internet stock messages can predict market volatility, although not necessarily returns. In contrast, Tetlock (2007) shows compellingly that news media content can predict stock market movements. He constructs a simple measure of media pessimism—the number of negative words—from the content of the Wall Street Journal column "Abreast of the Market" and finds that high levels of media pessimism robustly negatively predict market prices, followed by a reversion to fundamentals. In addition, he finds that unusually high or low values of media pessimism forecast high market trading volume. Subsequently, studies in accounting and finance have applied textual analysis to many problems; Loughran & McDonald (2016) provide an excellent survey of these studies. For example, Bodnaruk, Loughran & McDonald (2015) apply it to analysis of financial constraints, and Manela & Moreira (2017) use it to study volatility and disasters.

On the topic of market predictability, García (2013) computes the fraction of positive and negative words in two New York Times financial news columns and shows that the predictability of stock returns using news content is concentrated in recessions. (This is consistent with findings in the literature on predictability; see Rapach, Strauss & Zhou 2010; Henkel, Martin & Nadari 2011.) Da, Engelberg & Gao (2015) construct a new measure of investor sentiment called FEARS (financial and economic attitudes revealed by search) by aggregating the volume of queries from millions of US households related to concerns such as recession, unemployment, and bankruptcy. They find that FEARS predicts market returns and fund flows. In an arms race of measures of investor sentiment, measures are being produced at daily and minute-by-minute levels. Sun, Najand & Shen (2016) show, on the basis of a proprietary sentiment measure using textual analysis, that the intraday S&P 500 is predictable every half-hour using investor sentiment lagged by a half-hour, even after controlling for the intraday momentum effect of Gao et al. (2017).

**Table 5 Sentiment measures based on text and media data**

| Measure | Start period | $\beta$ | $t$-Statistic | $R^2$ | Mean | Standard deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|
| MS | January 2003 | −1.26 | −3.57 | 9.75 | 0.00 | 1.00 | −1.46 | 5.59 |
| FEARS | July 2004 | −0.75 | −1.96 | 2.71 | 0.00 | 1.00 | −2.05 | 16.25 |
| EW | July 2004 | −1.53 | −2.84 | 10.76 | 0.00 | 1.00 | −0.97 | 8.84 |
| PCA | July 2004 | −1.63 | −3.07 | 12.22 | 0.00 | 1.00 | 0.76 | 7.02 |

This table reports predictive regression results of the S&P 500 excess return on two sentiment measures based on text and media data. MS (manager sentiment), developed by Jiang et al. (2017), is based on firms' financial disclosures. FEARS (financial and economic attitudes revealed by search), developed by Da, Engelberg & Gao (2015), is based on Internet search volume for issues of concern. All variables are standardized, and $R^2$ is in percentage points. Equal weighting (EW) and principal component analysis (PCA) are two pooling procedures that combine information from the proxies. Data begin in months as shown; MS data end in December 2014, and FEARS data end in December 2011.



Jiang et al. (2017) construct an index called MS (manager sentiment) on the basis of the aggregated textual tone of corporate financial disclosures, exploiting managers' information advantage about their companies over outside investors. Using the financial and accounting dictionaries of Loughran & McDonald (2011), they measure textual tone as the difference between the number of positive and negative words in a disclosure scaled by the total word count of the disclosure. In contrast to existing studies, theirs is an aggregate index to gauge overall manager sentiment in the market, and the data are monthly instead of quarterly, facilitating comparison with macroeconomic predictors commonly measured on a monthly basis. They find that higher MS precedes lower aggregate earnings surprises and greater aggregate investment growth. Most importantly, MS predicts well the market return. In consistency with the work of Baker & Wurgler (2006), they also find that MS predicts cross-sectional stock returns, particularly for firms that are difficult to value and costly to arbitrage.

**Table 5** provides predictive regression results with available data for both FEARS and MS. Both of them forecast the stock market negatively and highly significantly. The former has an $R^2$ of 2.71%, whereas the latter has an $R^2$ of 9.57%, more than three times greater. The $R^2$ of the PCA index is almost equal to the sum of the individual values, indicating that the two predictors offer complementary information.

In comparison with market- and survey-based measures, it is surprising that measures based on textual analysis perform better by far. This may indicate that the stock market is likely to overlook information from the latter. Of course, more research is needed to show whether this is the case and to uncover any other reasons why measures based on market data underperform those based on text data.

## 5. UNDERSTANDING SENTIMENT

The presence of investor sentiment is apparent in manias, panics, and crashes. Shiller (1981) observes that the volatility of the stock market is too high to be justified by the volatility of the fundamental value, i.e.,

$$\mathrm{Var}[P_t] \gg \mathrm{Var}[P_t^*], \qquad 12.$$

where $\mathrm{Var}[P_t]$ is the observed variance of the market price and $\mathrm{Var}[P_t^*]$ is the theoretical or fundamental variance.

Interestingly, this is analogous to the well-known bound of Hansen & Jagannathan (1991),

$$\mathrm{Var}[m(\mathbf{x})] \geq \mathrm{Var}[m_0], \qquad 13.$$

where $m(\mathbf{x})$ is the stochastic discount factor (SDF) of an asset pricing model, with $\mathbf{x}$ as a vector of the state variables, and $m_0$ is an observed SDF from the data. While some new models satisfy the Hansen–Jagannathan bound, many old ones do not.

Kan & Zhou (2006) show, under some stringent assumptions, that

$$\mathrm{Var}[m(\mathbf{x})] \geq \frac{1}{\rho^2_{\mathbf{x},m_0}} \mathrm{Var}[m_0], \qquad 14.$$

where $\rho_{\mathbf{x},m_0} \leq 1$ is the multiple correlation coefficient between $\mathbf{x}$ and $m_0$. Since $\mathbf{x}$ in existing models has a small correlation with the market, the above bound can be dozens of times greater than the Hansen–Jagannathan bound. As a result, there does not appear to be any known SDF that can satisfy it. Alternatively, existing models also fail to satisfy certain bounds on predictability (Ross 2005, Zhou 2010, Huang & Zhou 2017). In short, using either anecdotal history or theory, stock return movements cannot be adequately explained by fundamental valuation models.

In general, let $\epsilon_t$ be the pricing error between a model price $P_t^{\mathrm{m}}$ and the true price $P_t^*$. In this case, the measured sentiment is

$$S_t = P_t - P_t^{\mathrm{m}} + \epsilon_t. \qquad 15.$$

To the extent that the model captures a large portion of the true value, $\epsilon_t$ should be small. Hence, despite estimation errors, large fluctuations in $S_t$ indicate exuberant valuations.

How can large overvaluation be possible? In an ideal economy, any mispricing from fundamental values should be impossible with costless arbitrage. However, as argued by Shleifer & Vishny (1997), among others, there are limits to arbitrage in the real world. In the dot-com mania, for example, smart investors such as hedge funds invested into the bubble instead of correcting it (Brunnermeier & Nagel 2004), and institutions bought more new technology supply than did individuals (Griffin et al. 2011). This evidence suggests that it is difficult to correct mispricing in the real world.

Empirically, as suggested by Baker & Wurgler (2006), there are several desirable properties for a good candidate measure of sentiment (see Section 3.1). First, its ups and downs should echo the manias and crashes of the relevant assets. Second, it should be related to alternative measures of investor over- and underreactions such as fund flows. Third, more speculative and harder-to-arbitrage assets should be more sensitive to it. Fourth, high sentiment should wane and prices should eventually revert to fundamentals. However, a test is yet to be developed to determine whether a given series qualifies as a sentiment measure.

Since high-sentiment periods are associated with optimistic valuations and corporate overinvestment, extremely high sentiment likely leads to a bubble. Phillips, Wu & Yu (2011) and Phillips, Shi & Yu (2015) provide a formal, statistical test. Assume a general autoregressive process for an asset price,

$$p_t = \mu + \delta p_{t-1} + \sum_{j=1}^{J} \phi_j (p_{t-j} - p_{t-j-1}) + \epsilon_t, \qquad 16.$$

where $p_t$ is the logarithmic price; $\mu$, $\delta$, and the $\phi_j$ are parameters; and $\epsilon_t$ is the noise. If $\delta = 1$, the above is the standard model that decomposes the logarithmic price into a random walk and a stationary component. A bubble occurs if $\delta > 1$. Phillips, Wu & Yu (2011) provide a statistical method for identifying both the origination date and the collapse date of an explosive bubble. However, their procedure allows only one bubble in the data. Phillips, Shi & Yu (2015) extend the framework to allow multiple bubbles.

Theoretically, Shiller (1984) explains sentiment in terms of social dynamics, and De Long et al. (1990) explain it using the concept of noise traders introduced by Black (1986). (There are





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various issues with the early models; see, e.g., Loewenstein & Willard 2006). Subsequently, several models have been proposed to explain sentiment. Thaler (1993) and Brunnermeier (2001) review some of the first advances. Shefrin (2008) provides a synthesis of various theories in the popular stochastic discount framework of asset pricing. Baker & Wurgler (2012) review the implications of sentiment models in the context of corporate decision making. In recent work, Greenwood, Hanson & Jin (2016) use extrapolation learning to explain credit sentiment.

An interesting question is how sentiment is related to the real economy. Graham & Harvey (2001), among others, show that optimistic valuation affects firm issuance. Lamont & Stein (2006) show that it also has substantial impact on corporate financing and investment decisions. Angeletos & La'O (2013) attribute certain business cycle fluctuations to sentiment. In their three-period model, Benhabib, Liu & Wang (2016) show that exuberant financial market sentiment can signal strong fundamentals to the real side of the economy, leading to a boom in real output and employment. However, in comparison with studies in rational asset pricing models, more research is needed to test model implications by calibrating models with real data.

## 6. OPEN ISSUES

While there are many unsolved problems in the previous sections, we focus below on three major issues that have received little attention in the literature.

### 6.1. Aggregation Methods

Since there are many proxies of investment sentiment available with the increasing use of big data and data management tools (such as machine learning), it is important to provide the best estimate of the unobservable sentiment by aggregating various proxies from different sources and at different time horizons.[2]

One approach is to aggregate the inputs to get an index of investor sentiment. A popular approach is to identify the first principal component of the proxies using PCA, as is done for the Baker–Wurgler index. Generally, one can consider using a linear combination of the proxies,

$$x_t = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n, \qquad 17.$$

where $x_1, x_2, \ldots, x_n$ are the proxies and $w_1, w_2, \ldots, w_n$ are the weights. It should be noted that the optimal choice of weights depends on the intended usage of the index.[3]

In terms of using $x_1, x_2, \ldots, x_n$ for forecasting market returns, Huang & Lee (2010) analyze the use of the simple average of the proxies, which implies using equal weights,

$$w_1 = w_2 = \cdots = w_n = \frac{1}{n}, \qquad 18.$$

yielding the EW predictor in **Tables 1–4**. Noting that PCA captures the variation of the proxies, but not necessarily the most relevant information for forecasting returns, Huang et al. (2015) advocate the use of the PLS approach, which extracts $S_t$, the investor sentiment, from a factor structure model,

$$x_{i,t} = \eta_{i,0} + \eta_{i,1} S_t + \eta_{i,2} E_t + e_{i,t}, \qquad i = 1, \ldots, n, \qquad 19.$$

[2]This perspective differs from that of Harvey, Liu & Zhu (2016), who suggest that a few factors need to be identified out of many.

[3]Here we focus on forecasting a univariate variable. For multiple variables, the combination puts a rank restriction on the regression coefficients (Zhou 1999).

where $\eta_{i,1}$ is the factor loading that summarizes the sensitivity of sentiment proxy $x_{i,t}$ to movements in $S_t$; $E_t$ is the common approximation error component of all the proxies, which is irrelevant to returns; and $e_{i,t}$ is the idiosyncratic noise associated only with measure $i$. Mathematically, the index, $S^{\mathrm{PLS}} = (S_1^{\mathrm{PLS}}, \ldots, S_T^{\mathrm{PLS}})'$, can be expressed as a one-step linear combination of the $x_{i,t}$:

$$S^{\mathrm{PLS}} = \mathbf{X}\mathbf{J}_n\mathbf{X}'\mathbf{J}_T\mathbf{R}(\mathbf{R}'\mathbf{J}_T\mathbf{X}\mathbf{J}_n\mathbf{X}'\mathbf{J}_T\mathbf{R})^{-1}\mathbf{R}'\mathbf{J}_T\mathbf{R}, \qquad 20.$$

where $\mathbf{X} = (x_1', \ldots, x_T')$ is a $T \times n$ matrix of individual investor sentiment measures, $\mathbf{R} = (R_2, \ldots, R_{T+1})'$ is a $T \times 1$ vector of stock returns, $\mathbf{J}_T = \mathbf{I}_T - (1/T)\iota_T\iota_T'$, $\mathbf{J}_n = \mathbf{I}_n - (1/n)\iota_n\iota_n'$, $\mathbf{I}_T$ is a $T$-dimensional identity matrix, and $\iota_T$ is a $T \times 1$ vector of ones. The PLS approach is due to Wold (1966, 1975). Kelly & Pruitt (2013, 2015) seem to be the first to find its valuable applications in finance. Lin, Wu & Zhou (2017) provide a new interpretation for PLS.

An alternative approach is to aggregate the outputs to incorporate information from various proxies. In the literature on forecasting, such combination methods (see, e.g., Timmermann 2006) are well known. The idea is to first run the predictive regression on each predictor,

$$r_{t+1} = a_j + b_j x_{jt} + \epsilon_{t+1,j}, \qquad 21.$$

to obtain an individual forecast,

$$\hat{r}_{t+1,j} = \hat{a}_j + \hat{b}_j x_{jt}, \qquad 22.$$

where $\hat{a}_j$ and $\hat{b}_j$ are the regression coefficients from the individual predictive regression on the $j$-th predictor, where $\epsilon_{t+1,j}$ is, as usual, the disturbance, with a mean equal to zero. Then a combination of the $n$ individual forecasts yields a forecast that utilizes the information of all predictors. A simple and popular combination is the average forecast,

$$\hat{r}_{t+1}^{\mathrm{MC}} = \frac{1}{n}\hat{r}_{t+1,1} + \frac{1}{n}\hat{r}_{t+1,2} + \cdots + \frac{1}{n}\hat{r}_{t+1,n}, \qquad 23.$$

which is also known as the mean combination forecast, which sets the weights as $1/n$. Rapach, Strauss & Zhou (2010) find that the average forecast of the US market risk premium performs the best among alternative weighting schemes in the literature. Moreover, Huang & Lee (2010) find that the average forecast outperforms the average of the predictors. In recent work, Lin, Wu & Zhou (2017) propose a further combination of the average forecast with a benchmark and show that it beats the average forecast substantially in predicting corporate bond returns. They also show that PLS can be viewed as an iterated combination method.

Aggregating the outputs is a classical statistical analog to Bayesian model averaging, which Pástor & Stambaugh (2000) and Avramov (2002), for example, apply to forecast stock returns. An implicit assumption in Bayesian model averaging is that one of the models contains the true data generating process. Relaxing this assumption, Geweke & Amisano (2011) propose linearly pooled models based on their logarithmic predictive scorings. It will be interesting to find out what improvements these methods can make in forming new sentiment indices. Unexplored methods are those used for macroeconomic forecasting, such as diffusion indexes and dynamic factors (see, e.g., Stock & Watson 2002, 2010). In recent work, Barone-Adesi, Mancini & Shefrin (2017) take a structural approach based on behavioral pricing kernels.

Indeed, given the increasingly large number of sentiment proxies, it is important to understand their properties and develop suitable methods to aggregate all information.[4] This will then likely generate more informative and more accurate sentiment measures on both the market and firms,

[4]The methods of Timmermann (2018), such as incorporating economic constraints of Pettenuzzo, Timmermann & Valkanov (2014), can potentially be applied to improve forecasting power.

potentially yielding a systematic sentiment factor that can compete with well-known factors, e.g., those of Fama & French (2015) and Hou, Xue & Zhang (2015), in explaining the entire cross section of asset returns.

### 6.2. Technical Analysis

Technical analysis has perhaps as a long history as the stock market itself. It uses primarily past prices and volume to predict future price movements (for an excellent survey of the methods involved, see Murphy 1986). In practice, major newspapers and brokerage firms publish technical graphs and commentary (though reduced substantially in recent years because of easy Internet access to such information) on the market, and many advisory services are based on technical analysis. More importantly, many top traders and successful fund managers use technical analysis to help make their investment decisions (see, e.g., Schwager 1989; Lo & Hasanhodzic 2009, 2010; Narang 2013).

Empirically, despite earlier mixed conclusions, Brock, Lakonishok & LeBaron (1992) and especially Lo, Mamaysky & Wang (2000) find strong evidence of the profitability of using technical analysis. More recently, Han, Yang & Zhou (2013) show that it can generate substantial alphas in portfolios sorted by volatility, and Neely et al. (2014) find that technical indicators have forecasting power on the stock market matching or exceeding that of macroeconomic variables. Han, Zhou & Zhu (2016) find that technical analysis can yield a trend factor in the stock market that is highly profitable and remarkably stable. Lin, Wu & Zhou (2018) show that technical analysis is highly profitable in the corporate bond market as well. Detzel et al. (2018) show that technical analysis is particularly useful for assets, such as Bitcoin, whose fundamentals are very difficult to determine.

Theoretically, Brown & Jennings (1989) show, in a two-period model, that rational investors can gain from forming expectations based on historical prices. In a model with volume playing a role, Blume, Easley & O'Hara (1994) show that traders who use information contained in market statistics do better than otherwise. Under information asymmetry, Grundy & Kim (2002) also show that there is value in using technical analysis. Edmans, Goldstein & Jiang (2015) provide a rationale for feedback trading. Calibrating data to a model, Zhu & Zhou (2009) show that, when stock returns are predictable but there is model uncertainty, technical analysis outperforms the prior-dependent optimal learning rule when the prior is not too informative, due to its easy estimation and robustness. On the basis of work by Wang (1993), Han, Zhou & Zhu (2016) provide a general equilibrium model of rational and technical traders. They show that the predictability of technical indicators can change sign depending on the proportion of technical traders in the market.

In technical analysis, there are many overbought and oversold indicators that are precisely designed to capture unsustainable levels of optimism and pessimism. These sentiment measures are quite intuitive and arithmetically simple. For example, the well-known Williams $\%R$ is defined as

$$\%R = \frac{\text{highest high} - \text{closing price}}{\text{highest high} - \text{lowest low}} \times 100, \qquad 24.$$

where the highest high and lowest low prices of an asset over, say, the past $n = 10$ days are used, and closing price is the closing price today. If $\%R$ is less than 20, the asset is regarded as overbought, as it is close to the highest high. Likewise, when $\%R$ is greater than 80, the asset is regarded as oversold. The measure is clear when the asset price oscillates around a certain price level. If there is a price trend, then the detrended prices can be used to compute $\%R$. It is an open question how measures of overbuying and overselling perform compared to more sophisticated sentiment measures.

Indeed, technical analysis is an area in which simple analytical tools are used to make important investment decisions. It provides concrete examples of how many investors form their beliefs. Although technical analysis is widely used in the stock market, its applications in the foreign exchange market are even more impressive. Taylor & Allen (1992) find more than 90% usage of technical analysis among currency dealers, and Gehrig & Menkhoff (2006) find that technical analysis is as important as fundamental analysis to currency mangers. Interestingly, Burghardt, Duncan & Liu (2010) show that a simple moving average strategy does a good job of replicating the performance of a typical managed futures fund and generates a return history with a 0.67 correlation to a popular managed futures index.

Decision making based on simple and naive rules is clearly a research subject of behaviorial finance, but there are few studies that tie what theories assume to what practitioners use. In particular, existing sentiment studies almost completely ignore technical sentiment indicators. Understanding the link between the two is likely to shed light on why and how market prices revert to fundamentals after being driven away by sentiment.

### 6.3. What Sentiment Features to Use?

Typically, the sentiment level is used to estimate an asset's sensitivity to sentiment or to forecast asset returns. The optimal functional form, which should vary from one application to another, has not been studied. In addition, it is unknown what lag length should be used and how to estimate the trend of sentiment. It is unknown how conclusions of major sentiment studies may be altered with better econometrically designed sentiment measures.

What can we learn from the volatility of investor sentiment? Are there any insights to be gained from the skewness and higher moments?[5] Although sentiment regimes play an extremely important role in many studies, no study has defined the regimes rigorously. Statistically, it is unknown what stochastic process can fit a sentiment measure well.

To make the optimal use of sentiment, it is necessary to know its stochastic process to solve the usual utility maximization problem. Solutions to the problem can clearly enhance the economic value of trading based on sentiment information. It will also help to understand the risk premium associated with taking risk related to sentiment.

## 7. CONCLUSION

Investors' emotions go up and down with asset prices, as do the asset values from their economic fundamentals. Measuring investor sentiment is important for both theoretical asset pricing and practical investment. This article reviews various investor sentiment measures and applications based on market data, surveys, text, and news media.

It is well established that sentiment can explain returns on stocks that are difficult to value and costly to arbitrage, such as unprofitable stocks, nondividend-paying stocks, extreme growth stocks, and distressed stocks. However, much remains to be done. We examine three open issues. The first is developing efficient methods that pool all information across various measures. The second is making connections with technical analysis. The final issue is using sentiment information

[5] The question is especially of interest in light of work by Colacito et al. (2016), who show that the skewness of macroeconomic variables matters for the predictability of equity returns.

optimally. Solutions to these problems are likely to produce more accurate sentiment measures, potentially yielding a systematic sentiment factor that explains the cross section of asset returns; to help understand how sentiment is used in practice and how it affects prices; and to enhance the economic value of using sentiment information and to understand the corresponding risk premium.

## DISCLOSURE STATEMENT

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