Investor Sentiment and Analysts’ Earnings Forecast Errors

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We correlate analysts’ forecast errors with temporal variation in investor sentiment. We find that when sentiment is high, analysts’ forecasts of one-year-ahead earnings and long-term earnings growth are relatively more optimistic for “uncertain” or “difficult-to-value” firms. Adding these forecast errors to a regression of stock returns on sentiment absorbs a sizable fraction of the explanatory power of sentiment for the cross section of future returns. This finding provides direct support for the notion that investor sentiment affects the earnings expectations of hard-to-value firms. Additional tests suggest that this bias in expectations is unlikely to be strategic in nature. Our results provide new insight into the mechanism through which investor sentiment affects returns.

Key words: accounting; finance; asset pricing

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1. Introduction

Prior work in behavioral finance theorizes that investor sentiment drives stock prices away from fundamental value and that betting against sentimental investors can be costly and risky (De Long et al. 1990, Shleifer and Vishny 1997). Several stock market episodes, such as the crash of October 1987 or the tech bubble of the new millennium, appear consistent with the notion that sentiment affects stock prices. Recent empirical evidence offered by Baker and Wurgler (2006, 2007) indicates that time-varying sentiment has dramatic implications for the cross section of future stock returns. Using an aggregate measure of investor sentiment, they find that when sentiment is high, young, volatile, and other “hard-to-value” stocks earn relatively low subsequent future returns. When sentiment is low, these patterns attenuate or reverse.

Underlying the prior work on investor sentiment is the notion that sentiment reflects errors in investors’ expectations about future payoffs. Despite this belief, however, there has been little direct evidence of whether these return patterns reflect systematic errors in earnings expectations. Baker and Wurgler (2006) attempt to address this concern, but find little evidence of cross-sectional return patterns related to sentiment using earnings announcement period returns. They attribute this lack of consistent evidence to the fact that this test “has only limited power to detect how expectational errors affect our results…[because] a firm’s announcement event return picks up the expectational corrections that occur only to it alone, within its own announcement window” (p. 1675).

In this paper, we use an alternative approach to test whether expectational errors drive the association between investor sentiment and stock returns. We examine whether time-series variation in sentiment is related to time-series variation in security analysts’ earnings forecast errors. Analysts’ forecasts provide a direct measure of earnings expectations, which we can use to test whether shifts in sentiment are associated with shifts in the average level of forecast optimism or pessimism. It also allows us to overcome some of the tricky timing issues associated with knowing exactly when investors’ expectational errors will be corrected. By measuring forecast errors with beginning of the year forecasts, we allow the correction in returns to come through at any point during the year. Moreover, adding analyst forecast errors to cross-sectional regressions of stock returns on sentiment allows us to estimate the extent to which earnings forecast errors explain the relation between sentiment and the cross section of returns.

Our analysis is important for two reasons. First, without evidence that sentiment is related to a bias in earnings expectations, it is difficult to rule out rational explanations for the link between sentiment and stock returns. For example, sentiment tends to be high (low) in good (bad) economic times. Prior research suggests
discount rates and expected returns vary with the business cycle (e.g., Fama and French 1989). Thus, the relation between time-varying sentiment and returns could be because of either irrational expectations or an omitted risk factor from a conditional asset pricing model.

Second, if sentiment is a manifestation of investor irrationality, the precise mechanism by which sentiment affects stock prices is unclear. One theory suggests sentiment affects investor beliefs more significantly in stocks that are inherently more uncertain or difficult to value (Baker and Wurgler 2006, 2007). Examples include firms that are small, young, unprofitable, and whose stocks have high volatility or pay no dividends.1 Another theory posits that limits to arbitrage vary cross sectionally such that uncertain stocks with the most subjective valuations are also likely to be the costliest to arbitrage (Shleifer and Vishny 1997, De Long et al. 1990, Baker and Wurgler 2006). Thus, even if sentiment affects expectations for all stocks in a similar fashion, mispricing may arise more extensively in uncertain stocks simply because of limits to arbitrage. Our analysis tests both theories.

We find that from 1983 to 2005, sentiment affects analyst earnings per share (EPS) expectations mostly in the cross section. When sentiment is high, earnings forecasts become more optimistic for small firms, young firms, unprofitable firms, stocks with high volatility, and stocks with no dividends relative to their more certain counterparts. When sentiment is low, this pattern attenuates. Furthermore, we find that adding the one-year-ahead earnings forecast error as an intermediating variable in the relation between sentiment and future stock returns reduces the coefficient on sentiment between 29% and 70%.

Examining analyst forecasts of long-term earnings growth reveals fairly similar patterns. Long-term growth forecasts are relatively more optimistic in high-sentiment periods, particularly among uncertain firms. Adding long-term growth forecast errors as an intermediating variable in the relation between sentiment and future stock returns reduces the coefficient on sentiment between 10% and 71%. Adding both earnings forecast errors and long-term growth errors to the regression reduces the coefficient on sentiment between 29% and 96%, eliminating its statistical significance in all cases.

In sum, our results indicate biases in expected future earnings and growth are responsible, at least to some degree, for the association between sentiment and future stock returns. Importantly, our evidence implies this association is not driven solely by limits to arbitrage. Although limits to arbitrage may disproportionately affect the price of uncertain stocks, there is little reason to suspect that limits to arbitrage lead to larger earnings forecast errors for uncertain stocks.2 Our findings therefore provide evidence that sentiment affects investor expectations more strongly in hard-to-value firms.

Our approach is novel in that we use average forecast errors at the portfolio level to help explain stock returns on hedge portfolios long on uncertain stocks and short on certain stocks. That stock returns are related to earnings forecast errors is not surprising. However, by conducting our analysis at the portfolio level, we are able to couch our tests in a traditional asset pricing framework, where portfolio returns are regressed on a vector of explanatory factors. Our approach can therefore be used to test whether errors in earnings expectations contribute to anomalous stock price patterns at the portfolio level.

To our knowledge, our study is the first to provide direct evidence on the role of forecast errors in explaining the association between sentiment and stock prices. By using forecasts generated by sell-side analysts, we show that sophisticated investors are affected by sentiment. Sell-side analysts are among the subset of market participants who should be the most informed about a stock’s fundamentals. In that sense, studying the effect of sentiment on analyst forecasts provides us with a lower bound on the effect that sentiment might have on nonprofessional or less informed investors.

Our research follows a number of prior studies that have used security analysts to provide insight into anomalous stock returns patterns (e.g., Debondt and Thaler 1990, Abarbanell and Bernard 1992, La Porta 1996). The basic tenor of results from many prior studies is that analyst forecasts are predictably biased (e.g., Butler and Lang 1991, Easterwood and Nutt 1999) and forecast bias appears consistent with several stock price anomalies (e.g., Debondt and Thaler 1990, Abarbanell and Bernard 1992, La Porta 1996, Bradshaw et al. 2001). In the context of our study, analyst forecasts provide us with a window into otherwise unobservable investor expectations. The fact that analyst forecast bias aligns with temporal variation in sentiment helps lend support to investor irrationality as an explanation for the link between sentiment and future returns.

1 Throughout the paper, we refer to firms that exhibit these five characteristics as “uncertain” or “difficult to value,” and we use these terms interchangeably.

2 To the extent that analysts use past stock price movements to forecast earnings, limits to arbitrage could get reflected in their earnings forecasts. For this to be the sole explanation, however, analyst forecasts would have to mimic price without adding new information about expected earnings. We believe this is unlikely to be causing our results because of the evidence that analyst forecasts are a good proxy for investor earnings expectations (see Kothari 2001 for a review).
This study is complemented by the recent work of Seybert and Yang (2012), who show that the low returns of uncertain firms following high-sentiment periods are concentrated around the release of managerial earnings guidance. Whereas our findings imply that variation in investor sentiment leads to errors in earnings expectations for uncertain stocks, Seybert and Yang (2012) provide insight as to how these expectations are corrected and manifested in stock prices. Moreover, their findings help explain why theseexpectational errors are not detectable when using short-window returns analysis around subsequent earnings announcements.

One possible concern with the use of analyst forecasts to study the effect of sentiment on stock prices is that analysts may have strategic reasons to intentionally bias their forecasts. For example, if analysts are aware of the underlying investor sentiment, they might bias their earnings forecasts upward in periods of high sentiment, hoping to generate additional trading or please managers to attract investment banking business. If so, then a documented association between analyst earnings forecast errors and sentiment might not reflect the manifestation of an unwitting bias, but rather the strategic exploitation of a known bias among less-informed investors by rational, profit maximizing analysts. We conduct a variety of tests and find no evidence that the link between sentiment and forecast errors is strategic in nature. However, we acknowledge that we cannot definitively rule out this possibility.

The rest of this paper proceeds as follows. The next section describes our data sources. Section 3 discusses our methodology, results, and additional tests. Section 4 concludes.

2. Data
We collect consensus (mean) annual EPS forecasts and long-term earnings growth forecasts from the Institutional Brokers’ Estimate System (I/B/E/S) summary each month from August 1983 to December 2006, primarily because I/B/E/S data before 1983 is sparse. Earnings forecasts, actual earnings, and announcement dates are taken from I/B/E/S. All other accounting variables come from COMPSTAT, and stock returns come from the Center for Research in Securities Prices (CRSP). We obtain the investor sentiment data directly from Jeffrey Wurgler’s website (http://pages.stern.nyu.edu/~jwurgler). Sentiment is the first principal component from the time series of the average closed-end fund discount, the equity share in new issues, New York Stock Exchange (NYSE) share turnover, number of IPOs, first-day IPO returns, and the dividend premium.3 Prior work (e.g., Diether et al. 2002, Payne and Thomas 2003) finds that stock splits can compromise inferences from studies using I/B/E/S forecast data, when variables such as forecast dispersion or the forecast error bin (e.g., meeting versus just beating) is correlated with subsequent stock price performance. Problems arise because the I/B/E/S summary file rounds the forecast and actual earnings to the nearest penny after split adjusting. Thus, having exactly zero forecast error or zero dispersion in analyst forecasts would be correlated with the future success of the firm. This issue is unlikely to present a problem in our setting for two reasons. First, as we explain in detail below, we aggregate analyst forecast errors each month at the portfolio level. Although the rounding issue reduces dispersion and increases the coarseness of forecast errors for firms with multiple stock splits, the average forecast error will still be unbiased when averaged across multiple firms. Second, we check to see whether differences in the incidence of stock splits for uncertain firms relative to certain firms covary systematically with sentiment over time. In unabulated tests, we find that the average difference in the incidence of stock splits between uncertain and certain firms is small (less than 0.5%). Further, these average differences exhibit insignificant correlations with sentiment in all but one cross-sectional partition, with age being the exception. Overall, stock splits do not appear to be a major problem for our forecast error tests.

Conducting our main analysis at the portfolio level streamlines our tests, and makes them more consistent with prior work in empirical asset pricing. Moreover, it helps avoid problematic econometric issues with cross-sectional correlations among both forecast errors and returns that occur at the individual-firm level. Our final sample contains 646,046 firm-month observations. The average number of observations per month increases steadily from 839 in the first three years of our sample period, to 3,074 in the final three years of our sample period.

3. Empirical Methodology and Results
3.1. EPS Forecasts
We are interested initially in two questions. First, do analysts’ EPS forecasts become more optimistic for all stocks when sentiment is high? Second, do EPS forecasts become more optimistic for “uncertain” firms relative to other firms when sentiment is high, and less optimistic when sentiment is low?4 To answer the first question, we compute mean forecast errors

3 See Baker and Wurgler (2006) for additional details.

4 We use the terminology “more optimistic” and “less optimistic” to reflect the well-documented empirical regularity that long-horizon analyst forecasts are, on average, optimistically biased.
for all firms in our sample each month and correlate this time series with the monthly Baker and Wurgler sentiment index. We calculate earnings forecast errors for each firm each month as actual EPS minus the monthly consensus EPS forecast, scaled by the absolute value of the consensus EPS forecast. We do not scale by stock price because we wish to avoid concerns that scaling by a market price may induce our findings (Mian and Teo 2004). However, our results below are quite similar when we scale forecast errors by share price.\(^5\) To answer the second question, we follow the methodology of Baker and Wurgler (2006) (BW hereafter) and classify firms as more or less “uncertain” or hard to value on the basis of five firm characteristics: size (market value of equity (MVE)), age, return volatility, profitability, and dividend payments. Small, young, volatile, and unprofitable firms that do not pay dividends are categorized as uncertain. Size is market value of equity from CRSP, updated each June. Age is the number of months a firm has been listed on CRSP, updated each June. Return volatility is the standard deviation in returns over the prior 12 months ending each year in June. Profitability, measured as return on equity, is computed as earnings divided by book value of equity. Earnings are defined as income before extraordinary items (COMPUSTAT data 16) plus deferred taxes (data 50) less preferred dividends (data 19). Book value is book equity (data 60) plus balance sheet deferred taxes (data 35). Dividends (data 25 \times \text{data 26}) are measured via the dividend to book ratio. We also form equal-weight hedge stock portfolios similar to Baker and Wurgler (2006) using the characteristic sorts described above. Accounting data for the fiscal year ending in calendar year \(t - 1\) are matched to 12 months of returns beginning in July of calendar year \(t\). The variable \(\rho\) for the portfolio forecast errors is the first-order autocorrelation. The variable \(\rho\) for the stock portfolios is the first-order autocorrelation of the residuals from a regression of returns on the three factors of Fama and French (1993).

\(^5\)To assess the sensitivity of our findings to small scalars, we exclude firms with absolute forecasted earnings less than 10 cents per share. Results are similar.

### Table 1 Descriptive Statistics for Average Monthly Forecast Errors from 1983 to 2005

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std. dev.</th>
<th>10th</th>
<th>90th</th>
<th>(\rho)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: EPS forecast errors</strong> ((N = 269) months)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All stocks</td>
<td>-0.28</td>
<td>-0.28</td>
<td>0.09</td>
<td>-0.40</td>
<td>-0.14</td>
<td>0.91</td>
</tr>
<tr>
<td>Small minus big</td>
<td>-0.57</td>
<td>-0.54</td>
<td>0.24</td>
<td>-0.80</td>
<td>-0.34</td>
<td>0.75</td>
</tr>
<tr>
<td>Young minus old</td>
<td>-0.25</td>
<td>-0.24</td>
<td>0.14</td>
<td>-0.43</td>
<td>-0.05</td>
<td>0.83</td>
</tr>
<tr>
<td>Volatile minus smooth</td>
<td>-0.48</td>
<td>-0.49</td>
<td>0.20</td>
<td>-0.71</td>
<td>-0.20</td>
<td>0.58</td>
</tr>
<tr>
<td>Profitable minus unprofitable</td>
<td>-0.54</td>
<td>-0.49</td>
<td>0.30</td>
<td>-0.88</td>
<td>-0.23</td>
<td>0.56</td>
</tr>
<tr>
<td>Nonpayers minus payers</td>
<td>-0.35</td>
<td>-0.33</td>
<td>0.16</td>
<td>-0.58</td>
<td>-0.13</td>
<td>0.75</td>
</tr>
<tr>
<td><strong>Panel B: Returns (in percentages)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All stocks</td>
<td>1.27</td>
<td>1.60</td>
<td>5.17</td>
<td>-4.70</td>
<td>7.09</td>
<td></td>
</tr>
<tr>
<td>Small minus big</td>
<td>0.41</td>
<td>-0.22</td>
<td>5.15</td>
<td>-5.43</td>
<td>6.16</td>
<td>0.19</td>
</tr>
<tr>
<td>Young minus old</td>
<td>-0.01</td>
<td>-0.53</td>
<td>4.96</td>
<td>-4.55</td>
<td>4.65</td>
<td>-0.08</td>
</tr>
<tr>
<td>Volatile minus smooth</td>
<td>0.03</td>
<td>-0.25</td>
<td>7.32</td>
<td>-6.20</td>
<td>8.27</td>
<td>0.04</td>
</tr>
<tr>
<td>Profitable minus unprofitable</td>
<td>0.16</td>
<td>-0.24</td>
<td>5.29</td>
<td>-4.80</td>
<td>5.20</td>
<td>0.05</td>
</tr>
<tr>
<td>Nonpayers minus payers</td>
<td>0.14</td>
<td>0.11</td>
<td>4.75</td>
<td>-5.42</td>
<td>5.36</td>
<td>0.06</td>
</tr>
</tbody>
</table>

**Notes:** Each month, from August 1983 to December 2005, we collect consensus (mean) annual forecasts of EPS from I/B/E/S. We measure forecast errors as actual EPS from I/B/E/S less the forecast, scaled by the absolute value of the forecast. Each month, firms are sorted into deciles (using NYSE breakpoints) on size (MVE), age, return volatility, earnings to book ratio, and dividend to book ratio. We then calculate mean forecast errors for each decile and take the difference in the extreme deciles (1 and 10) to construct forecast error portfolios. These portfolio forecast errors measure the difference in average EPS forecast errors between uncertain (small, young, volatile, etc.) and certain firms (big, old, smooth, etc.). Size is market value of equity from CRSP, measured each June. Age is the number of months a firm has been listed on CRSP, updated each June. Return volatility is the standard deviation in returns over the 12 months ending each year in June. Profitability is earnings to book ratio. Earnings is income before extraordinary items (COMPUSTAT data 16) plus deferred taxes (data 50) less preferred dividends (data 19). Book value is book equity (data 60) plus balance sheet deferred taxes (data 35). Dividends (data 25 \times \text{data 26}) are measured via the dividend to book ratio. We also form equal-weight hedge stock portfolios similar to Baker and Wurgler (2006) using the characteristic sorts described above. Accounting data for the fiscal year ending in calendar year \(t - 1\) are matched to 12 months of returns beginning in July of calendar year \(t\). The variable \(\rho\) for the portfolio forecast errors is the first-order autocorrelation. The variable \(\rho\) for the stock portfolios is the first-order autocorrelation of the residuals from a regression of returns on the three factors of Fama and French (1993).
earnings forecast errors across all stocks and the five characteristic sorts. We emphasize two patterns. First, in every month, the average forecast error is negative, consistent with optimism in long-horizon forecasts (see Kothari 2001 for a review).6 Because we measure changes in forecast errors over time in relation to sentiment, we really capture the extent to which analysts’ forecasts are relatively more or less optimistic. Second, monthly forecast errors are strongly persistent, with first-order autocorrelation coefficients above 0.50. We control for autocorrelation in later tests when we relate forecast errors to sentiment (another slow moving variable). Panel B presents descriptive statistics for returns (in percentages) across all firms and the five characteristic portfolios. The average returns for the portfolios are fairly meager unconditionally (consistent with BW), except for the well-known size effect. In contrast to the portfolio forecast errors, the portfolio stock returns exhibit much lower autocorrelation.

Table 2 presents initial evidence on the relation between monthly forecast errors and the sentiment index, with simple correlations.7 Our goal is to observe whether the time series of aggregate forecast optimism/pessimism mirrors changes in investor sentiment. Prior research (e.g., Brown 2001) finds that analyst forecasts, across all firms, have become less optimistic over time, and we generally observe this pattern in our data. Consequently, we detrend the forecast error series, except for the young minus old portfolio, which exhibits no significant time trend. In general, our results are similar whether we detrend or use the raw forecast error time series.

There is generally a negative relationship between average forecast errors and the sentiment index. Negative forecast errors imply optimism (actual EPS lower than forecasted EPS). Given the high autocorrelation documented in Table 1, and the persistent nature of the investor sentiment variable, we adjust the p-values for autocorrelation.8 When sentiment is high, forecast errors for all firms are more negative, although the magnitude of the correlation is relatively modest and not significant at conventional levels (p = 0.310). Though not the primary focus of their paper, Bergman and Roychowdhury (2008) document a significant negative relation between analysts’ EPS forecast errors and sentiment. Our design differs from theirs, however, in that we focus on forecast errors at the portfolio level, rather than firm level, which may help explain these different findings.

More importantly, Table 2 shows that the effect of sentiment on analyst forecast errors varies cross-sectionally across certain and uncertain firms. The cross-sectional effects of sentiment on forecast errors appear more significant. Specifically, when sentiment is high, forecast errors are more negative (i.e., optimistic) for uncertain firms relative to certain firms. When sentiment is low, the opposite is true. Overall, the correlations are strongest for nonpayers versus payers (p = −0.50, p < 0.001) and unprofitable versus profitable firms (p = −0.23, p = 0.012), whereas the effect is statistically weakest for small versus big firms (p = −0.19, p = 0.114).

Overall, we find no statistically significant evidence that sentiment is negatively related to one-year-ahead earnings forecasts errors across all stock in general (p = 0.310). On the other hand, we do find significantly negative relations with our cross-sectionally sorted portfolios. The results in Table 2 suggest that the effect of sentiment on analyst forecasts is strongest in the hard-to-value firms, which is consistent with expectational errors being most affected when there is uncertainty about how to value the firm.

Although the results in Table 2 are consistent with analyst forecast errors contributing to the cross-sectional stock return patterns demonstrated by BW, we have not provided any direct evidence linking
these patterns to returns. One of the most compelling features of BW is that the sentiment index has sign-flipping implications for the cross section of returns. When sentiment is high, uncertain firms tend to earn lower future returns. When sentiment is low, the reverse tends to be true. In our next analysis, we examine whether earnings forecast errors explain a significant amount of the cross-sectional return patterns.

Answering this question poses challenges. According to the cross-sectional version of the expectational errors hypothesis, uncertain firms earn relatively low stock returns after periods of high sentiment because investors naively overestimate their future performance during high-sentiment periods. Identifying the precise period(s) when the future investors became aware of the overvaluation, and the form and amount of the news, is problematic. Earnings news is released gradually over an annual period in a variety of ways (quarterly earnings announcements, preannouncement warnings, conference calls, management forecasts, analyst forecast revisions, etc). This difficulty likely relates to why BW were unable to detect strong patterns in the data when using three-day earnings announcement windows. However, to examine whether forecast errors affect the return patterns related to sentiment, we have to try to line up the average forecast errors used in Table 2 with the future periods in which the news embodied by the forecast errors is realized by the market.

Bearing this limitation in mind, we employ the following methodology to try to document an association. For each firm-year, we measure the forecast error as actual annual EPS less the first consensus after the announcement of fourth-quarter EPS from the prior year. We assume the total announcement window for this forecast error stretches over the 12-month period beginning the month after last year’s fourth-quarter earnings announcement, and this forecast error is assigned to the firm for each calendar month in the announcement window. Note that this procedure essentially allows the correction of the beginning of the year forecast error to take place any time over the following year. As before, we compute the mean forecast error for each characteristic decile and then take the difference between the most extreme deciles (10 minus 1) each month. Thus, for each of the five characteristics above, we have a monthly time series of the difference in average forecast errors between uncertain and certain firms (FEt), but unlike Table 2, the forecast errors are based only on the first forecast made during the year. Similar to BW, we also form portfolios of stocks each month by taking long (short) positions in the most uncertain (certain) deciles of the five firm characteristics. We then calculate equally weighted returns for each portfolio every month (Rett) and estimate the following time-series regression:

\[
\text{PortfolioRet}_t = \alpha + \beta_1 \text{Sentd}_t + \beta_2 \text{MKT}_t + \beta_3 \text{SMB}_t + \beta_4 \text{HML}_t + \beta_5 \text{FE}_t + \varepsilon_t, \tag{1}
\]

Following BW, Sentd, is an indicator variable equal to 1 if the beginning of the year sentiment index is positive, and 0 otherwise. The coefficient \(\beta_1\) estimates the extent to which uncertain firms underperform following periods of high sentiment. The coefficients \(\beta_2\) through \(\beta_4\) estimate the loadings on the three factors from Fama and French (1993). The coefficient \(\beta_5\) measures the relation between future returns on the hedge portfolios and the difference in average earnings forecast errors between uncertain and certain firms.

Table 3 presents the results from estimating Equation (1). Returns are stated on a percentage basis. The first column includes only the Sentd variable, the second column adds the Fama–French factors, and the third column adds FE to the regression. Results in the first column are consistent with the findings of BW. Uncertain stocks earn relatively lower monthly returns following periods of high sentiment. This difference in future returns ranges from roughly 86 basis points for unprofitable versus profitable firms \((p = 0.096)\) to almost 160 basis points for firms with volatile versus smooth returns \((p = 0.041)\). Adding the three Fama–French factors in the second column generally attenuates the coefficient on sentiment, mostly because of the inclusion of the size factor (SMB). This attenuation is not surprising, because the characteristics associated with valuation uncertainty (age, profitability, volatility, etc.) are correlated with firm size.

In the third column of Table 3, we add the analyst forecast error variable to the regression to test whether it significantly alters the explanatory power of sentiment. If analyst forecast errors act as an intermediating variable in the relation between sentiment and stock returns, then we expect to see a coefficient on FE that is significantly positive and a reduction

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8 Unlike the analysis in Table 2, we do not update the forecast error variable every month to reflect changes in the monthly consensus. Instead, we construct a single forecast error for each firm-year intended to capture the total earnings news released over the year and ask whether this revelation of news can help explain the relation between prior sentiment and stock returns. However, when we update forecasts every month to reflect changes in the consensus, results are inferentially similar.

10 An alternative would be to use the prevailing sentiment in the month immediately prior to the issuance of the analyst forecast. We opted to use the beginning of the year sentiment index to maintain consistency with the original BW analysis, such that our only innovation is adding an additional variable to their regression.

11 We also conduct our main analysis without the Fama–French factors and the tenor of the results is similar to those reported in the paper.
Importantly, the earnings forecast variable appears to absorb a significant amount of the association between sentiment and stock returns. In the last column of Table 3, we calculate the percentage reduction in the slope on Sentd, from the second to the third column, after inclusion of the forecast error variable. The reduction in slope ranges from 29% (p < 0.05) for the unprofitable minus profitable portfolio to 60% for the unprofitable minus profitable portfolio.

Watson (1951) tests reveal no significant autocorrelation in the residuals for Equation (1) except the small minus big portfolio (p < 0.01). When we adjust p-values for this portfolio (and all other portfolios) using a Newey–West (1987) correction at four lags, inferences are identical. Thus, autocorrelation does not appear to be a concern for our returns tests.

Table 3: Portfolio Returns, Investor Sentiment, and Analysts’ Earnings Forecast Errors

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>p-value</th>
<th>Estimate</th>
<th>p-value</th>
<th>Estimate</th>
<th>p-value</th>
<th>Reduction in slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.846</td>
<td>0.107</td>
<td>1.153</td>
<td>0.028</td>
<td>3.760</td>
<td>&lt;0.001</td>
<td>−37%***</td>
</tr>
<tr>
<td>Sentd</td>
<td>−0.659</td>
<td>0.153</td>
<td>−0.654</td>
<td>0.150</td>
<td>−0.411</td>
<td>0.257</td>
<td>p = 0.003</td>
</tr>
<tr>
<td>Mkt</td>
<td>−0.221</td>
<td>0.006</td>
<td>−0.217</td>
<td>0.007</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HML</td>
<td>−0.381</td>
<td>0.006</td>
<td>−0.370</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel A: Small minus big

| Intercept        | 0.696    | 0.167   | 0.594    | 0.079   | 1.055    | 0.011   | −70%**            |
| Sentd            | −1.066   | 0.043   | −0.679   | 0.048   | −0.204   | 0.333   | p = 0.027          |
| Mkt              | 0.048    | 0.348   | 0.046    | 0.372   |          |         |                    |
| SMB              | 0.833    | <0.001  | 0.818    | <0.001  |          |         |                    |
| HML              | −0.433   | <0.001  | −0.459   | <0.001  |          |         |                    |
| FE               |          |         |          |         |          |         |                    |

Panel B: Young minus old

| Intercept        | 1.082    | 0.147   | 0.421    | 0.359   | 1.498    | 0.089   | −30%*             |
| Sentd            | −1.591   | 0.041   | −0.873   | 0.058   | −0.611   | 0.148   | p = 0.076          |
| Mkt              | 0.597    | <0.001  | 0.599    | <0.001  |          |         |                    |
| SMB              | 1.064    | <0.001  | 1.047    | <0.001  |          |         |                    |
| HML              | −0.447   | <0.001  | −0.455   | <0.001  |          |         |                    |
| FE               |          |         |          |         |          |         |                    |

Panel C: Volatile minus smooth

| Intercept        | 0.729    | 0.175   | 0.572    | 0.199   | 1.560    | 0.023   | −29%**            |
| Sentd            | −0.861   | 0.096   | −0.559   | 0.149   | −0.395   | 0.233   | p = 0.028          |
| Mkt              | 0.037    | 0.585   | 0.044    | 0.516   |          |         |                    |
| SMB              | 0.818    | <0.001  | 0.802    | <0.001  |          |         |                    |
| HML              | −0.169   | 0.095   | −0.174   | 0.085   |          |         |                    |
| FE               |          |         |          |         | 1.207    | 0.029   |                    |

Panel D: Unprofitable minus profitable

| Intercept        | 0.785    | 0.105   | 0.388    | 0.180   | 1.073    | 0.021   | −60%**            |
| Sentd            | −0.994   | 0.047   | −0.530   | 0.065   | −0.210   | 0.294   | p = 0.029          |
| Mkt              | 0.342    | <0.001  | 0.344    | <0.001  |          |         |                    |
| SMB              | 0.748    | <0.001  | 0.740    | <0.001  |          |         |                    |
| HML              | −0.300   | <0.001  | −0.303   | <0.001  |          |         |                    |
| FE               | 0.955    | 0.030   |          |         |          |         |                    |

Panel E: Nonpayers minus payers

Notes. Each month, from August 1983 to December 2005, we sort firms into deciles (using NYSE breakpoints) on size, age, return volatility, earnings to book equity, and dividends to book equity. We construct portfolio returns that go long in the most uncertain decile (small, young, volatile, etc.) and short in the most certain decile (big, old, smooth, etc.). We also collect the first consensus (mean) annual forecasts of EPS each year along with actual EPS from I/B/E/S to construct forecast errors (actual EPS-consensus EPS, scaled by abs[consensus EPS]). We assign this forecast error for each firm to an announcement window that begins the month after fourth quarter EPS from the prior year is announced and ends 12 months later. Each month we average across firms to construct portfolio forecast errors that measure the difference in average EPS forecast errors between uncertain (small, young, volatile, etc.) and certain firms (big, old, smooth, etc.). Finally, in panels A–E, we regress portfolio returns on sentiment and portfolio EPS forecast errors. Sentd is a dummy variable equal to 1 if beginning of the year sentiment from Baker and Wurgler (2006) is positive, and 0 otherwise. We test the significance of the change in the coefficient on Sentd using the test in Clogg et al. (1995).

* *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Because monthly portfolio returns are not generally persistent over time, we do not control for autocorrelation in Table 3. Durbin–Watson (1951) tests reveal no significant autocorrelation in the residuals for Equation (1) except the small minus big portfolio (p < 0.01). When we adjust p-values for this portfolio (and all other portfolios) using a Newey–West (1987) correction at four lags, inferences are identical. Thus, autocorrelation does not appear to be a concern for our returns tests.

in the coefficient on Sentd,. We measure the statistical significance of the reduction in the coefficient on Sentd, using the test formulated by Clogg et al. (1995). This procedure tests whether the change in a coefficient is significant when a new variable is introduced to the model.

Overall, the results in Table 3 are broadly consistent with expectational errors having a significant impact on the association between sentiment and returns. FE, is positive and statistically significant in every specification.12 Importantly, the earnings forecast variable

12 Because monthly portfolio returns are not generally persistent over time, we do not control for autocorrelation in Table 3. Durbin–
(p < 0.05) for the nonpayers minus payers portfolio. To put this in perspective, the difference in factor-adjusted future returns between nonpayers and payers decreases by roughly 50 basis points per month after periods of high sentiment. After controlling for the difference in earnings forecast errors, however, this difference shrinks to roughly 20 basis points per month. In addition, the coefficients on the sentiment variable generally lose their statistical significance in the presence of the earnings forecast error variable. We note, however, that the size of the coefficient on sentiment remains fairly large in economic terms across the portfolios.

The findings in Table 3 support the notion that cross-sectional differences in expectational errors help explain the relation between sentiment and future returns. Note that if sentiment affected all stocks equally, but cross-sectional variation in arbitrage costs drove the relation between sentiment and future returns, cross-sectional differences in forecast errors between uncertain and certain firms should have little explanatory power. Table 3 indicates this is not the case. Moreover, given the difficulty specifying the precise period over which analyst forecast errors are revealed to be overly optimistic or pessimistic, it is encouraging that the results are as robust as they are.

### 3.2. Long-Term Growth

In addition to EPS forecasts, many analysts also provide a forecast of long-term earnings growth to I/B/E/S. Because the expectational errors hypothesis assumes that uncertain firms are mispriced due to valuation difficulties, it is reasonable to suspect that this difficulty will be particularly acute in forecasting long-term performance, where there is arguably even greater uncertainty in the forecast. Thus, we conduct tests similar to those in Tables 2 and 3 using long-term growth earnings growth forecasts instead of annual EPS forecasts.

Each month over the sample period, we collect consensus (summary file) long-term earnings growth forecasts from I/B/E/S. Following Dechow and Sloan (1997) and I/B/E/S methodology, actual long-term growth is measured as the slope from a regression of log(EPS) on a time trend over a five-year period beginning in the forecast year. Firms are sorted into deciles (using NYSE breakpoints) on size (MVE), age, return volatility, and dividend to book ratio. We then calculate correlation with sentiment for each decile and take the difference in the extreme deciles (1 and 10) to construct forecast error portfolios. These portfolio forecast errors measure the difference in average long-term growth errors between uncertain (small, young, volatile, etc.) and certain firms (big, old, smooth, etc.). Finally, we correlate the time series of portfolio forecast errors with the monthly sentiment index from Baker and Wurgler (2007). The p-values are based on a Newey–West (1987) correction for autocorrelation using four lags.

<table>
<thead>
<tr>
<th>Table 4</th>
<th>Differences in Analysts’ Long-Term Growth Forecast Errors and Investor Sentiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast error portfolio</td>
<td>Correlation with sentiment</td>
</tr>
<tr>
<td>All stocks</td>
<td>−0.39</td>
</tr>
<tr>
<td>Small minus big</td>
<td>−0.04</td>
</tr>
<tr>
<td>Young minus old</td>
<td>−0.29</td>
</tr>
<tr>
<td>Volatile minus smooth</td>
<td>−0.44</td>
</tr>
<tr>
<td>Nonpayers minus payers</td>
<td>−0.65</td>
</tr>
</tbody>
</table>

Notes: Each month, from August 1983 to December 2004, we collect consensus (median) long-term earnings growth forecasts from I/B/E/S. We measure forecast errors as actual long-term growth less the forecast. Actual long-term growth is measured as the slope from a regression of log(EPS) on a time trend over a five-year period beginning in the forecast year. Firms are sorted into deciles (using NYSE breakpoints) on size (MVE), age, return volatility, and dividend to book ratio. We then calculate mean forecast errors for each decile and take the difference in the extreme deciles (1 and 10) to construct forecast error portfolios. These portfolio forecast errors measure the difference in average long-term growth errors between uncertain (small, young, volatile, etc.) and certain firms (big, old, smooth, etc.). Finally, we correlate the time series of portfolio forecast errors with the monthly sentiment index from Baker and Wurgler (2007). The p-values are based on a Newey–West (1987) correction for autocorrelation using four lags.

We note, however, that the size of the coefficient on sentiment remains fairly large in economic terms across the portfolios.

Notes: Each month, from August 1983 to December 2004, we collect consensus (median) long-term earnings growth forecasts from I/B/E/S. We measure forecast errors as actual long-term growth less the forecast. Actual long-term growth is measured as the slope from a regression of log(EPS) on a time trend over a five-year period beginning in the forecast year. Firms are sorted into deciles (using NYSE breakpoints) on size (MVE), age, return volatility, and dividend to book ratio. We then calculate mean forecast errors for each decile and take the difference in the extreme deciles (1 and 10) to construct forecast error portfolios. These portfolio forecast errors measure the difference in average long-term growth errors between uncertain (small, young, volatile, etc.) and certain firms (big, old, smooth, etc.). Finally, we correlate the time series of portfolio forecast errors with the monthly sentiment index from Baker and Wurgler (2007). The p-values are based on a Newey–West (1987) correction for autocorrelation using four lags.

Note that sentiment affects bias in analysts’ growth forecasts equally, but cross-sectional variation in arbitrage costs drive the relation between sentiment and future returns. Unlike the one-year-ahead forecast errors in Table 2, we do not observe any clear trends in the long-term growth forecast error series, so we present correlations using only the raw data in Table 4. We adjust p-values for autocorrelation using the method of Newey and West (1987). Here, we find evidence that sentiment affects bias in analysts’ growth forecasts across all stocks in general. The correlation between sentiment and long-term growth forecast errors for all stocks is −0.39 (p < 0.001). We find further evidence of negative correlations between sentiment and differences in long-term growth forecast errors using the cross-sectional sorts. The correlations are almost all significant, ranging from −0.29 for young versus old firms (p < 0.01) to −0.65 for nonpayers versus payers (p < 0.01). The exception is small versus big firms, particularly when there could be substantial nonrecurring items.

13 Dechow and Sloan (1997) argue that discrete annualized geometric growth rates can be extremely volatile when the base year is close to zero and when the base year or final year in the series contains significant nonrecurring items. Computing five-year annualized growth rates by fitting a least squares growth line to the logarithms of the annual earnings observations avoids extreme outliers due to discrete compounding and avoids placing excessive weight on the first and last observations in the growth series, particularly when there could be substantial nonrecurring items.
where the correlation is small and insignificant ($\rho = -0.04$, $p = 0.411$). As before, negative forecast errors imply optimism (i.e., actual growth less forecasted growth). When sentiment is high, analysts become relatively more optimistic about the growth prospects of uncertain firms, and when sentiment is low, they become relatively less optimistic about these firms.

Analogous to Table 3, we next examine whether long-term growth forecast errors help explain the return patterns related to sentiment. To construct forecast errors for these tests, we follow a similar procedure to the one used in Table 3. We collect the first consensus forecast of long-term earnings growth each year after the announcement of fourth quarter earnings, and measure the forecast error as actual long-term growth minus this forecast. We assign this forecast error for each firm to a window that begins the month after fourth quarter EPS from the prior year is announced and ends 12 months later.

Each month, we subtract the average forecast error for the most certain decile (across each of the four characteristics) from the most uncertain decile. We use the same monthly equal-weight portfolio returns as in Table 3, except we end the sample in 2004 to ensure enough data to calculate long-term growth forecast errors. We note, however, the difficulty in lining up the realization of forecast errors with monthly returns is even more pronounced when considering long-term earnings growth instead of annual EPS estimates. Our long-term growth forecast errors use actual earnings measured over a five-year window, yet our returns’ specification will only capture the realization of errors in long-term growth estimates that are realized in the first year of the five-year series.

Table 5 presents estimates of Equation (1) using long-term growth forecast errors. Estimates from (1) including only the sentiment variable are similar to those in Table 3: uncertain firms tend to underperform following periods of high sentiment. As before, when the three Fama–French factors are added in the second column, the coefficient on sentiment attenuates (again, mostly because of the size factor). When long-term growth forecast errors are added to the regression in the third column, the coefficients are positive and statistically significant for two of the characteristics: size ($p = 0.004$) and age ($p = 0.023$). The coefficient on $LTG_{FE}$ in the return volatility and dividend paying sorts is not statistically significant. The reduction in the slope on $Sent_{t-d}$ after inclusion of the forecast error term is also much larger for these two characteristics ($-71\%$, $p < 0.01$; $-35\%$, $p < 0.05$) compared to return volatility ($-10\%$, $p > 0.10$) and dividend payments ($-16\%$, $p > 0.10$). This finding is a bit surprising, given that forecast errors related to volatility and dividends are more highly negatively correlated with sentiment in Table 4 than size or age.

Together, Tables 3 and 5 suggest that errors in both one-year-ahead earnings estimates and long-term growth rates play a role in the documented relation between sentiment and stock returns. Although we do not explore further, our results might suggest that the effect of sentiment on expected future earnings and returns is more concentrated in the long-term growth forecasts for small and young firms, and it is more concentrated in the one-year ahead forecast for volatile and nondividend paying firms. Alternatively, this might simply reflect the fact that both one-year-ahead forecast errors and long-term growth forecast errors measure the underlying construct of interest (i.e., investor bias in expected future earnings) with noise, and sometimes one measure fares better than the other.

In Table 6, we include both forecast error measures to observe the joint effect of $FE$ and $LTG_{FE}$ on the relation between sentiment and returns in our time-series regressions. Notably, adding forecast errors and both the one-year-ahead and long-term growth explains a significant portion of the relation between sentiment and returns. The reduction in the slope on the sentiment variable now ranges from a minimum of a 29% reduction ($p > 0.10$) for volatility to a 96% reduction ($p < 0.01$) for age.

As an alternative to the specifications estimated in Tables 3, 5, and 6, we also estimate regressions where we exclude the forecast error variables but split the sentiment variable into two pieces: the portion correlated with average forecast errors and the portion orthogonal to average forecast errors. Using one-year-ahead forecast errors (analogous to Table 3), five of the five specifications show that the part of sentiment explained by forecast errors is significantly related to portfolio returns. In none of these cases is the residual statistically significant. Using long-term growth forecast errors (analogous to Table 5), two of the four specifications find predicted sentiment is significantly related to portfolio returns. In none of the cases is the residual statistically significant. Finally, using both one-year-ahead and long-term growth forecast errors (analogous to Table 6), the predicted part of sentiment is statistically significant in four of four specifications, whereas the residual is never significant. Overall, these untabulated results indicate that portfolio returns are explained by the part of sentiment that is related to forecast errors and are unexplained by the part of sentiment that is unrelated to average earnings forecast errors.

### 3.3. Are Forecast Error Patterns Strategic?

One possible concern with our findings of cross-sectional patterns in the association between forecast
Past research has used the test in Clogg et al. (1995). Let $Sentd$ be a dummy variable equal to 1 if beginning of the year sentiment from Baker and Wurgler (2006) is positive, and 0 otherwise. We test the significance of the change in the coefficient between uncertain (small, young, volatile, etc.) and certain firms (big, old, smooth, etc.). Finally, in panels A–D, we regress portfolio returns on sentiment and portfolio LTG forecast errors.

### Table 5: Portfolio Returns, Investor Sentiment, and Analysts’ Long-Term Growth Forecast Errors

<table>
<thead>
<tr>
<th></th>
<th>Panel A: Small minus big</th>
<th></th>
<th>Panel B: Young minus old</th>
<th></th>
<th>Panel C: Volatile minus smooth</th>
<th></th>
<th>Panel D: Nonpayers minus payers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.165</td>
<td>0.086</td>
<td>1.447</td>
<td>0.031</td>
<td>1.648</td>
<td>0.014</td>
<td>276</td>
</tr>
<tr>
<td>$Sentd$</td>
<td>-0.947</td>
<td>0.113</td>
<td>-0.901</td>
<td>0.120</td>
<td>-0.261</td>
<td>0.371</td>
<td>279</td>
</tr>
<tr>
<td>Mkt</td>
<td>-0.254</td>
<td>0.003</td>
<td>-0.260</td>
<td>0.002</td>
<td></td>
<td>p = 0.003</td>
<td></td>
</tr>
<tr>
<td>HML</td>
<td>-0.398</td>
<td>&lt;0.001</td>
<td>-0.439</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
<td>0.023</td>
</tr>
<tr>
<td>LTG_FE</td>
<td>0.176</td>
<td>0.004</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-10%</td>
</tr>
</tbody>
</table>

|          | Panel A: Small minus big |          | Panel B: Young minus old |          | Panel C: Volatile minus smooth |          | Panel D: Nonpayers minus payers |
| Intercept | 1.252                   | 0.054    | 0.980                    | 0.023    | 1.643                         | 0.003    | 453                         |
| $Sentd$  | -1.598                  | 0.017    | -1.077                   | 0.015    | -0.705                        | 0.090    | 425                         |
| Mkt      | 0.082                   | 0.246    | 0.046                    | 0.400    |                               |          | 0.001                       |
| SMB      | 0.854                   | <0.001   | 0.848                    | <0.001   |                               |          | -16%                        |
| HML      | -0.425                  | <0.001   | -0.425                   | <0.001   |                               |          | -16%                        |
| LTG_FE   | 0.015                   | 0.397    |                          |          |                               |          | -16%                        |

### Notes
Each month, from August 1983 to December 2004, we sort firms into deciles (using NYSE breakpoints) on size, age, return volatility, earnings to book equity, and dividends to book equity. We construct portfolio returns that go long in the most uncertain decile (small, young, volatile, etc.) and short in the most certain decile (big, old, smooth, etc.). We also collect the first consensus (median) forecasts of long-term earnings growth (LTG) each year along with actual EPS from I/B/E/S to construct forecast errors (actual long-term growth-consensus forecast). Actual LTG is measured as the slope from a regression of log(EPS) on a time trend over a five-year period beginning in the forecast year. We assign this forecast error for each firm to a window that begins the month after fourth quarter EPS from the prior year is announced and ends 12 months later. Each month we average across firms to construct portfolio forecast errors that measure the difference in average LTG forecast errors between uncertain (small, young, volatile, etc.) and certain firms (big, old, smooth, etc.). Finally, in panels A–D, we regress portfolio returns on sentiment and portfolio LTG forecast errors. $Sentd$ is a dummy variable equal to 1 if beginning of the year sentiment from Baker and Wurgler (2006) is positive, and 0 otherwise. We test the significance of the change in the coefficient on $Sentd$ using the test in Clogg et al. (1995).

"*" and "+" indicate statistical significance at the 5% and 1% levels, respectively.

Errors and sentiment is that it might not reflect bias on the part of the analysts, but rather a strategic attempt by analysts to exploit the investor sentiment in the market. To try to rule out this possibility, we conduct three additional tests. First, we examine analyst recommendations. Second, we examine the evolution of analyst forecast errors over the annual forecast period. Third, we correlate variation in insider selling with sentiment. In general, the results from these tests, though not definitive, do not indicate the patterns we observe are driven by strategic actions on the part on analysts.

### 3.3.1. Recommendation Test
Past research has examined the strategic use of analyst recommendations (e.g., “buy,” “sell,” “hold”) to generate investment banking business or trading (e.g., Ljungqvist et al. 2006, Bradshaw et al. 2006, Agrawal and Chen 2008). Irvine (2004) explicitly tests whether earnings forecasts or recommendations are more likely to generate additional trading, and finds that recommendations are more effective. Thus, if there is a strategic intent to provide biased analyst research to exploit sentiment, we should be as likely to see it in analyst recommendations as we are in earnings forecast errors.

To test this assertion, we collect monthly consensus stock recommendations from I/B/E/S for each firm in our sample from November 1993 to December 2005 (recommendation levels begin appearing in IBES in 1993). The recommendations range from 5 (strong sell) to 1 (strong buy). We follow the same sorting procedure as described above, and calculate mean recommendations for each decile. We then take the difference in the extreme deciles (1 and 10) to
measure the difference in average recommendation levels between uncertain and certain firms. If analysts become relatively more bullish (bearish) about uncertain stocks during high- (low)-sentiment periods, we expect to observe a negative correlation between differences in average recommendation levels and sentiment.

Table 7 presents the correlations. Overall, the evidence does not suggest a negative relationship between sentiment and differences in recommendation levels between uncertain and certain stocks. The only significantly negative correlation we observe is for unprofitable versus profitable firms (p = −0.36, p < 0.01), whereas we find significantly positive correlations for two of the sorts: small versus big firms (p = 0.63, p < 0.01) and nonpayers versus payers (p = 0.27, p < 0.01). Because there is no evidence of a consistently negative relationship between sentiment and recommendation levels, we do not present the returns analysis. Overall, the findings from Table 7 suggest that analyst recommendations do not vary with sentiment in a way that would suggest analysts are strategically using sentiment to generate additional trading by issuing more biased recommendations.\textsuperscript{14} It is difficult to hypothesize a reason

\textsuperscript{14} To ensure differences between our forecast error tests and recommendations tests are not simply because of differences in time
why analysts would intentionally bias their earnings and long-term growth forecasts during high-sentiment times but not their recommendations.\footnote{On the other hand, the results above also raise an interesting question: If sentiment leads to unintentional bias in analysts’ earnings forecasts, why are recommendation levels generally unaffected? Prior work indicates analyst recommendation levels are typically based on, or justified by, relatively crude metrics such as the forward price-to-earnings ratio (Block 1999, Bradshaw 2004, Demirakis et al. 2004). If so, it is not clear that variation in sentiment, which the evidence suggests leads both to shifts in share prices high for uncertain firms during these periods, we reran our forecast error correlations with sentiment from 1993 to 2005. Correlations between forecast errors and sentiment are actually more negative over this time period than those in Table 2.

3.3.2. Evolution of Analyst Forecast Errors over the Forecast Horizon. For our second test, we examine whether the relations we document between sentiment and forecast errors are eliminated or reversed when forecasts are measured over shorter horizons. The literature on analyst agency conflicts emphasizes that analysts have incentives to be overly optimistic in the long run but pessimistic in the short run so that managers can beat short-term earnings targets (Richardson et al. 2004, Malmendier and Shanthikumar 2009). This pattern of forecast errors presumably helps analysts curry favor with managers and leads to better future prospects for analysts (Ke and Yu 2006). Thus, if the patterns we document are part of a strategic effort on the part of analysts to, say, attract investment banking business, we would expect short-term forecast errors to be relatively pessimistic for uncertain firms in high-sentiment periods.

To test this conjecture, we estimate the following regression at the firm-month level:

\[
FE_i = \alpha + \beta_1 Sentd_t + \beta_2 Characteristic \\
+ \beta_3 Characteristic \times Sentd_t + \epsilon_{it},
\]

where \(FE_i\) is the forecast error for firm \(i\) in month \(t\). The indicator variable \(Sentd\) is equal to 1 if sentiment in month \(t\) is positive and 0 otherwise. \(Characteristic\) is the ranked value of size, age, volatility, earning to book, and dividends to book, with higher values connoting more uncertainty. Standard errors are clustered by firm–fiscal year. We expect \(\beta_2\) to be negative because forecast errors are generally more negative or optimistic for uncertain or unpredictable firms and \(\beta_3\) to be negative, which is our main finding that this pattern strengthens in high-sentiment times. We estimate the regression separately for forecasts early in the year (12, 11, and 10 months before the annual earnings announcement) and late in the year (3, 2, and 1 month before the annual earnings announcement). If strategic choices on the part of analysts contribute to our findings, \(\beta_2\) and \(\beta_3\) should become insignificantly different from zero or even positive for forecasts late in the year.

The results reported in Table 8, however, are not consistent with this pattern. Although forecasts exhibit the well-documented pattern of becoming less optimistic late in the year, analysts are still more optimistic for uncertain firms and this relation strengthens in high-sentiment periods, even for short-term forecasts. It does therefore not appear that the time-varying patterns we document are driven by analyst incentives to strategically please company managers with optimistic long-term forecasts.

3.3.3. Insider Trading. Richardson et al. (2004) suggest insider selling is linked to analysts’ incentives to please managers. If this potential agency conflict contributes to our findings, one would expect the difference in insider selling between uncertain and certain firms to be larger in high-sentiment periods, thus giving analysts an incentive to be optimistic and keep share prices high for uncertain firms during these periods. In unbatabulated analyses, however, we do not find evidence consistent with this phenomenon. We find that the average difference in net insider selling between uncertain firms and certain firms is not significantly related to sentiment across all five characteristic sorts. Thus, it does not appear that the time-varying patterns we document are driven by analyst incentives to cater to managerial insider trading incentives.

<table>
<thead>
<tr>
<th>Recommendation difference portfolio</th>
<th>Correlation with sentiment</th>
<th>(p)-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small minus big</td>
<td>0.63</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Young minus old</td>
<td>0.05</td>
<td>0.780</td>
</tr>
<tr>
<td>Volatile minus smooth</td>
<td>-0.03</td>
<td>0.399</td>
</tr>
<tr>
<td>Unprofitable minus profitable</td>
<td>-0.36</td>
<td>0.001</td>
</tr>
<tr>
<td>Nonpayers minusayers</td>
<td>0.27</td>
<td>0.036</td>
</tr>
</tbody>
</table>

Notes. Each month, from November 1993 to December 2005, we collect consensus (mean) stock recommendations from I/B/E/S. The recommendations range from 5 (strong sell) to 1 (strong buy). Firms are sorted into deciles (using NYSE breakpoints) on size (MVE), age, return volatility, earnings to book ratio, and dividend to book ratio. We then calculate mean recommendations for each decile and take the difference in the extreme deciles (1 and 10) to construct recommendation difference portfolios. These portfolio recommendations measure the difference in average recommendation levels between uncertain (small, young, volatile, etc.) and certain firms (big, old, smooth, etc.). Finally, we correlate the time series of portfolio recommendation differences with the monthly sentiment index from Baker and Wurgler (2007).
One question that we have not addressed is that forecast errors are a proxy for information risk, as defined in Easley and O’Hara (2004). In particular, when analyst forecasts are poorer, it suggests that public information about the firm is lacking. This lack of information means that the risks to an uninformed investor of facing a privately informed investor are higher, and leads to a difference in expected returns. Analyst forecast properties have been used as a proxy for information risk in prior work (Zhang 2006). To assess the possibility our results are driven by time variation in information risk, we substitute differences in absolute forecast errors at the portfolio level into Equation (1) in lieu of signed forecast errors. Unsigned forecast errors arguably pick up information uncertainty more cleanly than signed forecast errors. In untabulated results, we find that unsigned portfolio forecast errors, however, have almost no explanatory power for future returns and that sentiment generally retains its significance in these regressions. Thus, it appears that information risk is unlikely to explain our findings.

3.4. Other Sentiment Measures. Prior work (Lemmon and Portniaguina 2006, Qui and Welch 2006) shows that the BW index displays fairly low correlations with survey-based measures of sentiment, such as the Michigan Consumer Confidence Index, over certain time periods. As a result, we also conduct tests using the Michigan Index as an alternative to the BW sentiment index. In general, the correlation between forecast errors and the Michigan index is similar to our main findings. For example, the correlations between forecast errors and sentiment are negative and range from a high of $-0.43$ for payers versus nonpayers ($p < 0.001$) to a low of $-0.11$ for unprofitable versus profitable firms ($p = 0.033$), all of which are statistically significant.

For long-term growth forecast errors, the correlations range from a high of $-0.55$ for volatile versus smooth return firms ($p < 0.01$) to a low of $0.01$ for old versus young firms ($p = 0.409$). For our sample period, the correlation between the monthly BW sentiment index and the Michigan Index is 0.46 ($p < 0.01$). Thus, the cross-sectional associations between sentiment and forecast errors seem to hold using the Michigan index as well as the BW index. For the returns’ tests, however, we find a substantially weaker ability of the Michigan index to predict future returns using our characteristic sorts. Accordingly, we do not explore the extent to which forecast errors absorb the explanatory power of sentiment for future returns using the Michigan index because there is nothing for the forecast variable to explain.

4. Conclusion

In this paper, we examine whether the expectational errors hypothesis explains the cross-sectional stock pricing relation...
returns patterns documented by BW. We use analyst forecasts to test whether analysts have relatively more optimistic forecasts in uncertain firms in periods of high sentiment, and relatively less optimistic forecasts in uncertain firms in periods of low sentiment. Our evidence is overall supportive of this theory, finding significant negative associations between sentiment and the relative amount of optimism in certain versus uncertain firms.

We further test the extent to which adding analyst forecast errors to the regression relating stock returns to the sentiment reduces the ability of sentiment to explain cross-sectional stock returns. Adding both one-year-ahead forecast errors and long-term growth forecast errors to the returns regressions reduces the slope coefficient on sentiment by 49% in small versus large firms, by 29% in volatile versus smooth firms, by 41% in dividend payers versus nonpayers, and by 96% in young versus old firms. It therefore appears that analyst forecast errors are a significant intermediate variable in the cross-sectional patterns documented between sentiment and stock returns. Our results provide direct evidence on the expectation errors hypothesis advanced by BW and suggest that the patterns they documented are not simply reflective of limits to arbitrage.16

Finally, our results suggest that the documented relation between analyst forecast errors and stock returns is unlikely to be intentional or strategic in nature on the part of analysts. We find no reliable association between cross-sectional patterns in analyst forecast recommendations and sentiment, despite the fact that prior research suggests that recommendations are a more effective tool for generating trading or investment banking. In addition, we do not find that the patterns we document reverse over shorter forecast horizons, as would be expected if analysts wanted to strategically deliver beatable short-term forecast to managers. In general, our results are consistent with the view that errors in short- and long-term earnings expectations contribute to the relation between sentiment and future stock returns.

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16 Note that limits to arbitrage still might contribute to the returns’ patterns as there remains cross-sectional patterns relating sentiment and returns after controlling for forecast errors.

References
Bradshaw, M. T., S. A. Richardson, R. G. Sloan. 2006. The relation between corporate financing activities, analysts’ forecasts and stock returns. J. Accounting Econ. 42(1–2) 53–85.
*J. Accounting Econ.* 30(1–3) 105–231.

La Porta, R. 1996. Expectations and the cross-section of stock

Lemmon, M., E. Portniaguina. 2006. Consumer confidence and
1499–1529.

Ljungqvist, A., F. Marston, W. J. Wilhelm. 2006. Competing for securi-
ties underwriting mandates: Banking relationships and analy-

in two tongues? Working paper, University of California, Berkeley.

Mian, G., T. Teo. 2004. Do errors in expectations explain the
cross section of stock returns? *Pacific-Basin Finance J.* 12(2)
197–217.

Mikhail, M., B. Walther, R. Willis. 1999. Does forecast accuracy mat-
ter to security analysts? *Accounting Rev.* 74(2) 185–200.

Newey, W. K., K. D. West. 1987. A simple, positive semi-definite,
heteroskedasticity and autocorrelation consistent covariance

adjusted I/B/E/S data in empirical research. *Accounting Rev.*
78(4) 1049–1067.

to beatable analyst forecasts: The role of equity issuance and
insider trading incentives. *Contemporary Accounting Res.* 21(4)
885–924.

Seybert, N., H. I. Yang. 2012. The party’s over: The role of earnings
guidance in resolving sentiment-driven overvaluation. *Manage-
ment Sci.* 58(2) 308–319.

52(1) 35–55.

paper, Brown University, Providence, RI.

Zhang, F. 2006. Information uncertainty and stock returns. *J. Finance*
61(1) 105–137.