The Relative Profitability of Analysts' Stock Recommendations: What Role Does Investor Sentiment Play?

Mark Bagnoli
Purdue University

Michael Clement
University of Texas at Austin

Michael Crawley
University of Texas at Austin

Susan Watts
Purdue University

January 26, 2010

Abstract: We investigate whether analysts who respond to investor sentiment issue more profitable stock recommendations than their peers. We find that, on average, analysts issue more favorable recommendations when recent and future sentiment is more bullish. However, only those who respond to recent sentiment and follow stocks that are most sensitive to sentiment offer relatively more profitable recommendations. Our results suggest that analysts recommend stocks based, in part, on signals that are not theoretically related to firms' intrinsic value. Moreover, they may help explain prior research which finds that analysts fail to fully incorporate their own earnings forecasts into their recommendations.

We thank Linda Bamber, Larry Brown, Yonca Ertimur, Ross Jennings, Kevin Kobelsky, David Koo, Hai Lu, Bill Mayew, Philip Shane, Senyo Tse, Jenny Tucker, Richard Willis, Yong Yu, workshop participants at Baylor University, Purdue University, and the University of Georgia, and conference participants at the 2009 American Accounting Association annual meeting and the 2009 Conference on Financial Economics and Accounting for helpful comments.

1. Introduction

This study investigates whether analysts who respond to investor sentiment issue more or less profitable stock recommendations than their peers. Baker and Wurgler (2006) define investor sentiment as either a driver for the relative demand for speculative investments or investors' collective optimism or pessimism about stocks in general. Although traditional valuation theory suggests that stock prices should be determined solely by fundamentals (e.g. earnings, cash flows, and discount rates), recent empirical research suggests that investor sentiment may also affect stock prices. For example, Baker and Wurgler (2006, 2007) and Frazzini and Lamont (2008) find evidence that a subset of stocks may be overpriced (underpriced) when investor sentiment is high (low).

Abreu and Brunnermeier (2003) and DeLong et al. (1990) show that sophisticated market participants can benefit from riding waves of investor sentiment.[1] Similarly, analysts' recognition and treatment of sentiment may affect the relative profitability of their stock recommendations. For example, consider an analyst who believes a particular stock is overvalued based on her private estimate of the firm's intrinsic value. The analyst may be hesitant to issue a Sell recommendation if she believes that sentiment will continue to exert upward pressure on asset prices in the near term. Moreover, the analyst may actually issue a Buy recommendation if she believes that sentiment will become even more bullish in the near future. If the analyst (1) correctly predicts a bullish (bearish) shift in sentiment which ultimately increases (decreases) asset prices and (2)

[1] Within Abreu and Brunnermeier's (2003) model, rational investors continue to invest in overpriced assets until a sufficient number of arbitrageurs coordinate to eliminate the mispricing. Within the noise trader model of DeLong et al. (1990), rational investors buy in response to positive investor sentiment and push asset prices beyond their fundamental value in anticipation of selling to feedback traders in the future. See also Barberis et al. (1998) and Daniel et al. (1998) for models of how sentiment can affect asset prices.

issues a more favorable (unfavorable) recommendation in response, then the analyst's recommendation may be more profitable than the recommendations of her peers.[2]

While responding to investor sentiment could lead to relatively more profitable stock recommendations, it could also lead to relatively less profitable stock recommendations for several reasons. First, firms' stock prices may be differentially sensitive to movements in investor sentiment, and sentiment may affect the prices of different stocks at different times. Second, timing movements in investor sentiment can be difficult in practice (Abreu and Brunnermeier 2003), and sentiment may drive prices even further from fundamental value before a correction occurs (DeLong et al. 1990, Shleifer and Vishny 1997). Thus, even if a firm's fundamentals remain constant and an analyst can perfectly predict future investor sentiment, she must issue timely favorable (unfavorable) recommendations ahead of bullish (bearish) periods of sentiment for her recommendations to be more profitable than those of her peers. Whether analysts are ultimately successful in increasing recommendation profitability by incorporating investor sentiment is an empirical question that we investigate.[3]

Our research design classifies an individual analyst as responding to sentiment in a given year if her recommendations issued during the year are correlated with recent or future sentiment after controlling for her incentives and a proxy for her private estimate of the firm's intrinsic value. In order to ascertain whether analysts who respond to

[2] Anecdotal evidence suggests that analysts and other sophisticated market participants consciously pay attention to investor sentiment. For example, analysts within a major brokerage house issued the following comment on an aerospace stock: "*our conversations with investors…imply sentiment is likely shifting, and we recommend investors Buy the stock now*" (Goldman Sachs 2009). See also Brunnermeier and Nagel (2004) who find that hedge funds earned significant profits during the technology bubble by riding the positive sentiment and reducing their positions before the downturn.

[3] We do not take a stand as to whether asset prices can deviate from fundamental value. Rather, we attempt to determine how analysts' beliefs about investor sentiment are manifested within their recommendations and whether analysts who respond to sentiment issue more or less profitable recommendations.

sentiment issue relatively more or less profitable stock recommendations than their peers, we create a measure of relative recommendation profitability for each analyst-firm-year. We determine relative recommendation profitability on a calendar year basis by assigning an analyst "credit" based on her recommendation and the firm's return. For each day the analyst has a Buy (Strong Buy) recommendation outstanding, the analyst receives daily credit equal to (double the) the stock's daily return. Conversely, for each day the analyst has a Sell (Strong Sell) recommendation outstanding, the analyst's daily credit is equal to (double) the negative of the stock's daily return. The analyst is awarded a daily risk free rate for days with an outstanding Hold recommendation.[4] We aggregate an analyst's credit for a given firm-year and then compare each analyst to other analysts who had a recommendation outstanding for the same stock over the same calendar year.

Our measure of relative stock recommendation profitability is unique because it controls for firm and time effects by holding constant the environment facing all analysts following a specific firm in a given year. Controlling for firm and time effects is important because prior research finds that the level and profitability of analysts' recommendations are correlated with firm characteristics. For example, Jegadeesh et al. (2004) find that analysts make more favorable recommendations for glamour stocks (i.e. stocks with positive momentum, high trading volume, and strong sales growth), and such recommendations are less profitable. However, a firm's characteristics in a given year are the same for all analysts following the firm. Hence, the impact of the firm's trading volume, sales growth, size, age, etc. on the task of issuing profitable stock recommendations is constant across analysts and can be controlled for through the use of

[4] Our performance measure is similar to the measure used by *The Wall Street Journal* when compiling the annual "Best on the Street" survey (*The Wall Street Journal* May 26, 2009). Our results are qualitatively similar when using alternative performance measures (see Section 5).

a relative performance measure. The variation in our measure of relative recommendation profitability should therefore be due to analyst or recommendation characteristics rather than firm effects (e.g. whether a firm is a glamour or value stock) or time effects (e.g. whether the recommendation took place during a bull or bear market). Further, as noted earlier, our measure of relative recommendation profitability is analyst-firm-year specific as opposed to being only analyst specific. Thus, in contrast to previous studies, our methodology may allow investors to identify an analyst who consistently makes profitable stock recommendations for one firm or industry while also consistently making poor recommendations for other firms or industries.

Next, we regress our measure of relative stock recommendation profitability on a proxy for the analyst's earnings forecasting ability, other analyst characteristics previously shown to be associated with forecast accuracy and recommendation profitability, a proxy for the boldness of the analyst's recommendation (i.e. the degree to which the analyst's recommendation deviates from the consensus), and our measures for whether the analyst's recommendations are correlated with investor sentiment.

Our major findings are as follows. First, we find that, on average, analysts issue more favorable recommendations when recent and future sentiment is more bullish. This suggests that at least some analysts may view the task of issuing recommendations as a Keynesian beauty contest (Keynes 1936).[5] In other words, some analysts appear to recommend stocks based, in part, on signals that may affect price but that are not theoretically related to firms' intrinsic value. Second, we find that analysts whose

[5] Keynes described a beauty contest as a situation in which judges pick who they think other judges will pick rather than who they consider to be the most beautiful. Keynes originally applied this reasoning to stock prices (see also Allen et al. (2006) and Gao (2008) for formal models of this idea), but the concept also applies to the incorporation of investor sentiment into analyst recommendations.

recommendations are positively correlated with recent or future sentiment issue relatively less profitable recommendations on average. This finding is consistent with evidence that other sophisticated market participants have difficulty when trying to time movements in sentiment. For example, Seybert and Wang (2009) find that short sellers often lose money when using analyst signals and betting that asset prices will decline after a period of bullish sentiment.[6] However, for stocks that are most sensitive to investor sentiment (i.e. firms with large sentiment betas), we find that analysts who follow recent trends in sentiment are able to issue relatively more profitable recommendations on average.

We believe our study makes several contributions to the literature. First, we find that at least a subset of analysts issue more favorable stock recommendations when recent and future investor sentiment is more bullish. Second, we show that, on average, analysts who respond to investor sentiment issue less profitable stock recommendations than their peers. However, analysts who follow stocks that are most sensitive to investor sentiment and who follow recent trends in sentiment are able to offer more profitable recommendations than their peers. Third, we introduce a new analyst-firm-year measure of relative recommendation profitability that provides strong controls for both firm and time effects. Fourth, we demonstrate that bold recommendations, which may reflect a greater degree of analyst conviction, are generally more profitable. Finally, we find that analyst teams tend to produce more profitable recommendations than individual analysts.

[6] See also Abreu and Brunnermeier (2003) for anecdotal evidence that attempts to time investor sentiment can be costly. For example, a prominent hedge fund manager who lost his job after the technology bubble burst defended his choice not to sell internet stocks even though he believed they were overvalued by saying "We thought it was the eighth inning, and it was the ninth". Abreu and Brunnermeier (2002) also provide anecdotal evidence that arbitrageurs may be able to recognize mispricing (e.g. due to sentiment) but may lose money if they act on the mispricing too early due to synchronization risk.

This benefit of teamwork complements Brown and Hugon (2009) who find that teams provide less accurate but timelier earnings estimates, and thus our results may help explain the existence of analyst teams.

Our results should be of interest to researchers and a variety of capital market participants. Given analysts' role as information intermediaries, researchers seek to understand the information and processes that analysts use when making stock recommendations. Investors may also gain insights into how to use both analysts' earnings forecasts and stock recommendations in concert with one another to maximize the profitability of their investment strategies. Further, our results may help analysts efficiently allocate their effort by helping analysts decide whether or not to devote costly time and effort towards considering investor sentiment. Finally, brokerage firms could find our methodology and results useful when hiring, training, evaluating, and compensating analysts, particularly given recent regulatory developments which prevent analyst compensation from being directly tied to investment banking revenues.

The remainder of the paper is structured as follows. Section 2 reviews the prior literature, and Section 3 describes our model of the analyst's stock recommendation task. Section 4 outlines our research design. Section 5 describes the data and reports the results, and Section 6 concludes.

2. Prior Research

Our study is related to two streams of literature. The first stream identifies systematic differences in stock recommendation profitability across analysts and investigates the determinants of these differences. The second stream investigates the

mapping of earnings forecasts into stock recommendations (i.e. how analysts utilize their own earnings forecasts when making recommendations). We discuss each of these research streams and our contributions to the literature in more detail below.

Prior research documents that not only can investors profit from the recommendations of analysts, but also that systematic differences in stock recommendation profitability exist. For example, Barber et al. (2001) find that purchasing (selling) stocks with the most (least) favorable recommendations yields abnormal returns. Mikhail et al. (2004) and Li (2005) extend this finding by showing that analysts whose recommendations earned the greatest abnormal returns in the past continue to outperform in the future. Loh and Mian (2006) help explain differences in recommendation profitability by showing that analysts who issue more accurate earnings forecasts also issue more profitable stock recommendations.[7] Ertimur et al. (2007) re-examine this issue and find that, after controlling for expertise, more accurate analysts make more profitable stock recommendations, but only for firms with value-relevant earnings. Muslu and Xue (2009) find that analysts upgrade (downgrade) firms after stock price increases (declines), and that such momentum recommendations earn abnormal returns for up to six months. Finally, Mikhail et al. (2006) find that analysts who issue the most profitable recommendations follow fewer industries, have better resources at their disposal, issue their recommendations before their peers, and have a greater ability to predict which firms will experience deterioration in their future performance.

A second related set of studies investigates the extent to which analysts fail to incorporate their own earnings forecasts into their stock recommendations, i.e. analysts'

[7] Hall and Tacon (2009) replicate this result but find that persistence in relative forecast accuracy is insufficient to allow investors to use historical forecast accuracy to identify those analysts whose current recommendations will be more profitable.

transformational inefficiency. Bradshaw (2004) finds that analysts do not appear to generate stock recommendations by using their own earnings forecasts as inputs into formal present value models. Instead, he finds evidence that analysts rely on valuation heuristics (e.g. using PEG ratios) to generate their recommendations. Brown and Huang (2010) find that consistent analysts (i.e. analysts whose earnings forecasts and stock recommendations are both above or below the consensus) make more accurate earnings forecasts and more profitable stock recommendations. Ke and Yu (2009) identify analyst attributes related to the level of transformational inefficiency and suggest transformational inefficiencies may result for several reasons. First, analysts may simply be unable to efficiently transform their earnings forecasts into stock recommendations. Second, analysts may manipulate recommendations to aid in the acquisition of private information. Finally, analysts may be subconsciously affected by psychological biases.

Although frictions in the process of transforming earnings forecasts into stock recommendations may exist, Groysberg et al. (2008a) show that the market for sell-side financial analysts is liquid and characterized by high salaries and frequent performance reviews. Hence, analysts who either are unable to transform their earnings forecasts into stock recommendations or underperform their peers due to behavioral biases should be eliminated from the market if a key criterion for success is recommendation profitability. Consequently, we propose an alternative explanation for why inconsistencies between analysts' earnings forecasts and their recommendations may arise. Given evidence that analysts are sensitive to investor sentiment when making earnings forecasts (Clement et al. 2010, Mikhail et al. 2009, Hribar and McInnis 2009) and the possibility that sentiment affects asset prices, we postulate that analysts may be consciously attempting to

incorporate sentiment into their recommendations. Our results suggest that some analysts respond to investor sentiment when issuing recommendations. In doing so, analysts' stock recommendations may not be justified by their own earnings forecasts for the firm, and analysts' apparent transformational inefficiency may instead represent their attempt to incorporate the impact of sentiment on asset prices into their recommendations.

3. The Analyst's Stock Recommendation Task

In this section we describe our model of the analyst's stock recommendation task. Although analysts' objective functions are unobservable, prior research indicates analyst reputation and compensation may be increasing in stock recommendation profitability. For example, Emery and Li (2009) find that the probability of an analyst consistently being classified as "Best on the Street" by *The Wall Street Journal* is increasing in stock recommendation profitability. Additionally, *Institutional Investor* magazine indicates that stock picking ability is a consideration when electing analysts to its All-America Research Team. Finally, while Groysberg et al. (2008b) find no econometric relation between recommendation profitability and analyst compensation, the authors provide anecdotal evidence that research directors at high-status investment banks track and care about the stock recommendation profitability of their analysts.

We model an analyst focused on making the most profitable stock recommendations possible as an agent who compares her expectation of the firm's future stock price with its current price.[8] The analyst offers a Buy (Strong Buy) recommendation when she expects the stock price increase to be large (very large), a Sell

[8] Our model differs from prior research that implicitly assumes analysts compare their estimate of intrinsic value to the current stock price to make a stock recommendation.

(Strong Sell) recommendation when she expects the stock price decrease to be large (very large) and a Hold recommendation otherwise. Differences in recommendations therefore arise from differences in analysts' expectations about future stock prices. We separate the analyst's expectation about the firm's future stock price into two components: (1) the analyst's estimate of the firm's intrinsic value and (2) the analyst's expectation of all other signals incremental to intrinsic value that may affect the firm's stock price (at least in the short run). Our analyses focus on investor sentiment as a signal that may affect a firm's stock price, but not its intrinsic value.

We use two proxies for the analyst's private estimate of the firm's intrinsic value. First, we implement an empirical residual income model following Frankel and Lee (1998) and Bradshaw (2004) where the analyst's private estimate of a firm's intrinsic value per share at the time of a recommendation is estimated as:

$$V = B_t + \frac{(FROE_t - r_e)}{(1+r_e)} B_t + \frac{(FROE_{t+1} - r_e)}{(1+r_e)^2} B_{t+1} + \frac{(FROE_{t+2} - r_e)}{(1+r_e)^2 r_e} B_{t+2} \qquad (1)$$

Where:

$FROE_t$ = The analyst's forecast of the firm's return on equity for fiscal year *t* and is defined as $FY1/[(B_{t-1}+B_{t-2})/2]$;

$FROE_{t+1} = FY2/[(B_t+B_{t-1})/2]$;

$FROE_{t+2} = [FY2(1+LTG)]/[(B_{t+1}+B_t)/2]$;[9]

FY1 (FY2) = The analyst's most recent one (two) year ahead earnings per share forecast for fiscal year *t* (*t*+1) issued prior to the recommendation;

LTG = The analyst's most recent long-term growth forecast issued prior to the recommendation;

[9] If an analyst's long-term growth forecast (LTG) is unavailable, then $FROE_{t+2}$ is set to $FROE_{t+1}$ to avoid dropping the observation.

B_{t-1} = The firm's book value of equity (Compustat item *ceq*) divided by common shares outstanding (Compustat item *csho*) as of the firm's most recent fiscal year-end prior to the recommendation;

$B_t = B_{t-1}[1+FROE_t(1-k)]$;

$B_{t+1} = B_t\ [1+FROE_{t+1}(1-k)]$;

$B_{t+2} = B_{t+1}\ [1+FROE_{t+2}(1-k)]$;

k = The firm's dividend payout ratio defined as common stock dividends (Compustat item *dvc*) divided by net income before extraordinary items (Compustat item *ib*) in the most recent fiscal year prior to the recommendation;[10]

r_e = An estimate of the firm's cost of equity capital calculated as the sum of the risk-free rate in the month prior to the recommendation and the industry risk premium based on four-digit SIC code membership from Fama and French (1997).[11]

Following Dechow et al. (1999), we form our second proxy for the analyst's private estimate of the firm's intrinsic value as of the recommendation date by capitalizing the analyst's most recent forecast of next period's earnings in perpetuity.

$$V = \frac{FY_1}{r_e} \tag{2}$$

The residual income method in Equation (1) has the theoretical advantage of generating estimates that should equate to the firm's true intrinsic value provided inputs are accurate and the clean surplus relation is not violated. However, both assumptions are somewhat problematic, and the residual income method imposes strict data requirements that sharply reduce our sample size. The method in Equation (2) has the advantage of maximizing our sample size, and both Dechow et al. (1999) and Liu et al. (2002) find that capitalizations of analysts' earnings forecasts better explain the cross-section of observed prices than valuation estimates from more formal valuation models.

[10] If net income before extraordinary items is less than or equal to 0, then the dividend payout ratio is set to 6% of total assets (Compustat item *at*).
[11] Monthly risk free rates are obtained from the Fama and French data set ff.factors_monthly available from Wharton Research Data Services (WRDS).

Next, we attempt to measure the analyst's expectation of other signals that may affect the firm's stock price but not the firm's intrinsic value. Specifically, we investigate whether the analyst appears to respond to investor sentiment when making her stock recommendations by estimating the following regression model:

$$Rec_{i,j,t} = \alpha_0 + \alpha_1 LagRec_{i,j,t} + \alpha_2 VP_{i,j,t} + \alpha_3 IBank_{i,t} + \alpha_4 TopTier_{i,t} + \alpha_5 MktSent_t + \alpha_6 MktSentLag_t + \alpha_7 MktSentLead_t + \nu_{i,j,t} \quad (3)$$

Where:

$Rec_{i,j,t}$ = Analyst *i*'s recommendation for firm *j* issued on day *t*. Recommendations from I/B/E/S are manipulated such that 5 = Strong Buy, 4 = Buy, 3 = Hold, 2 = Sell, and 1 = Strong Sell;

$LagRec_{i,j,t}$ = Analyst *i*'s previous recommendation for firm *j*;[12]

$VP_{i,j,t}$ = The proxy for analyst *i*'s private estimate of firm *j*'s intrinsic value as of the recommendation date scaled by firm *j*'s stock price at the end of the month prior to the recommendation;

$IBank_{i,t}$ = One of two dummy variables that combine to measure the relative importance of investment banking business to analyst *i*'s broker as of the recommendation date. Our measurement of the relative importance of investment banking to the broker is based on the rankings created by Carter and Manaster (1990) and modified by Loughran and Ritter (2004). The rankings range from 1 to 9 with higher values representing more prestigious underwriters with more dependence on investment banking revenues and a higher probability of conflicts of interest. *IBank* = 1 if the broker is ranked and the maximum ranking for the broker over the period 1993 to 2007 is greater than or equal to 1 and less than 9, and *IBank* = 0 otherwise;

$TopTier_{i,t}$ = The second dummy variable that combines with *IBank* to measure the relative importance of investment banking business to analyst *i*'s broker. *TopTier* = 1 if the maximum ranking for the broker over the period 1993 to 2007 equals 9, and *TopTier* = 0 otherwise. Thus, *TopTier* brokers tend to be the largest and most prestigious underwriters with the greatest expected conflicts of interest;

$MktSent_t$ = A proxy for current investor sentiment. $MktSent_t$ is defined as the monthly Baker and Wurgler (2006) investor sentiment index for the month of the

[12] We estimate Model (3) to investigate whether analyst recommendation levels are correlated with the level of investor sentiment. Although we include the lag of the analyst's recommendation as an explanatory variable, we do not restrict the regression coefficient to equal 1. Thus, Model (3) remains a levels specification as opposed to a changes analysis.

recommendation. The Baker and Wurgler (2006) investor sentiment index is constructed from market level proxies including the closed-end fund discount, New York Stock Exchange share turnover, the number and average returns on initial public offerings, and the dividend premium;

$\mathbf{MktSentLag_t}$ = A proxy for recent investor sentiment. $MktSentLag_t$ is defined as the average of the Baker and Wurgler (2006) investor sentiment index for the 3 months prior to the month of the recommendation;

$\mathbf{MktSentLead_t}$ = A proxy for future investor sentiment. Because analysts' expectations about future investor sentiment at the time of the recommendation are not directly observable, we use ex-post realizations as a proxy. $MktSentLead_t$ is defined as the average of the Baker and Wurgler (2006) investor sentiment index for the 3 months subsequent to the month of the recommendation;[13]

To test whether analysts' recommendation as a whole are correlated with investor sentiment we first estimate separate cross-sectional specifications of Model (3) where the *VP* variable is constructed according to Equations (1) and (2). We expect α_1, the coefficient on *LagRec*, to be positive to the extent that analysts' recommendations are "sticky". We also expect α_2, the coefficient on *VP*, to be positive indicating that analysts' recommendations are more bullish when their own private estimate of intrinsic firm value is high relative to the firm's current price. We make no predictions for *IBank* and *TopTier* because Ertimur et al. (2007) show the effect of potential conflicts of interest on recommendation levels depends on the regulatory regime in place at the time the recommendation was made. Similarly, we make no predictions for the sentiment variables because it is *a priori* unclear whether analysts' recommendations are correlated with investor sentiment. A positive (negative) α_6 coefficient in the cross-section would indicate that analysts as a group issue more favorable (unfavorable) recommendations when recent investor sentiment was more bullish. Similarly, a positive (negative) α_7

[13] Results for all empirical tests are quantitatively and qualitatively similar when using the average of the Baker and Wurgler (2006) investor sentiment index for the 6 months prior (subsequent) to the month of the recommendation to form the *MktSentLag* (*MktSentLead*) variables.

coefficient would suggest analysts as a group issue more favorable (unfavorable) recommendations when future investor sentiment is more bullish.

We then re-estimate Model (3) for each analyst-year combination to determine whether an individual analyst appears to respond to investor sentiment when making stock recommendations in a given year.[14] In these tests the *VP* variable is constructed using Equation (2) in order to prevent a loss of sample size and statistical power. We classify an analyst as responding to investor sentiment by measuring whether or not her stock recommendations are correlated with investor sentiment a given year. More specifically, we set a dummy variable *Correlate* equal to 1 if either the α_6 or α_7 coefficients from Model (3) estimated for a given analyst-year combination are significantly different from zero at the 5% level, and *Correlate* is set to zero otherwise.[15]

We then match the analyst-year specific value for the *Correlate* variable to each firm the analyst followed during the year. Lastly, we determine whether characteristics previously shown to be associated with forecasting or stock recommendation

[14] Model (3) implicitly treats investor sentiment as exogenous with respect to individual analysts. We maintain that endogeneity concerns are mitigated in our setting for several reasons. First, an analyst issuing recommendations for individual firms is *a priori* unlikely to influence investors' collective optimism about the entire market. Second, O'Brien and Tian (2008) fail to find evidence that analysts' bullish recommendations on technology stocks contributed to the substantial price increases in the late 1990's (a period of high sentiment as measured by Baker and Wurgler). Finally, if an analyst's recommendations affect investor sentiment and investor sentiment influences prices, then one might expect the analyst's recommendations to be more profitable than her peers. However, as we will later show, analysts who appear to respond to sentiment actually issue relatively less profitable stock recommendations on average.

[15] IBES recommendation data is available at a daily frequency while the Baker and Wurgler (2006) investor sentiment index is available only monthly. Thus, we do not use the correlation between an analyst's recommendation level and the level of investor sentiment in the month of the recommendation when determining whether the analyst responds to investor sentiment. For example, if an analyst's recommendations are positively correlated with investor sentiment in the month of the recommendation, we can not determine whether the analyst was responding to investor sentiment in the days before the recommendation, on the day of the recommendation, or in the days following the recommendation.

performance make an analyst more or less likely to respond to sentiment in a given year by estimating the following logistic regression.[16]

$$\Pr(\text{Correlate}) = \Gamma_0 + \Gamma_1\text{Bold1} + \Gamma_2\text{Bold2} + \Gamma_3\text{Accuracy} + \Gamma_4\text{Industries} + \Gamma_5\text{Companies} + \Gamma_6\text{ForeFreq} + \Gamma_7\text{BrokerSize} + \Gamma_8\text{GenExp} + \Gamma_9\text{IndExp} + \Gamma_{10}\text{FirmExp} + \Gamma_{11}\text{IBank} + \Gamma_{12}\text{TopTier} + \Gamma_{13}\text{Team} + \mu \quad (4)$$

Analyst, firm, and year subscripts have been omitted for brevity, and regression variables not previously defined are defined as follows:

Bold1 is a measure of how often an analyst's recommendation deviates from the consensus recommendation for a given stock (i.e. how "bold" an analyst is relative to her peers) in a given year. If the absolute deviation of an analyst's stock recommendation for a given stock on a given day from the mean recommendation for that stock on that day is greater than one level (i.e. a Strong Buy of 5 compared to a Hold of 3), a dummy variable is set to 1. *Bold1* is the mean of this dummy variable for each analyst-firm-year and proxies for the analyst's conviction about her recommendation time series over the calendar year;

Bold2 is a measure of how bold an analyst is for a given firm-year relative to her own past history for the stock. *Bold2* equals the *Bold1* value for a given analyst-firm-year less the mean of the analyst's *Bold1* value over the past three years for the same stock;

Accuracy is a measure of analyst *i*'s forecast accuracy for firm *j* in calendar year *t*, calculated as the absolute difference between the analyst's most recent annual earnings forecast and actual earnings per share;

Industries is the number of unique 2-digit SIC codes for which analyst *i* issued at least one annual earnings forecast in calendar year *t*;

Companies is the number of unique firms for which analyst *i* issued at least one annual earnings forecast in calendar year *t*;

ForeFreq is a proxy for the effort the analyst expended while following the firm in a given year, calculated as the number of annual earnings forecasts analyst *i* issued for firm *j* in calendar year *t*;

[16] See Mikhail et al. (1997), Clement (1999), Jacob et al. (1999), Ertimur et al. (2007) and Brown and Hugon (2009) for examples of studies that identify analyst characteristics that are associated with analysts' earnings forecasting and stock recommendation performance.

BrokerSize is a measure of the size and resources available to the analyst's broker, calculated as the number of analysts employed by analyst *i*'s broker who issue at least one annual earnings forecast during calendar year *t*;

GenExp is a measure of the analyst's general experience, calculated as the number of calendar years in which analyst *i* has issued at least one annual earnings forecast for any firm;

IndExp is a measure of the analyst's industry experience, calculated as the number of calendar years for which analyst *i* has issued at least one annual earnings forecast for any firm with the same 2-digit SIC code as firm *j*;

FirmExp is a measure of the analyst's firm-specific experience, calculated as the number of calendar years for which analyst *i* has issued at least one annual earnings forecast for firm *j*;

Team is a dummy variable set to 1 if the recommendation is made by a team of analysts as opposed to an individual analyst, and *Team* = 0 otherwise. Teams of analysts were identified manually based on the analyst name field from I/B/E/S. Teams may include industry groups (e.g. Airlines), country groups (e.g. Norway), or other groups (e.g. Smith, Jones, and Walker);

We estimate Model (4) using standardized independent variables in order to eliminate firm and time effects. That is, the *Bold2*, *Accuracy*, *Industries*, *Companies*, *ForeFreq*, *BrokerSize*, *GenExp*, *IndExp*, and *FirmExp* variables are scaled to become relative measures where an analyst's raw values are compared to all other analysts following the same firm in the same year. More specifically, the scaled variable for analyst *i* for firm *j* in calendar year *t* is equal to the difference between the raw variable value for analyst *i* for firm *j* in year *t* and the minimum value for any analyst following firm *j* in year *t*, all divided by the difference between the maximum value for any analyst following firm *j* in year *t* and the minimum value for any analyst following firm *j* in year *t*. The scaled variables take the following form:

$$\text{scaled}_{ijt} = \frac{\text{raw}_{ijt} - \min_{jt}}{\max_{jt} - \min_{jt}}$$

Thus, scaled variables are restricted to the interval [0,1] with greater scaled values indicating higher relative values (e.g. a scaled *GenExp* value of 1 means the analyst was the most experienced analyst following firm *j* in year *t*). All other variables remain unscaled because they are either dummy variables (*IBank*, *TopTier*, and *Team*) or are already restricted to the interval [0,1] (*Bold1*).

4. The Determinants of Stock Recommendation Profitability

Now we turn to the task of identifying the determinants of relative stock recommendation profitability. To answer this question and to determine whether analysts who respond to investor sentiment issue more or less profitable stock recommendations than their peers, we estimate the following regression model:

$$\text{Money} = \beta_0 + \beta_1\text{LagMoney} + \beta_2\text{Bold1} + \beta_3\text{Bold2} + \beta_4\text{MktSentLag1} + \beta_5\text{MktSentLag2} + \beta_6\text{MktSentLead1} + \beta_7\text{MktSentLead2} + \beta_8\text{Accuracy} + \beta_9\text{Industries} + \beta_{10}\text{Companies} + \beta_{11}\text{ForeFreq} + \beta_{12}\text{BrokerSize} + \beta_{13}\text{GenExp} + \beta_{14}\text{IndExp} + \beta_{15}\text{FirmExp} + \beta_{16}\text{IBank} + \beta_{17}\text{TopTier} + \beta_{18}\text{Team} + \varepsilon \qquad (5)$$

Analyst, firm, and year subscripts have been omitted for brevity, and regression variables not previously defined are defined as follows:

Money is our measure of the relative profitability of analyst *i*'s stock recommendation for firm *j* in calendar year *t* which is calculated as follows. Each day for a given stock for which an analyst has a stock recommendation outstanding, the analyst is awarded a daily "credit" based on her outstanding recommendation and the stock's daily return. If the analyst has a Buy (Sell) recommendation outstanding, the analyst receives credit equal to the stock's return (the negative of the stock's return) for that day. If the analyst has a Strong Buy (Strong Sell) recommendation outstanding, the analyst receives credit equal to double the stock's return (double the negative of the stock's return) for that day. In other words, a Buy (Sell) recommendation for a given stock on a given day yields credit to the analyst as if the analyst was long (short) one share of the firm's stock. Similarly, a Strong Buy (Strong Sell) generates credit for the analyst as if the analyst was long (short) two shares of the firm's stock. If the analyst had a Hold recommendation outstanding,

the analyst's daily credit is set to an amount that would equate to a constant annual risk free rate of 3%. Each of analyst *i*'s daily credits for firm *j* are arithmetically summed for calendar year *t* to form an analyst-firm-year observation for the *Money* variable;

LagMoney is the relative profitability of the analyst's stock recommendation for the same firm from the prior calendar year (i.e. the relative profitability of analyst *i*'s stock recommendation for firm *j* over calendar year *t*-1);

MktSentLag1 is the first of four dummy variables that measure whether an individual analyst's recommendations were correlated with investor sentiment in a given year. *MktSentLag1* = 1 if the α_6 coefficient from regression Model (3) is positive and significant at the 5% level for a given analyst-year combination, and *MktSentLag1* = 0 otherwise. In other words, a value of 1 for *MktSentLag1* indicates analyst *i* issued more favorable recommendations in year *t* when recent investor sentiment was more bullish;

MktSentLag2 is a dummy variable set to 1 if the α_6 coefficient from regression Model (3) is negative and significant at the 5% level for a given analyst-year combination, and *MktSentLag2* = 0 otherwise. A value of 1 for *MktSentLag2* indicates analyst *i* issued less favorable recommendations in year *t* when recent investor sentiment was more bullish (i.e. the analyst was a contrarian with respect to recent investor sentiment);

MktSentLead1 is a dummy variable set to 1 if the α_7 coefficient from regression Model (3) is positive and significant at the 5% level for a given analyst-year combination, and *MktSentLead1* = 0 otherwise. A value of 1 for *MktSentLead1* indicates analyst *i* issued more favorable recommendations in year *t* when future investor sentiment was more bullish;

MktSentLead2 is a dummy variable set to 1 if the α_7 coefficient from regression Model (3) is negative and significant at the 5% level for a given analyst-year combination, and *MktSentLead2* = 0 otherwise. A value of 1 for *MktSentLead2* indicates analyst *i* issued less favorable recommendations in year *t* when future sentiment was more bullish;

We estimate Model (5) using standardized dependent and independent variables in order to eliminate firm and time effects and to discern the relative contribution of each variable to the relative profitability of stock recommendations. Because (1) we expect earnings forecasts to be inputs to recommendations; (2) some of the independent variables in Model (5) have been previously shown to be associated with forecast accuracy; and (3) forecast accuracy has previously been shown to be positively associated with stock recommendation profitability, we predict that the coefficients will have the

same signs that they would have in explaining forecast accuracy. For example, we expect positive coefficients for *Accuracy* (β_8), *ForeFreq* (β_{11}), *BrokerSize* (β_{12}), *GenExp* (β_{13}), *IndExp* (β_{14}), and *FirmExp* (β_{15}), and negative coefficients for *Industries* (β_9) and *Companies* (β_{10}) based on Clement (1999) and Jacob et al. (1999).

We also predict a positive coefficient for *LagMoney* (β_1) based on Mikhail et al. (2004) and Li (2005) who document persistence in recommendation profitability. Clement and Tse (2005) find bold earnings forecast revisions (revisions that move away from the consensus forecast) to be more accurate than herding forecast revisions (revisions that move toward the consensus forecast), and thus we anticipate positive coefficients for *Bold1* (β_2) and *Bold2* (β_3). Ertimur et al. (2007) find that non-conflicted analysts better translate accurate earnings forecasts into profitable recommendations, and thus we expect negative coefficients for *IBank* (β_{16}) and *TopTier* (β_{17}). We make no prediction for the sign of the *Team* (β_{18}) coefficient because Brown and Hugon (2009) find that teams are less accurate at forecasting earnings but issue forecasts earlier, and it is unclear how a team's tradeoff between timeliness and accuracy of earnings forecasts translates into recommendation profitability.

We also make no directional predictions for the sign of the coefficients on the variables measuring the correlation between analysts' recommendations and investor sentiment. Given empirical evidence that suggests investor sentiment affects asset prices (Baker and Wurgler 2006), we might expect the recommendations of analysts who incorporate sentiment into their recommendations to be relatively more profitable. However, as noted previously, responding to sentiment may lead to relatively less profitable recommendations due to the difficulty in timing movements in investor

sentiment (Abreu and Brunnermeier 2003), noise trader risk (DeLong et al. 1990, Shleifer and Vishny 1997), and synchronization risk (Abreu and Brunnermeier 2002). As a result, we also examine whether the degree to which a stock's price movements are correlated with sentiment affects the relative profitability of responding to sentiment.

5. Data and Empirical Results

All data used in this study are publicly available. Stock recommendation and earnings forecast data are obtained from I/B/E/S.[17] All price and return data are from The Center for Research in Security Prices (CRSP) database, and necessary data for the residual income model are from Compustat. Monthly investor sentiment data are available on Professor Jeffrey Wurgler's website at http://pages.stern.nyu.edu/~jwurgler. Reputation rankings for brokerage houses as created by Carter and Manaster (1990), modified by Loughran and Ritter (2004), and used by Ertimur et al. (2007) are available on Professor Jay Ritter's website at http://bear.cba.ufl.edu/ritter/ipodata.htm.

Our sample begins with all stock recommendations in the I/B/E/S detail file beginning in 1994, the first full year of I/B/E/S recommendation coverage. To be included in the sample, we require that an analyst have a recommendation outstanding for the firm for all trading days within a calendar year, be associated with a brokerage house, and have issued an annual earnings forecast for the same firm within the same calendar year. Our methodology evaluates analysts' recommendation profitability relative to all other analysts following the same firm in the same year, and we therefore exclude instances where there is only one analyst following a firm and where there is no between-analyst variation in any of the primary regression variables for a given firm-year. Our

[17] We use the corrected version of the I/B/E/S recommendation file (see Ljungqvist et al. 2009).

sample period ends in 2005, the last year in which Baker and Wurgler (2006) monthly sentiment data are publicly available. Requiring all regression variables for Model (5) described in the previous section to be non-missing results in a final sample of 107,826 analyst-firm-year observations from 1995 to 2005.

Table 1 provides descriptive statistics for I/B/E/S stock recommendations over time. There is a general upward trend in the number of recommendations, analysts, and brokers from 1994 to 2005. In contrast, there has been a reduction in the mean recommendation level and a change in the distribution of recommendations over the same period. The percentage of all recommendations issued as a Buy steadily climbs from 31.6% in 1994 to 39.9% in 2000 before declining to 24% in 2005. Similarly, the percentage of recommendations issued as a Strong Buy reaches a high of 30.9% in 2000 before declining to 21.8% in 2005. The bearish shift in the distribution of recommendations may have been precipitated by the Global Research Settlement reached on April 23, 2003 which required brokerages to publish the distribution of their recommendations. After the enforcement action, the percentage of recommendations issued as a Hold consistently exceeds 45%, and over 54% are issued as a Hold, Sell, or Strong Sell. Finally, the median recommendation duration exhibits no clear pattern over the sample period. However, the median recommendation duration ranges from 313 days to 573 days suggesting recommendation revisions are relatively infrequent events, particularly compared to the frequency of analysts' earnings forecast revisions.[18]

Tables 2 and 3 present descriptive statistics for the unscaled regression variables. Table 2 shows the *Money* variable varies between -0.072 and 0.251 across years

[18] As described above, we exclude observations where the analyst did not issue an annual earnings forecast for the firm in a year. We also include a variable which proxies for the level of effort the analyst expended while following the firm in the year to further minimize the impact of any stale recommendations.

suggesting there is significant variation in recommendation profitability for our model to explain. In addition, the large 75th and 90th percentile values for *Money* suggest that any methodology providing a means for investors to better identify analysts on an ex-ante basis who are most likely to issue the most profitable stock recommendations may allow investors to improve upon the returns identified in previous studies. Notably, the mean for the *Money* variable presented in Table 3 would loosely approximate a portfolio return of 10.5% if an investor followed the recommendations of the mean analyst over the sample period. However, values for our *Money* variable will not exactly equate to an investment return because our methodology implies daily portfolio rebalancing and ignores transactions costs.

For the explanatory variables from the earnings forecasting literature, the means presented in Table 3 are consistent with prior studies. For example, the average analyst has approximately 8 years of general experience, follows nearly 18 companies across 5 industries, and issues almost 4 annual earnings forecasts per firm each year. Additionally, approximately 52.7% (22.3%) of the observations consist of recommendations made by analysts at brokers classified as an *IBank* (*TopTier*), and analyst teams constitute around 3% of all observations in our sample. Further, 20.8% of the recommendations are bold relative to the consensus, and 1.8% are bold relative to the analyst's prior recommendations. Perhaps most notably, 26.8% of observations contain recommendations that appear to be correlated with investor sentiment.

Table 4 presents the cross-sectional regression results from Model (3) which examines whether analysts' stock recommendations as a whole are correlated with investor sentiment. Panel A reports results where the proxy for the analyst's private

estimate of the firm's intrinsic value is calculated using the residual income model described by Equation (1). Panel B reports results where the proxy for the analyst's private estimate of the firm's intrinsic value is calculated by capitalizing the analyst's 1-year ahead earnings forecast in perpetuity as described by Equation (2). Results are consistent, both statistically and economically, across both specifications, and we discuss the results reported in Panel A.

As expected, the coefficient on *LagRec* is positive and significant indicating analysts' recommendations are "sticky", and the positive and significant coefficient on the *VP* variable of 0.141 indicates analysts' recommendations are more bullish when the analyst perceives the firm's intrinsic value to be high relative to the current price. Thus, the analyst's current recommendation is influenced by her views about the firm and her perception of the firm's current intrinsic value. Somewhat surprisingly, the coefficient on *TopTier* of -0.076 is significantly negative indicating analysts' actually issue more bearish recommendations when ex-ante expected conflicts of interest are greater. However, untabulated results show the coefficient on the *TopTier* variable is only negative and significant after the Global Research Settlement suggesting the enforcement action may have reduced the effect of analysts' conflicts of interest or increased the perceived cost of appearing to issue overly optimistic recommendations.

Turning to the relation between investor sentiment and analysts' stock recommendations, the significant coefficient on the *MktSentLag* variable of 0.067 indicates analysts, on average, tend to issue more favorable recommendations when investor sentiment over the prior 3 months has been more bullish. Similarly, the significant coefficient on *MktSentLead* of 0.122 indicates analysts tend to issue more

favorable recommendations when future investor sentiment is more bullish. The positive coefficient on *MktSentLead* suggests that at least a subset of analysts may be able to predict future investor sentiment, and such behavior may partially explain why analysts appear to fail to fully convert their earnings forecasts into stock recommendations.

Table 5 presents the results of our logistic regression designed to determine which analyst characteristics are associated with an individual's propensity to respond to sentiment. In order to interpret the impact of a one unit change in an independent variable on the probability that the analyst's stock recommendations are correlated with investor sentiment in a year, we focus on the marginal effects. Because marginal effects are nonlinear functions of the parameter estimates and the levels of the independent variables, we compute the marginal effect of each variable at each observation and report the average across observations.

The results in Table 5 suggest that the most statistically and economically significant variable in influencing whether an analyst's recommendations are correlated with investor sentiment in a given year is the number of companies followed. The marginal effect associated with the *Companies* variable of 0.08 indicates that amongst analysts following the same firm in the same year, the analyst following the most companies is approximately 8% more likely to respond to investor sentiment compared to the analyst who follows the least number of companies. Similarly, the probability that an analyst's stock recommendations are correlated with investor sentiment is increasing in both the number of industries followed and the number of earnings forecasts issued. Collectively, these results suggest that analysts who follow more firms and cover a wider variety of industries may be more likely to incorporate signals that might affect price but

that are not theoretically related to intrinsic value when developing their recommendations. Moreover, analyst teams and analysts facing potential conflicts of interest are more likely to respond to sentiment while analysts with more firm-specific experience are less likely to respond to sentiment.

Finally, Table 6 identifies the determinants of relative stock recommendation profitability. Because we use standardized variables, the magnitude of the regression coefficients allows us to determine the relative contributions of each variable to relative recommendation profitability. Our results show that the variable with the largest impact on relative recommendation profitability is past relative recommendation profitability (*LagMoney*) with a coefficient of 0.089. Consistent with Mikhail et al. (2004) and Li (2005), this result suggests that the ability to issue profitable stock recommendations is somewhat persistent. We extend the literature by showing that the analyst's level of conviction about her recommendation is a key determinant of relative recommendation profitability. Interestingly, the coefficient on *Bold1* (0.063) is positive while the coefficient on *Bold2* (-0.015) is negative. This suggests that recommendations deviating from the consensus tend to be relatively more profitable, but that recommendations which are bolder than the analyst's own prior recommendations are relatively less profitable.

The next most important variable is team designation (*Team*) indicating whether the recommendation was issued by a team as opposed to by an individual analyst. The positive and significant coefficient on *Team* (0.021) suggests teams of analysts issue more profitable stock recommendations, and this result complements the findings in Brown and Hugon (2009) that teams issue timelier but less accurate earnings forecasts. This differential impact of being part of a team on forecasting accuracy and

recommendation profitability signifies that accurately forecasting earnings and issuing profitable stock recommendations may require two separate but related skill sets and that teams appear to have an advantage in stock picking.

Collectively, the variables measuring the correlation between an analyst's recommendations and investor sentiment contain the next most explanatory power for relative stock recommendation profitability. The significantly negative coefficient on *MktSentLag1* (-0.010) suggests that analysts whose recommendations are positively correlated with recent investor sentiment tend to issue relatively less profitable recommendations. This result is consistent with Baker and Wurgler (2006) and Frazzini and Lamont (2008) who find that stocks tend to underperform after periods of bullish sentiment. Similarly, the significantly negative coefficient on *MktSentLead1* (-0.011) suggests that analysts whose recommendations are positively correlated with future investor sentiment also tend to issue relatively less profitable recommendations. This result is somewhat surprising, but it does not necessarily imply that analysts who respond to investor sentiment issue unprofitable recommendations. Because our measure of recommendation profitability is relative, recommendations issued by analysts who respond to sentiment may be profitable on an absolute basis.

Consistent with our predictions, earnings forecasting ability (*Accuracy*), earnings forecast frequency (*ForeFreq*), and industry experience (*IndExp*) are all positively related to relative recommendation profitability. However, in contrast to our prediction, the employer size variable (*BrokerSize*) is negatively associated with relative recommendation profitability. This result is surprising because employer size is positively associated with forecast accuracy. Future research may provide a more

rigorous investigation into this interesting contrast, but one possible explanation is that analysts who are employed at big brokers may have access to managers' private information that helps them forecast earnings but not stock prices.

The last set of statistically significant variables captures potential conflicts of interest facing the analyst. The positive coefficient on *IBank* of 0.005 indicates that analysts working for brokers with investment banking operations tend to issue more profitable stock recommendations. However, consistent with Ertimur et al. (2007), we find that analysts working for the most prestigious *TopTier* underwriters issue less profitable stock recommendations on average.

5.1 Additional Analysis

We perform a variety of supplemental empirical tests. First, we perform a sub-sample analysis. Although the results in Table 6 suggest that analysts whose stock recommendations are positively correlated with recent or future investor sentiment issue relatively less profitable recommendations on average, there may be situations in which responding to investor sentiment actually leads to relatively more profitable stock recommendations. In order to identify the firms who are most sensitive to investor sentiment, we follow Glushkov (2006) and estimate the following regression by firm:

$$\mathrm{Ret}_{i,t} = \beta_{0,i} + \beta_{1,i}\mathrm{MKT}_t + \beta_{2,i}\mathrm{SMB}_t + \beta_{3,i}\mathrm{HML}_t + \beta_{4,i}\Delta\mathrm{SENT}_t + \varepsilon_{i,t} \qquad (6)$$

Where $Ret_{i,t}$ is firm i's return in month t, MKT_t, SMB_t, and HML_t are the monthly Fama and French (1993) factors in month t, and $\Delta\mathrm{SENT}_t$ is the change in the Baker and Wurgler (2006) sentiment index from month t-1 to t. The β_4 coefficient for each firm represents the covariance of the firm's returns with changes in investor sentiment (i.e. a sentiment beta). Firms with higher sentiment betas are more sensitive to investor

sentiment, and thus a strategy of incorporating investor sentiment into one's stock recommendations may be particularly beneficial for these firms.

In order to investigate this possibility, we rank firms into deciles according to the magnitude of their sentiment betas. Next, we re-estimate Model (6) by decile portfolio to reduce sentiment beta estimation error. Finally, we assign the portfolio's sentiment beta to all firms in the portfolio, and we scale the resulting firm's sentiment beta (*SentBeta*) to lie within the interval [0,1]. We add the *SentBeta* variable to our primary regression in Model (5), and we also interact the *SentBeta* variable with the *MktSentLag1*, *MktSentLag2*, *MktSentLead1*, and *MktSentLead2* variables. The results are presented in Table 7. The coefficients on *MktSentLag1* and *MktSentLead1* remain negative and significant which suggests that analysts who respond to investor sentiment underperform their peers on average. However, the sum of the coefficient on *MktSentLag1* of -0.051 and the coefficient on *MktSentLag1***SentBeta* of 0.085 is positive and significant. Thus, consistent with theoretical evidence that sophisticated market participants can reap private gains by timing movements in sentiment (Abreu and Brunnermeier 2003, DeLong et al. 1990), our results suggest that some analysts are able to increase the relative profitability of their stock recommendations for certain firms (i.e. firms that are most sensitive to investor sentiment) by riding recent waves in sentiment.

We also perform two sensitivity checks related to our measure of relative stock recommendation profitability (results untabulated). First, we adjust the construction of the *Money* variable such that an analyst with an outstanding Strong Buy recommendation receives daily credit equal to double the stock's daily return less a daily risk free rate. This adjustment supposes that a hypothetical investor purchases twice as many shares in

response to a Strong Buy recommendation as compared to a Buy recommendation and that those extra shares are financed by shorting the risk-free asset. Hence, the recommendation profitability for an analyst with an outstanding Strong Buy recommendation is based on the same endowment as the recommendation profitability for an analyst with an outstanding Buy recommendation for the same stock. All results remain quantitatively and qualitatively unchanged. Second, although Fama (1998) argues for the use of arithmetic return measures in order to avoid potential extreme skewness associated with compounded monthly returns, we also construct the *Money* variable by geometrically aggregating an analyst's credits for a given firm-year. Analysts whose stock recommendations are positively correlated with recent or future investor sentiment continue to appear to issue relatively less profitable recommendations on average.

6. Conclusion

This study investigates whether analysts who respond to investor sentiment issue more or less profitable stock recommendations than their peers. We find that analysts, on average, issue more favorable stock recommendations when recent and future investor sentiment is more bullish. Hence, some analysts appear to recommend stocks based, in part, on signals that may affect price but that are not theoretically related to firms' underlying intrinsic value as opposed to making a recommendation strictly based on a comparison of the firm's current stock price to the analyst's private estimate of the firm's intrinsic value.

Our research design utilizes an analyst-firm-year specific measure of relative stock recommendation profitability that provides strong controls for firm and time effects

and allows us to assess each analyst and recommendation characteristic's relative contribution to relative recommendation profitability. Consistent with prior research, we show that earnings forecasting ability and several analyst characteristics associated with forecast accuracy also have explanatory power for relative stock recommendation profitability. We extend the literature by demonstrating that the analyst's level of conviction about her recommendation and whether the analyst is a member of a team are also key determinants of relative recommendation profitability. Finally, and perhaps most interestingly, we find that, on average, analysts who respond to investor sentiment issue less profitable stock recommendations than their peers. However, analysts who follow stocks that are most sensitive to investor sentiment and who follow recent trends in sentiment are able to offer more profitable recommendations than their peers.

Our results should be of interest to academic researchers and a variety of capital market participants. Given analysts' role as information intermediaries, researchers seek to understand the information and processes that analysts use when making stock recommendations. Investors may also gain insights into how to use both analysts' earnings forecasts and stock recommendations in concert with one another to maximize the profitability of their investment strategies. Further, our results may help analysts efficiently allocate their effort by helping analysts decide whether or not to devote costly time and effort towards considering investor sentiment. Finally, brokerage firms could find our methodology and results useful when hiring, training, evaluating, and compensating analysts, particularly given recent regulatory developments which prevent analyst compensation from being directly tied to investment banking revenues.

References

Abreu, D., and M.K. Brunnermeier. 2002. Synchronization Risk and Delayed Arbitrage. *Journal of Financial Economics* 66: 341-360.

Abreu, D., and M.K. Brunnermeier. 2003. Bubbles and Crashes. *Econometrica* 71: 173-204.

Allen, F., S. Morris, and H.S. Shin. 2006. Beauty Contests and Iterated Expectations in Asset Markets. *Review of Financial Studies* 19: 719-752.

Baker, M., and J. Wurgler. 2006. Investor Sentiment and the Cross-Section of Stock Returns. *Journal of Finance* 61: 1645-1680.

Baker, M., and J. Wurgler. 2007. Investor Sentiment in the Stock Market. *Journal of Economic Perspectives* 21: 129-151.

Barber, B., B. Lehavy, M. McNichols, and B. Trueman. 2001. Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns. *Journal of Finance* 56: 531-563.

Barberis, N., A. Shleifer, and R. Vishny. 1998. A Model of Investor Sentiment. *Journal of Financial Economics* 49: 307-343.

Bradshaw, M.T. 2004. How Do Analysts Use Their Earnings Forecasts in Generating Stock Recommendations? *The Accounting Review* 79: 25-50.

Brown, L., and K. Huang. 2010. Recommendation-Forecast Consistency. Working paper, Georgia State University.

Brown, L., and A. Hugon. 2009. Team Earnings Forecasting. *Review of Accounting Studies* 14: 587-607.

Brunnermeier, M.K., and S. Nagel. 2004. Hedge Funds and the Technology Bubble. *Journal of Finance* 59: 2013-2040.

Carter, R., and S. Manaster. 1990. Initial Public Offerings and Underwriter Reputation. *Journal of Finance* 45: 1045-1067.

Clement, M. 1999. Analyst Forecast Accuracy: Do Ability, Resources, and Portfolio Complexity Matter? *Journal of Accounting and Economics* 27: 285-303.

Clement, M., J. Hales, and Y. Xue. 2010. Understanding Analysts' Use and Under-use of Stock Returns and Other Analysts' Forecasts when Forecasting Earnings. Working paper, University of Texas at Austin.

Clement, M., and S. Tse. 2005. Financial Analyst Characteristics and Herding Behavior in Forecasting. *Journal of Finance* 60: 307-341.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam. 1998. Investor Psychology and Security Market Under- and Overreactions. *Journal of Finance* 53: 1839-1885.

Dechow, P.M., A.P. Hutton, and R.G. Sloan. 1999. An Empirical Assessment of the Residual Income Model. *Journal of Accounting and Economics* 26: 1-34.

DeLong, J.B., A. Shleifer, L.H. Summers, and R.J. Waldmann. 1990. Noise Trader Risk in Financial Markets. *Journal of Political Economy* 98: 703-738.

Emery, D.R., and X. Li. 2009. Are the Wall Street Analyst Rankings Popularity Contests? *Journal of Financial & Quantitative Analysis* 44: 411-437.

Ertimur, Y., J. Sunder, and S.V. Sunder. 2007. Measure for Measure: The Relation between Forecast Accuracy and Recommendation Profitability of Analysts. *Journal of Accounting Research* 45: 567-606.

Fama, E.F. 1998. Market Efficiency, Long-term Returns, and Behavioral Finance. *Journal of Financial Economics* 49: 283-306.

Fama, E.F., and K.R. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33: 3-56.

Fama, E.F., and K.R. French. 1997. Industry Costs of Equity. *Journal of Financial Economics* 43: 153-193.

Frankel, R., and C. Lee. 1998. Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns. *Journal of Accounting and Economics* 25: 283-319.

Frazzini, A., and O.A. Lamont. 2008. Dumb Money: Mutual Fund Flows and the Cross-Section of Stock Returns. *Journal of Financial Economics* 88: 299-322.

Gao, P. 2008. Keynesian Beauty Contest, Accounting Disclosure and Market Efficiency. *Journal of Accounting Research* 46: 785-807.

Glushkov, D. 2006. Sentiment Beta. Working paper, The University of Pennsylvania.

Goldman Sachs Group, Inc. 2009. Comment: Spirit AeroSystems Holdings, Inc. December 9, 2009.

Groysberg, B., P.M. Healy, and C.J. Chapman. 2008a. Buy-Side Versus Sell-Side Analysts' Earnings Forecasts. *Financial Analysts Journal* 64: 25-39.

Groysberg, B., P.M. Healy, and D. Maber. 2008b. What Drives Sell-Side Analyst Compensation at High-Status Banks? Working paper, Harvard Business School.

Hall, J., and P.B. Tacon. 2009. Forecast Accuracy and Stock Recommendations. Working paper, University of Queensland.

Hribar, P., and J. McInnis. 2009. Investor Sentiment and Analysts' Earnings Forecast Errors. Working paper, University of Iowa.

Jacob, J., T. Lys, and M. Neale. 1999. Expertise in Forecasting Performance of Security Analysts. *Journal of Accounting and Economics* 28: 27-50.

Jegadeesh, N., J. Kim, S.D. Krische, and C.M.C. Lee. 2004. Analyzing the Analysts: When Do Recommendations Add Value? *Journal of Finance* 59: 1083-1124.

Ke, B., and Y. Yu. 2009. Why Don't Analysts Use Their Earnings Forecasts in Generating Stock Recommendations? Working paper, Pennsylvania State University.

Keynes, J.M. 1936. *The General Theory of Employment, Interest and Money*. Macmillan, London.

Li, X. 2005. The Persistence of Relative Performance in Stock Recommendations of Sell-Side Financial Analysts. *Journal of Accounting and Economics* 40: 129-152.

Liu, J., D. Nissim, and J. Thomas. 2002. Equity Valuation Using Multiples. *Journal of Accounting Research* 40: 135-172.

Loh, R.K., and G.M. Mian. 2006. Do Accurate Earnings Forecasts Facilitate Superior Investment Recommendations? *Journal of Financial Economics* 80: 455-483.

Loughran, T., and J. Ritter. 2004. Why Has IPO Underpricing Changed Over Time? *Financial Management* 33: 5-37.

Ljungqvuist, A., C. Malloy, and F. Marston. 2009. Rewriting History. *Journal of Finance* 64: 1935-1960.

Mikhail, M.B., B.R. Walther, and R.H. Willis. 1997. Do Security Analysts Improve their Performance with Experience? *Journal of Accounting Research* 35: 131-166.

Mikhail, M.B., B.R. Walther, X. Wang, and R.H. Willis. 2006. Determinants of Superior Stock Picking Ability. Working paper, Arizona State University.

Mikhail, M.B., B.R. Walther, and R.H. Willis. 2004. Do Security Analysts Exhibit Persistent Differences in Stock Picking Ability? *Journal of Financial Economics*, 74: 67-91.

Mikhail, M.B., B.R. Walther, and R.H. Willis. 2009. Does Investor Sentiment Affect Sell-Side Analysts' Forecast Accuracy? Working paper, Arizona State University.

Muslu, V., and Y. Xue. 2009. Greasing the Rollercoaster? Analysts' Momentum Recommendations. Working paper, University of Texas at Dallas.

O'Brien, P.C., and Y. Tian. 2008. Financial Analysts' Role in the 1996-2000 Internet Bubble. Working paper, University of Waterloo.

Seybert, N., and S. Wang. 2009. False Prophets: How Analysts Lead Short-Sellers Astray During Periods of High Investor Sentiment. Working paper, University of Texas at Austin.

Shleifer, A., and R.W. Vishny. 1997. The Limits of Arbitrage. *Journal of Finance* 52: 35-55.

The Wall Street Journal. May 26, 2009. "Best on the Street (A Special Report): 2009 Analysts Survey – How the Survey Was Conducted".

Table 1

Descriptive Statistics for I/B/E/S Stock Recommendations

Year	Number of Recommendations	Number of Analysts	Number of Brokers	Number of Firms	Median Duration	Mean Rec.	% Strong Sell	% Sell	% Hold	% Buy	% Strong Buy
1994	26,827	2,058	154	4,484	385	3.75	2.9%	2.4%	37.0%	31.6%	26.1%
1995	27,935	2,284	153	4,797	339	3.78	3.1%	2.5%	36.1%	30.0%	28.3%
1996	27,644	2,617	194	5,333	433	3.88	1.9%	2.5%	31.9%	32.7%	31.0%
1997	27,650	2,999	231	5,485	462	3.93	1.6%	1.6%	29.8%	36.1%	30.9%
1998	32,217	3,545	250	5,655	428	3.91	1.1%	1.4%	30.9%	38.8%	27.8%
1999	31,786	3,745	248	5,442	573	3.96	0.9%	1.7%	27.9%	39.1%	30.4%
2000	28,255	3,621	234	4,935	475	3.99	0.6%	1.2%	27.4%	39.9%	30.9%
2001	27,632	3,479	207	4,214	328	3.85	1.0%	1.8%	34.4%	37.1%	25.7%
2002	37,171	3,649	213	4,294	313	3.60	2.0%	7.1%	40.1%	30.3%	20.5%
2003	28,490	3,383	259	4,238	364	3.45	3.9%	8.0%	46.4%	22.5%	19.2%
2004	28,784	3,500	304	4,413	460	3.52	3.5%	6.3%	45.4%	24.3%	20.5%
2005	27,495	3,593	314	4,589	461	3.55	3.3%	5.9%	45.1%	24.0%	21.8%

This table presents descriptive statistics for analyst stock recommendations on the I/B/E/S detail file. The sample period begins in 1994, the first full calendar year in which stock recommendation data are available on I/B/E/S. The sample period ends in 2005, the last year in which Baker and Wurgler (2006) monthly sentiment are publicly available.

Number of Recommendations is the number of distinct stock recommendations recorded on the I/B/E/S recommendation detail file during the calendar year. *Number of Analysts* is the number of distinct analysts issuing at least one stock recommendation during the calendar year. *Number of Brokers* is the number of distinct brokerage houses employing at least one analyst who issued a stock recommendation during the calendar year. *Number of Firms* is the number of distinct firms for which at least one analyst issued a stock recommendation during the calendar year. *Median Duration* is the median length of time in days that recommendations made in the calendar year were outstanding before being revised or reiterated.

Mean Rec. is the mean recommendation level for all recommendations issued during the calendar year. Recommendation levels on I/B/E/S are on a 5-point scale, and recommendation levels are manipulated such that 5=Strong Buy, 4=Buy, 3=Hold, 2=Sell, and 1=Strong Sell. *% Strong Sell*, *% Sell*, *% Hold*, *% Buy*, and *% Strong Buy* summarize the distribution of recommendations issued during the calendar year.

Table 2

Descriptive Statistics By Year for Recommendation Profitability

Year	N	Mean	Std. Dev.	5th Percentile	25th Percentile	Median	75th Percentile	95th Percentile
1994	11,458	0.018	0.425	-0.630	-0.092	0.133	0.133	0.664
1995	24,222	0.228	0.538	-0.421	0.030	0.423	0.423	1.168
1996	33,358	0.163	0.488	-0.475	0.030	0.319	0.319	1.000
1997	43,290	0.183	0.531	-0.520	0.030	0.385	0.385	1.116
1998	53,680	0.067	0.627	-0.869	0.009	0.177	0.177	1.040
1999	65,928	0.183	0.803	-0.717	0.030	0.218	0.218	1.622
2000	77,459	0.073	0.794	-1.151	0.030	0.227	0.227	1.286
2001	87,647	0.105	0.643	-0.639	0.030	0.135	0.135	1.083
2002	96,655	-0.072	0.571	-1.047	-0.030	0.030	0.030	0.476
2003	106,843	0.251	0.618	-0.155	0.030	0.351	0.351	1.349
2004	115,390	0.100	0.361	-0.302	0.030	0.107	0.107	0.698
2005	125,248	0.057	0.355	-0.349	0.030	0.030	0.030	0.584

This table presents descriptive statistics for the *Money* variable, our measure for the profitability of analyst *i*'s stock recommendation for firm *j* in calendar year *t* which is calculated as follows. Each day for a given stock for which an analyst has a stock recommendation outstanding, the analyst is awarded a daily "credit" based on her outstanding recommendation and the stock's daily return. If the analyst has a Buy (Sell) recommendation outstanding, the analyst receives credit equal to the (negative of the) stock's return for that day. If the analyst has a Strong Buy (Strong Sell) recommendation outstanding, the analyst receives credit equal to double the (negative of the) stock's return for that day. If the analyst had a Hold recommendation outstanding, the analyst's daily credit is set to an amount that would equate to a constant annual risk free rate of 3%. Each of analyst *i*'s daily credits for firm *j* are arithmetically summed for calendar year *t* to form an analyst-firm-year observation for the *Money* variable.

The sample period begins in 1994, the first full calendar year in which stock recommendation data are available on I/B/E/S. The sample period ends in 2005, the last year in which Baker and Wurgler (2006) monthly sentiment are publicly available. For descriptive statistic purposes, the *Money* variable remains unscaled.

Table 3

Descriptive Statistics for the Determinants of Relative Stock Recommendation Profitability

Variable	N	Mean	Std. Dev.	Q1	Median	Q3
Money	841,178	0.1049	0.5851	0.03	0.03	0.15
LagMoney	715,739	0.1133	0.6161	0.03	0.03	0.18
Bold1	841,178	0.2078	0.3809	0.00	0.00	0.15
Bold2	715,739	0.0177	0.2207	0.00	0.00	0.00
MktSentLag1	230,158	0.0728	0.2598	0.00	0.00	0.00
MktSentLag2	230,158	0.0612	0.2398	0.00	0.00	0.00
MktSentLead1	230,158	0.0726	0.2595	0.00	0.00	0.00
MktSentLead2	230,158	0.0610	0.2394	0.00	0.00	0.00
Accuracy	202,149	0.1611	2.5641	0.01	0.04	0.11
Industries	216,622	5.0225	3.0464	3.00	4.00	6.00
Companies	216,622	17.8652	11.7357	12.00	16.00	21.00
ForeFreq	216,622	3.5538	2.2434	2.00	3.00	5.00
BrokerSize	216,622	67.0601	64.3009	20.00	49.00	96.00
GenExp	216,622	8.3354	4.9515	4.00	7.00	12.00
IndExp	215,937	6.9960	4.5624	3.00	6.00	10.00
FirmExp	216,622	4.5494	3.2484	2.00	3.00	6.00
IBank	841,178	0.5269	0.4993	0.00	1.00	1.00
TopTier	841,178	0.2234	0.4165	0.00	0.00	0.00
Team	841,178	0.0299	0.1704	0.00	0.00	0.00

This table presents descriptive statistics for the determinants of relative stock recommendation profitability. The sample period begins in 1994, the first full calendar year in which stock recommendation data are available on I/B/E/S. The sample period ends in 2005, the last year in which Baker and Wurgler (2006) monthly sentiment are publicly available. See Sections 3 and 4 for variable definitions. For descriptive statistic purposes, all variables remain unscaled.

Table 4

The Association Between Analysts' Stock Recommendations and Investor Sentiment

Model (3):

$$Rec_{i,j,t} = \alpha_0 + \alpha_1 LagRec_{i,j,t} + \alpha_2 VP_{i,j,t} + \alpha_3 IBank_{i,t} + \alpha_4 TopTier_{i,t} + \alpha_5 MktSent_t + \alpha_6 MktSentLag_t + \alpha_7 MktSentLead_t + \nu_{i,j,t}$$

Panel A				Panel B			
N	76,280			N	161,006		
Adjusted R^2	0.035			Adjusted R^2	0.029		
Variable	Coefficient	t-Statistic		Variable	Coefficient	t-Statistic	
Intercept	3.243	(97.40)	***	Intercept	3.267	(121.87)	***
LagRec	0.086	(12.44)	***	LagRec	0.101	(18.07)	***
VP	0.141	(12.43)	***	VP	0.047	(3.93)	***
IBank	0.022	(1.46)		IBank	0.018	(1.43)	
TopTier	-0.076	(-4.27)	***	TopTier	-0.054	(-3.68)	***
MktSent	0.035	(2.93)	***	MktSent	0.030	(3.48)	***
MktSentLag	0.067	(5.48)	***	MktSentLag	0.050	(5.55)	***
MktSentLead	0.122	(9.99)	***	MktSentLead	0.107	(11.42)	***

This table reports the results from cross-sectional regressions designed to test whether analysts' stock recommendations are, on average, correlated with investor sentiment. *Rec* represents analyst *i* 's recommendation for firm *j* on day *t* . Recommendations from I/B/E/S are manipulated such that 5 = Strong Buy, 4 = Buy, 3 = Hold, 2 = Sell, and 1 = Strong Sell.

LagRec is the analyst's previous recommendation for the firm. *VP* is a value to price ratio where a proxy for the analyst's private estimate of the firm's intrinsic value is scaled by the stock price as of the end of the month prior to the recommendation. Panel A reports results where the proxy for the analyst's private estimate of the firm's intrinsic value is calculated using the residual income model described by Equation (1). Panel B reports results where the proxy for the analyst's private estimate of the firm's intrinsic value is calculated by capitalizing the analyst's 1-year ahead earnings forecast in perpetuity as described by Equation (2).

IBank and *TopTier* are dummy variables that combine to proxy for the relative importance of investment banking business to analyst *i* 's broker as of the recommendation date based on the rankings created by Carter and Manaster (1990) and modified by Loughran and Ritter (2004). *IBank* = 1 if the broker is ranked and the maximum ranking for analyst *i* 's broker from 1993-2007 is greater than or equal to 1 and less than 9, and *IBank* = 0 otherwise. *TopTier* = 1 if the maximum ranking for analyst *i* 's broker equals 9, and *TopTier* = 0 otherwise. *MktSent* is the monthly Baker and Wurgler (2006) investor sentiment index for the month of the recommendation. *MktSentLag* (*MktSentLead*) is the average of the Baker and Wurgler (2006) investor sentiment index for the 3 months prior (subsequent) to the month of the recommendation.

The sample period begins in 1994, the first full calendar year in which stock recommendation data are available on I/B/E/S. The sample period ends in 2005, the last year in which Baker and Wurgler (2006) monthly sentiment are publicly available. ***, **, and * represent two-tailed significance at the 1%, 5%, and 10% levels, respectively. T-statistics are calculated based on standard errors that have been clustered by analyst.

Table 5

Characteristics Associated with the Correlation Between Investor Sentiment and Stock Recommendations

Model (4):

$$\Pr(\text{Correlate}) = \Gamma_0 + \Gamma_1\text{Bold1} + \Gamma_2\text{Bold2} + \Gamma_3\text{Accuracy} + \Gamma_4\text{Industries} + \Gamma_5\text{Companies} + \Gamma_6\text{ForeFreq} + \Gamma_7\text{BrokerSize} + \Gamma_8\text{GenExp} + \Gamma_9\text{IndExp} + \Gamma_{10}\text{FirmExp} + \Gamma_{11}\text{IBank} + \Gamma_{12}\text{TopTier} + \Gamma_{13}\text{Team} + \mu$$

N	107,914	
Pseudo R^2	0.026	
Likelihood Ratio	1478.529	***
% Correctly Predicted	59.60%	

Variable	Coefficient	Wald Chi-Square		Marginal Effect
Intercept	-2.855	(5530.41)	***	
Bold1	-0.024	(0.63)		-0.002
Bold2	0.063	(3.82)	*	0.007
Accuracy	0.031	(1.48)		0.003
Industries	0.136	(18.35)	***	0.014
Companies	0.774	(522.86)	***	0.080
ForeFreq	0.429	(252.92)	***	0.044
BrokerSize	0.051	(2.16)		0.005
GenExp	0.096	(3.52)	*	0.010
IndExp	0.100	(3.32)	*	0.010
FirmExp	-0.093	(7.64)	***	-0.010
IBank	0.073	(8.76)	***	0.008
TopTier	0.143	(21.25)	***	0.015
Team	0.477	(40.42)	***	0.049

This table reports the results from a cross-sectional logistic regression designed to identify characteristics associated with the probability that an analyst's stock recommendations are correlated with investor sentiment. *Correlate* = 1 if the analyst's stock recommendations in a given year are positively or negatively correlated with past or future investor sentiment. Specifically, *Correlate* = 1 for a given firm-analyst-year combination if either the α_6 or α_7 coefficients from Model (3) estimated for a given analyst-year combination are significantly different from zero, and *Correlate* = 0 otherwise.

For regression purposes, certain continuous independent variables are scaled such that each analyst is compared to other analysts following the same firm in the same calendar year. See Sections 3 and 4 for a complete description of each variable and its construction as well as a discussion of our scaling methodology. Analyst, firm, and year subscripts have been omitted for brevity. Requiring each variable to be non-missing results in a sample period of 1995-2005. ***, **, and * represent two-tailed significance at the 1%, 5%, and 10% levels, respectively.

The marginal effects represent the effect of a one unit change in the independent variable on the probability than the analyst's stock recommendations are correlated with investor sentiment in a year. The marginal effects are nonlinear functions of the parameter estimates and the levels of the independent variables. For presentation purposes, the marginal effect of each variable is computed at each observation and then averaged across observations.

Table 6

The Determinants of Relative Stock Recommendation Profitability

Model (5):

$$\text{Money} = \beta_0 + \beta_1\text{LagMoney} + \beta_2\text{Bold1} + \beta_3\text{Bold2} + \beta_4\text{MktSentLag1} + \beta_5\text{MktSentLag2} + \beta_6\text{MktSentLead1} + \beta_7\text{MktSentLead2} + \beta_8\text{Accuracy} + \beta_9\text{Industries} + \beta_{10}\text{Companies} + \beta_{11}\text{ForeFreq} + \beta_{12}\text{BrokerSize} + \beta_{13}\text{GenExp} + \beta_{14}\text{IndExp} + \beta_{15}\text{FirmExp} + \beta_{16}\text{IBank} + \beta_{17}\text{TopTier} + \beta_{18}\text{Team} + \varepsilon$$

N	107,826		
Adjusted R^2	0.014		
Variable	Coefficient	t-Statistic	
Intercept	0.462	(113.09)	***
LagMoney	0.089	(30.17)	***
Bold1	0.063	(20.01)	***
Bold2	-0.015	(-4.59)	***
MktSentLag1	-0.010	(-1.88)	*
MktSentLag2	0.001	(0.10)	
MktSentLead1	-0.011	(-2.02)	**
MktSentLead2	-0.002	(-0.28)	
Accuracy	0.012	(4.63)	***
Industries	-0.004	(-1.26)	
Companies	-0.001	(-0.22)	
ForeFreq	0.012	(4.18)	***
BrokerSize	-0.012	(-3.20)	***
GenExp	-0.008	(-1.45)	
IndExp	0.012	(2.10)	**
FirmExp	0.001	(0.37)	
IBank	0.005	(1.97)	**
TopTier	-0.006	(-1.84)	*
Team	0.021	(2.33)	**

This table reports the results from a cross-sectional regression of *Money*, our measure for the relative profitability of each analyst's stock recommendation for a given firm-year, on various analyst and recommendation characteristics. Analyst, firm, and year subscripts have been omitted for brevity. For regression purposes, certain continuous independent variables are scaled such that each analyst is compared to other analysts following the same firm in the same calendar year. See Sections 3 and 4 for a complete description of each variable and its construction as well as a discussion of our scaling methodology. Requiring each variable to be non-missing results in a sample period of 1995-2005. ***, **, and * represent two-tailed significance at the 1%, 5%, and 10% levels, respectively.

Table 7

The Impact Firms' Sentiment Betas on the Profitability of Responding to Investor Sentiment

$$\text{Money} = \beta_0 + \beta_1\text{LagMoney} + \beta_2\text{Bold1} + \beta_3\text{Bold2} + \beta_4\text{MktSentLag1} + \beta_5\text{MktSentLag2} + \beta_6\text{MktSentLead1} + \beta_7\text{MktSentLead2} + \beta_8\text{SentBeta} + \beta_9\text{MktSentLag1*SentBeta} + \beta_{10}\text{MktSentLag2*SentBeta} + \beta_{11}\text{MktSentLead1*SentBeta} + \beta_{12}\text{MktSentLead2*SentBeta} + \beta_{13}\text{Accuracy} + \beta_{14}\text{Industries} + \beta_{15}\text{Companies} + \beta_{16}\text{ForeFreq} + \beta_{17}\text{BrokerSize} + \beta_{18}\text{GenExp} + \beta_{19}\text{IndExp} + \beta_{20}\text{FirmExp} + \beta_{21}\text{IBank} + \beta_{22}\text{TopTier} + \beta_{23}\text{Team} + \varepsilon$$

N	104,094		
Adjusted R^2	0.015		
Variable	Coefficient	t-Statistic	
Intercept	0.458	(79.04)	***
LagMoney	0.090	(29.89)	***
Bold1	0.064	(19.84)	***
Bold2	-0.014	(-4.00)	***
MktSentLag1	-0.051	(-2.42)	**
MktSentLag2	-0.027	(-1.23)	
MktSentLead1	-0.037	(-1.79)	*
MktSentLead2	0.001	(0.03)	
SentBeta	0.006	(0.78)	
MktSentLag1*SentBeta	0.085	(2.03)	**
MktSentLag2*SentBeta	0.053	(1.26)	
MktSentLead1*SentBeta	0.054	(1.31)	
MktSentLead2*SentBeta	0.002	(0.03)	
Accuracy	0.012	(4.69)	***
Industries	-0.004	(-1.16)	
Companies	-0.001	(-0.29)	
ForeFreq	0.012	(4.12)	***
BrokerSize	-0.011	(-3.02)	***
GenExp	-0.009	(-1.66)	*
IndExp	0.013	(2.25)	**
FirmExp	0.001	(0.29)	
IBank	0.005	(2.07)	**
TopTier	-0.006	(-1.90)	*
Team	0.021	(2.25)	**

This table reports the results from a cross-sectional regression designed to determine whether the profitability of a strategy of responding to investor sentiment is conditional on firms' sensitivity to investor sentiment. To measure firms' sensitivity to investor sentiment, we estimate sentiment betas following Glushkov (2006). Specifically, we estimate regression Model (6) by firm:

$$\text{Ret}_{i,t} = \beta_{0,i} + \beta_{1,i}\text{MKT}_t + \beta_{2,i}\text{SMB}_t + \beta_{3,i}\text{HML}_t + \beta_{4,i}\Delta\text{SENT}_t + \varepsilon_{i,t} \quad (6)$$

Where $Ret_{i,t}$ is firm i's return in month t, MKT_t, SMB_t, and HML_t are the monthly Fama and French (1993) factors in month t, and ΔSENT_t is the change in the Baker and Wurgler (2006) sentiment index from month t-1 to t. The β_4 coefficient for each firm represents the covariance of the firm's returns with changes in investor sentiment (i.e. a sentiment beta). Firms with higher sentiment betas are more sensitive to investor sentiment.

We then rank firms into deciles according to the magnitude of their sentiment betas. Next, we re-estimate Model (6) by decile portfolio to reduce sentiment beta estimation error. Finally, we assign the portfolio's sentiment beta to all firms in the portfolio, and we scale the resulting firm's sentiment beta (*SentBeta*) to lie within the interval [0,1] to match all other independent variables.

See Sections 3 and 4 for definitions of all other variables and a discussion of our scaling methodology. Requiring each variable to be non-missing results in a sample period of 1995-2005. ***, **, and * represent two-tailed significance at the 1%, 5%, and 10% levels, respectively.