When Do Signals Counteract The Effects of Confirmation Bias? Evidence From Sell-Side Analysts' Forecasts

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Abstract: I empirically study whether strong signals counteract the effects of confirmation bias in sell-side analysts' stock price forecasts when these signals are contradictory. I use target prices to measure forecast bias and the growth in Earnings Per Share as signals, and regress analysts' forecast bias over different deciles of high signals interacted with prior negative forecast bias in a dynamic panel data model. I find that analysts underreact to favorable signals when the prior is pessimistic, except for sufficiently strong signals which cause analysts to issue more optimistic target prices. Also, that analysts underreact to low signals, except for sufficiently low signals.

Key words: Earnings growth, pessimistic prior, overreaction to signals, contradictory signals.

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1 Introduction

Rational forecasts are important for stock market efficiency. However, sell-side analysts, who provide public forecasts, are subject to cognitive biases such as confirmation bias and deliberate biases generated by their trading incentives. These two types of biases have different effects on forecasts when sell-side analysts receive a contradictory signal. Agents with confirmation bias "may ignore a signal when this signal is inconsistent with their prior beliefs" (Pouget et al., 2017), so that analysts with a pessimistic prior may ignore, completely or partially, a good current signal. On the other hand, if the signal that analysts receive is sufficiently strong, such that analysts expect informed investors to trade, then they should bias their forecast in the direction of the signal (Beyer and Guttman, 2011).

Do high signals counteract the effects of a negative prior? In this paper, I study whether the signal strength counteracts the effects of confirmation bias in sell-side analysts' stock price forecasts when these signals are contradictory. For each firm, I use the forecasts on its stock price as well as the realized price to measure analysts' bias and the growth in Earnings Per Share as signals, and regress analysts' forecast bias over different deciles of past high signals interacted with prior negative forecast bias. Differently to the literature on analysts' reaction to signals, which use consensus earnings forecasts to measure analysts' bias, I use the consensus of target prices (forecasts on stock prices) from Bloomberg[1] for 3169 firms included in the CRSP stock index. Forecasts of stock prices express analysts' opinions about the stock market in the most direct and intuitive manner[2], without the statistical problems that raise from earnings management[3] when using earnings forecasts or operating cash flows[4] to capture optimism. I use the consensus since analysts extract information from other analysts' reports to issue their own forecasts (Clement, Hales, and Xue, 2011) and based on the research which shows no evidence of persistent ability differentials across analysts in forecasting target prices (Bradshaw et al., 2013). Additionally, Loh and Stulz (2018) found that individual analyst characteristics are similar between crisis and non-crisis periods.

The production of investment reports is motivated by the investors' demand for analysts' products. Al-

[1]Using the Bloomberg terminal permits that this research is built upon information relevant for asset managers and stock markets. According to Ben-Rephael, Da, and Israelsen (2017), the majority of terminal users, as of August 26, 2016, were institutional investors with about 80% working in financial industries.

[2]This is supported by Asquith, Mikhail and Au (2005) who find that "the market reaction to price target revisions is stronger than that of an equal percentage change in earnings forecasts."

[3]Earnings management refers to the fact that "[m]anagement can improve or impair the quality of financial statements through the exercise of discretion over accounting numbers" (Beaver, 2002), e.g. estimation of accruals. Therefore, "some 'errors' in the distribution of [analyst] forecast errors may arise only because the forecast was inappropriately benchmarked with reported [manipulated] earnings, when in fact the analyst had targeted a different earnings number" (Abarbanell et al. 2003).

[4]Givoly, Hayn and Lehavy (2009) find that "cash flow forecasts appear to be a naïve extension of analysts' earnings forecasts."

though it is clear that the stock market moves according to the investors and money managers' decisions these obtain information from various sources including sell-side analysts (Fischer and Stocken, 2010), and accordingly, both small and large investors respond to the updates of analysts' forecast (Mikhail et al., 2007; Malmendier and Shanthikumar, 2014). Sell-side analysts are hired by brokerage firms whose revenue comes mainly from trading commissions and the analysts' income is linked to these commissions. Therefore, they try to increase the trading volume of the stocks they cover by issuing positively biased forecasts. Correspondingly, DeBondt and Thaler (1990) and Easterwood and Nutt (1999) found that analysts react optimistically to signals.

This paper adds to the literature on sell-side analysts and signals. For practitioners, and adding to the literature on how to use analysts reports, this research helps to understand the direction in which they should adjust analysts target prices conditional on the observed signals.

I estimate a dynamic panel data model by the generalized methods of moments as in Arellano and Bond (1991). I use analysts' forecast bias as my dependent variable and lags of the dependent variable as part of the regressors since the literature on analysts' optimism have shown that forecast errors are auto-correlated i.e. they have a dynamic structure. I find that analysts underreact to favorable signals when the prior is pessimistic, except for signals above the ninth decile for which analysts issue more optimistic target prices. In other words, when analysts have a negative prior belief their forecasts are consistent with confirmation bias, yet, for sufficiently strong high signals analysts do not underreact[5]. Also, I find that analysts underreact to low signals except for signals below the second decile.

This paper contains six sections including the introduction. In section two I expose the literature related to optimism and signals, as well as the literature related to analysts' confirmation bias and trading incentives. Later on, in section three, I describe the data and the variables. In sections four and five I explain the econometric specification and the results respectively. Finally, in section six I conclude.

2 Related Literature

My research is part of the empirical literature on how analysts respond to signals and on behavioral bias which include Pouget et al. (2017), Cen, Hilary, and Wei (2013), Easterwood and Nutt (1999), Abarbanell and Bernard (1992), Ali, Klein and Rosenfeld (1992) and DeBondt and Thaler (1990). Following Easterwood and Nutt (1999), I study how analysts react to prior signals dividing them in groups of high and low signals and, in line with Pouget et al. (2017), I also study analysts' reaction to contradictory signals. Additionally, and differently to the previous authors, I group signals by different levels of inten-

[5] I do not claim that confirmation bias disappears in any case since a forecast bias in the direction of the signal, but not as large as one issued by a purely Bayesian agent, is also consistent with confirmation bias.

sity and identify whether its strength induce analysts to bias their forecasts in the direction of the signals as predicted by the theoretical paper of Beyer and Guttman (2011). I find that analysts underreact to high contradictory signals, in line with Pouget et al. (2017), except for sufficiently high signals for which they bias their forecasts in the direction of the signals. Moreover, analysts underreact to poor earnings performance similarly to Easterwood and Nutt (1999).

The first paper studying how analysts respond to signals using observational data is DeBondt and Thaler (1990) who run a linear regression of current earnings changes over current forecast bias in earnings. They obtained a positive intercept and a negative slope which they interpreted as evidence of optimism and overreaction in analysts' forecasts (negative slope). However, as Abarbanell and Bernard (1992) pointed out about these results, the most overly optimistic consensus forecasts are for those companies with the weakest past performance. Thus, they run a linear regression of current forecast bias on past earnings changes where a slope equal to zero would indicate an efficient forecast. Their results are consistent with average optimism and underreaction[6]. Accordingly, I run regressions over past earning changes and find a positive relation between optimism and past earnings changes.

Easterwood and Nutt (1999) build on Abarbanell and Bernard (1992) by incorporating dummies for quartiles of earnings changes, separating values of performance into low, normal, and high groups. Thus, they run a linear regression of current forecast bias on past performance interacted with the dummies. From consensus forecasts, their results indicate that optimism is increasing in past performance. Also, that analysts overreact to prior signals in the upper quartile, and that analysts underreact to prior signals in the lower quartile. Overall, both results are consistent with systematic optimism. In line with Easterwood and Nutt (1999), I separate high, low and signals in the middle, and find that analysts underreact to low signals.

Pouget, Sauvagnat and Villeneuve (2017) empirically study how forecasters interpret signals inconsistent with prior beliefs. In particular, building on Rabin and Schrag (1999), the authors modeled a set of agents subject to confirmatory or confirmation bias who may ignore information that is inconsistent with their prior views[7]. The intuition of the definition of confirmation bias is that, if the signal and the belief updating have the same sign, the biased agent uses the signal to form his beliefs. If they are of different sign, the biased agent may bias the signal to form his beliefs. In other words, biased analysts may "ignore new evidence inconsistent with their favorite hypothesis regarding the state of the world" (Pouget et al., 2017).

[6]Similarly, Ali, Klein and Rosenfeld (1992) found that optimism is "most pronounced for firms that previously reported negative annual earnings."

[7]Confirmation bias "connotes the seeking or interpreting of evidence in ways that are partial to existing beliefs, expectations, or a hypothesis in hand" (Nickerson, 1998)

Pouget et al. (2017) utilize the standardized earnings changes as signals and prior forecasts as a proxy for prior beliefs, and run a linear probability model of a dummy that equals one if the sign of the direction of a current forecast revision and the sign of a previous signal are equal, over a dummy that equals one if the sign of a past forecast revision is different to the sign of a past signal (contradictory signal). The authors' null hypothesis (zero slope) is that on average analysts are rational, so they "revise their forecasts in the direction of the latest SUE [signal], irrespective of their prior beliefs about the prospect of the stock." Pouget, et al. (2017) estimate a negative slope which constitutes evidence in favor of the hypothesis that analysts are subject to confirmation bias: analysts are less likely to update their forecasts in the direction of a contradictory signal. As in Pouget et al. (2017) I consider a contradictory signal as one that is contrary to analysts' prior beliefs. More specifically, if today we verify that analysts were pessimistic and today they receive a high signal, then analysts received a contradictory signal. I find that analysts underreact to high contradictory signals above the seventh decile and below the ninth decile, but overreact to contradictory signals above the ninth decile.

The fact that analysts do not overreact when the signal is favorable and the prior is pessimistic except for sufficiently strong signals, is in line with the theoretical predictions of Beyer and Guttman (2011). When issuing forecasts, analysts do care about their reputation and thus about their accuracy (see Jackson, 2005; Mikhail et al., 1999; Groysberg et al., 2011). Still, since the income of analysts is linked to the revenues of their brokerage firms, then they try to increase the trading volume of the stocks they cover by issuing positively biased (optimistic) forecasts (Cowen et al., 2006; Jackson, 2005). Considering the trading incentives of analysts, Beyer and Guttman (2011) elaborate a model in which the analyst, whose payoff is a function of the expected trading volume and who is not confined to tell the truth, receives an exogenous signal. As a result (Bayesian equilibrium), when the signal is sufficiently favorable (unfavorable), such that analysts expect informed investors to buy (sell) shares, then they should bias their forecast upward (downward)[8].

My econometric design is different to those used in the literature in various aspects. First, differently to DeBondt and Thaler (1990), Abarbanell and Bernard (1992) and Easterwood and Nutt (1999) I take into account the effects of the prior beliefs when studying the response of analysts to signals. Differently to Pouget al. (2017), I make account not only for the effects of contradictory signals, but also for the direction of the signal. In addition, I include different levels of intensity for signals since, while analysts may not overreact to signals that are inconsistent with their priors, they may overreact in the direction of the signal when it is sufficiently strong. Lastly and differently to the abovementioned authors, I incorporate the autorregressive structure of the forecast bias in the same equation that relates signals with forecast bias. I do this in a dynamic panel data framework with unobserved heterogeneity as in Arellano and Bond (1991).

[8] Related models include Hayes (1998), Kartik et al. (2007) and Fischer and Stocken (2010)

3 Data and Variables

3.1 Data

My sample consists of firms included in the CRSP stock index which currently is composed of 3586 securities traded on NYSE, Amex or NASDAQ. For each firm in the sample, I observe the quarterly series of Earnings Per Share (EPS), as well as daily data on its stock price, market capitalization and number of analysts' recommendations. In addition, I observe daily data on the consensus target price, which is the average forecast of the stock price for the next 12 months from the analysts who cover that stock, and excludes forecasts older than three months when it is calculated. Also, I observe daily data on the "News Heat - Daily Max Readership" index of Bloomberg. This index is constructed by Bloomberg based upon the "number of times each article is read by its users, as well as the number of times users search for news for a specific stock" (Ben-Rephael et al., 2017) and takes higher values for higher levels of readers activity. Furthermore, I observe quarterly data on Corporate Profits of the U.S. National Income and Product Accounts as well as the quarterly forecasts on Corporate Profits from the Survey of Professional Forecasters[9].

3.2 Variables

My dependent variable is the quarterly forecast bias in terms of optimism in target prices. For each firm i and quarter t, I calculate the forecast bias as

$$y_{i,t} = \frac{TP_{i,t-4} - P_{i,t}}{P_{i,t-4}}$$

where $TP_{i,t-4}$ is the consensus forecast issued at the end of the quarter $t-4$ (see figure 1) for the next 4 quarters on stock i and $P_{i,t}$ is the stock price at the end of the quarter t[10].

[9]The Survey of Professional Forecasters, conducted by the Federal Reserve Bank of Philadelphia, includes panelists affiliated to different industries such as Universities, Manufacturers, Investment Advisors and Insurance Companies among others.

[10]Notice that $y_{i,t}$ is a very intuitive measure of optimism since it equals the difference between the projected growth in price $\frac{TP_{i,t-4}}{P_{t-4}}$ and the realized growth $\frac{P_{i,t}}{P_{i,t-4}}$

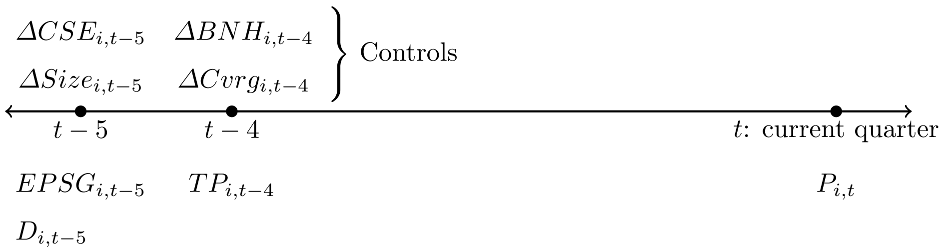

Figure 1: Timing of signals, forecasts, realized prices and controls

In order to measure the signal, which is the independent variable of interest in the model, I use growth in Earnings Per Share ($EPSG$). I calculate the signal as the change in Earnings Per Share ($EPSG_{i,t-5}$) scaled by the stock price, i.e. $EPSG_{i,t-5} = \frac{EPS_{i,t-5}-EPS_{i,t-6}}{P_{i,t-6}}$. I use the lag $t-5$ because when issuing a forecast at time $t-4$, analysts observe a past signal at $t-5$. It is important to note that this variable is not only sequentially exogenous to forecast bias but also strictly exogenous in the sense that analysts' forecasts on stock prices do not affect the present or the future realized earnings for any company. Reported earnings are determined by the accounting revenues and costs of firms and not by stock forecasts. Given that stock prices aggregate information from market participants, managers might use stock prices as a source of information to take decisions about corporate investments when this prices convey new information to managers (see e.g. Chen, et al. 2007 and Fishman and Hagerty, 1989). Nevertheless, as analysts forecasts are biased and are not determined by the aggregate decisions of market participants, it is not likely that managers use analysts' target prices to take decisions, and thus it is not likely that analysts' forecasts on stock prices affect realized earnings and free cash flows in the present or the near future, or that sell-side analysts' forecasts affect macroeconomic performance.

To measure different levels of signal intensity that allow me to distinguish, for example, a high signal from an extremely high signal or a low signal from an extremely low signal, I group them by cross-sectional deciles. As in Easterwood and Nutt (1999), I do not use standard deviations as a reference or z-scores to measure high and low signals but quantiles. The standard deviation as a measure of dispersion can bring an idea of how far is an observation from the mean and, in a symmetric distribution with a kurtosis around 3, how many observations are between the mean and a threshold. Therefore, in such a distribution, the standard deviation is useful as a reference to separate the sample in groups. Given that the cross-sectional distributions of EPS Growth are leptokurtic and not always symmetrical (i.e. some are skewed to the left and some to the right; see the Appendix), using the deciles (and not the mean as a reference point) allow me to group the sample in sets of high and low values with the same number of observations, notwithstanding how different are the skewness and kurtosis between cross-sectional distributions. As shown in table 8 in the Appendix, the seventh deciles are within 0.001 standard deviations and 0.04 standard deviations from the means, and in some distributions the seventh decile is less than the mean. Thus, using e.g. one standard deviation to the left for low signals and one to the right for high signals, would result in groups not only with few observations but also with a considerable different number of observations between the high and low signals. Consequently, high and low signals are defined in terms of their relative position with respect to other observed signals, and not in terms of the distance from a hypothetical value such as the average[11] signal.

I classify the observations of signals in the right tail of the distribution in high low (HL), high medium (HM) and high high (HH) signals (see figure 2). To do so, I construct the dummies $S^{HL}_{i,t-5}$ which takes the value of one for observations of $EPSG_{i,t-5}$ greater or equal than the seventh cross-sectional decile, $S^{HM}_{i,t-5}$ for the eighth decile and $S^{HH}_{i,t-5}$ for the ninth decile. Similarly, I classify the left tail of the distribution of signals in low high (LH), low medium (LM) and low low (LL) signals by calculating the dummies $S^{LH}_{i,t-5}$, which takes the value of one for observations of $EPSG_{i,t-5}$ lower or equal than the third cross-sectional decile, $S^{LM}_{i,t-5}$ for the second decile and $S^{LL}_{i,t-5}$ for the first decile. Therefore, in order to estimate the effects of high signals on forecast bias, I calculate high signals as $EPSG_{i,t-5}(S^{HL}_{i,t-5})$, $EPSG_{i,t-5}(S^{HM}_{i,t-5})$ and $EPSG_{i,t-5}(S^{HH}_{i,t-5})$. Also, in order to estimate the effects of low signals on forecast bias I calculate low signals as $EPSG_{i,t-5}(S^{LH}_{i,t-5})$, $EPSG_{i,t-5}(S^{LM}_{i,t-5})$ and $EPSG_{i,t-5}(S^{LL}_{i,t-5})$. Together, statistically positive estimates (overreaction) on high signals and statistically negative estimates (underreaction) on low signals, is consistent with systematic optimism. In addition, increasing analysts' overreaction upon the intensity of signals is consistent with the model of trading incentives of Beyer and Guttman (2011).

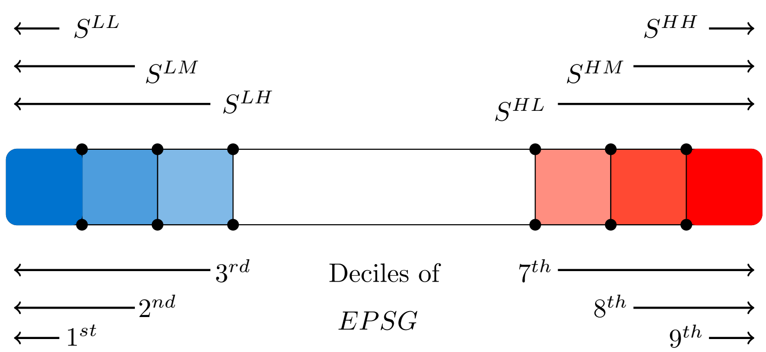

Figure 2: Dummies for Cross-Sectional Deciles of Signals

I estimate high contradictory signals as $EPSG_{i,t-5}(D_{i,t-5}S^{HL}_{i,t-5})$, $EPSG_{i,t-5}(D_{i,t-5}S^{HM}_{i,t-5})$ and $EPSG_{i,t-5}(D_{i,t-5}S^{HH}_{i,t-5})$ (see figure 3) where $D_{i,t-5}$ is a dummy that takes the value of one for a negative (pessimistic) forecast bias on stock prices, i.e. for $y_{i,t-5} < 0$. Since forecasts are issued at $t-4$, analysts observe a past signal at $t-5$ and past pessimism on stock prices is verified when $y_{i,t-5} = \frac{TP_{i,t-9} - P_{i,t-5}}{P_{i,t-9}}$

[11] The average is a value that might not correspond to any actual value. For instance, if the observations set is $\{0, 1\}$, its average of 0.5 is not an observation.

is negative. Alternatively and as a robustness check, from the forecasts of Corporate Profits, $D_{i,t-5}$ takes the value of one whenever the difference between the forecast (issued at $t-6$ for $t-5$) and its realized value (at $t-5$) is less than zero. This is in line with the practice of financial analysts of using aggregate Earnings Per Share or the Corporate Profits from the National Income and Product Accounts to predict movements in stock markets[12]. Statistically zero estimates or negative estimates (underreaction) on high contradictory signals is consistent with confirmation bias. Also, increasing estimates upon the intensity of signals is consistent with the model of Beyer and Guttman (2011).

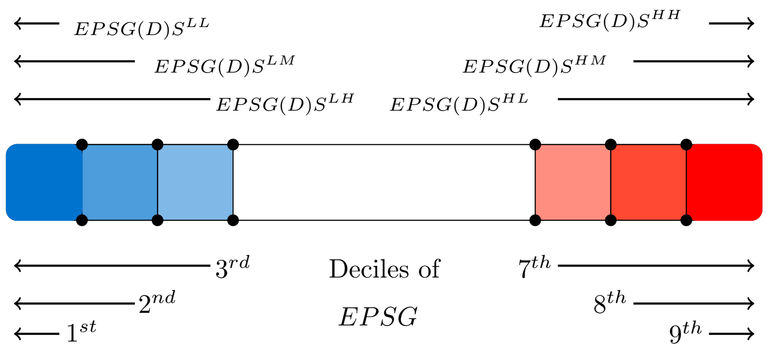

Figure 3: Signals Grouped by Deciles Interacted with $D_{i,t-5}$

To control for reputational incentives, I follow Butler and Saraoglu (1999) and calculate for each stock the standardized (across stocks) value of the squared forecast bias $[y_{i,t-5}]^2 = \left[\frac{TP_{i,t-9} - P_{i,t-5}}{P_{i,t-9}}\right]^2$. If analysts consider their reputation when issuing forecasts, they should correct their past relative inaccuracy (relative to the analysts that follow other stocks) and thus past values of the cross-standardized squared error ($CSE_{i,t-5}$) should be negatively related to present forecast bias. Following the literature I control for the size of the company using the log of market capitalization ($Size_{i,t-5}$), and also for analyst coverage ($\Delta Cvrg_{i,t-4}$). Since not all reports have a target price[13] I use the change in the number of recommendations to measure coverage (see e.g. Niehaus and Zhang, 2010). Also, considering that information seeking is fundamental to stock price formation (Grossman and Stiglitz, 1976; DeLong et al., 1990) and to analysts' precision (Fischer and Stocken; 2010, Hayes, 1998), I use the change in the quarterly average of the Bloomberg's measure for user activity at the terminals, "News Heat - Daily Max Readership" ($\Delta BNH_{i,t-4}$), to capture and control for the information gathering by stock market partic-

[12]For instance, the Cyclically Adjusted Price-Earnings Ratio (CAPE) popularized by Shiller, Campbell and Greenspan in 1996, equals the level of a stock market index divided by the 10-year average of aggregate earnings per share. Moreover, the forecasting ability of the CAPE model improves when using Corporate Profits instead of accounting earnings (Siegel, 2016).

[13]The description of the variable "Analyst Recommendation" provided by Bloomberg affirms that "[r]ecommendations may or may not have a target price associated with them." Asquith et al. (2005) analyzed more than 1000 analyst reports from 11 different investment banks covering 46 industries' during 1997 - 1999 and found that, while all reports included a stock recommendation, only 72.6% contained a target price.

ipants. Notice that while $Size_{i,t-5}$ and $EPSG_{i,t-5}$ are firm characteristics, $\Delta Cvrg_{i,t-4}$ and $\Delta BNH_{i,t-4}$ are characteristics of the informational environment at the moment of issuing a forecast. The summary statistics are in table 1.

Table 1: Summary Statistics.

The dependent variable y is calculated as $\frac{TP_{i,t-4}-P_{i,t}}{P_{i,t-4}}$; $TP_{i,t-4}$ is the target price on stock i for the next 4 quarters; CSE equals the standardized value of $\left[\frac{TP_{i,t-4}-P_{i,t}}{P_{i,t-4}}\right]^2$; $Size$ corresponds to the log of market capitalization; $\Delta Cvrg$ equals the first differences of the number of analysts' recommendations; ΔBNH equals the first differences of the quarterly average of Bloomberg's $News\ Heat - Daily\ Max\ Readership$; and $EPSG$ is $\frac{EPS_{i,t}-EPS_{i,t-1}}{P_{i,t-1}}$. The period goes from the second quarter of 2006 to the fourth quarter of 2016.

	CSE	$Size$	$\Delta Cvrg$	ΔBNH	y	$EPSG$
Min	-0.253	-4.538	-10.00	-4.00	-2.0773	-3.2625
1st Qu.	-0.142	5.402	0.00	0.00	-0.14	-0.0058
Median	-0.075	6.790	0.00	0.00	0.092	0.0002
Mean	-0.003	6.792	0.0829	0.0064	0.174	-0.0038
3rd Qu.	-0.032	8.139	0.00	0.00	0.401	0.0064
Max.	47.593	13.494	40.00	4.00	4.055	0.7653
N	91205	106609	105663	105663	90335	106845

3.3 Descriptive Statistics

In line with the literature on sell-side analysts I drop the extreme values of the sample of optimism eliminating the top 0.5% and the bottom 0.5% of $EPSG$ and y. The final sample consists of 3169 stocks included in the CRSP index with time-series from the second quarter of 2006 to the fourth quarter of 2016. From table 1 we can see that the mean and the median of the forecast bias are positive as we would expect from the empirical literature. Also, from table 1 and figure 5 we see that the distribution has a right tail that is longer than the left tail which Abarbanell and Lehavy (2003) call the tail asymmetry, and means that "far more extreme forecast errors of greater absolute magnitude are observed in the ex-post 'optimistic' tail of the distribution than in the 'pessimistic' tail." In my sample, the average forecast bias is larger than the median, the third quartile is more than three times the size observed for the first quartile, and the maximum is larger than the absolute value of the minimum.

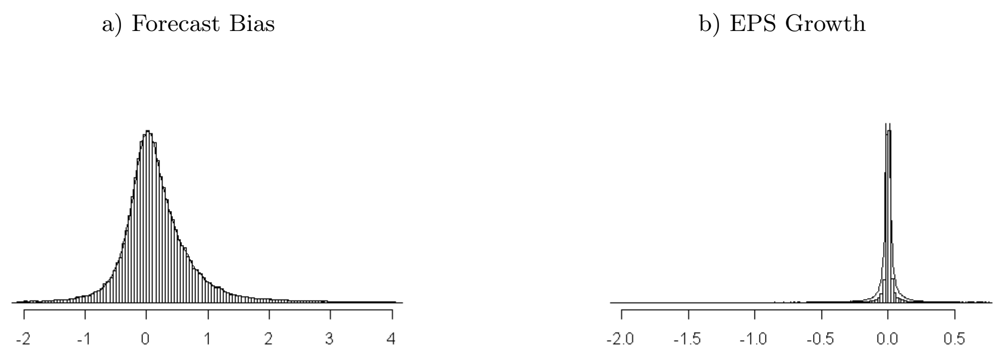

Figure 4: Histograms of Forecast Bias and EPS Growth. *Forecast Bias* and *EPS* Growth are calculated as $y_{i,t} = \frac{TP_{i,t-4} - P_{i,t}}{P_{i,t-4}}$ and $EPSG_{i,t} = \frac{EPS_{i,t} - EPS_{i,t-1}}{P_{i,t-1}}$ respectively.

The concern about the tail asymmetry is that, the likelihood of an observation of forecast bias falling into the tail asymmetry could be conditional on realizations of economic variables and thus, "differences in the manner in which researchers implicitly or explicitly weight observations that fall into these asymmetries contribute to inconsistent conclusions concerning analyst bias and inefficiency."

Table 2: Summary Statistics of Forecast Bias Partitioned by EPS Growth

Forecast Bias and *EPS Growth* are calculated as $y_{i,t} = \frac{TP_{i,t-4} - P_{i,t}}{P_{i,t-4}}$ and $EPSG_{i,t} = \frac{EPS_{i,t} - EPS_{i,t-1}}{P_{i,t-1}}$ respectively. * refers to the percentage of optimistic cases relative to the total number of observations; ** refers to the number of pessimistic forecasts divided by the number of optimistic forecasts.

	Cases in the Bottom 25% of EPSG		Cases in the Middle of EPSG		Cases in the Top 25% of EPSg	
	y	EPSG	y	EPSG	y	EPSG
Min	-2.071	-3.2625	-2.077	-0.0058	-2.071	0.0064
1st Qu.	-0.105	-0.0440	-0.144	-0.0016	-0.163	0.0104
Median	0.164	-0.0185	0.065	0.0002	0.098	0.0187
Mean	0.265	-0.0652	0.123	0.0003	0.197	0.0495
3rd Qu.	0.543	-0.0101	0.324	0.0023	0.456	0.0434
Max.	4.030	-0.0058	4.048	0.0064	4.055	0.7653
N	21399	26712	47674	53421	21262	26712
$y > 0$ $freq^*$.	0.6571		0.5818		0.5958	
$\frac{\#pessim}{\#optim}^{**}$	0.5210		0.7177		0.6768	

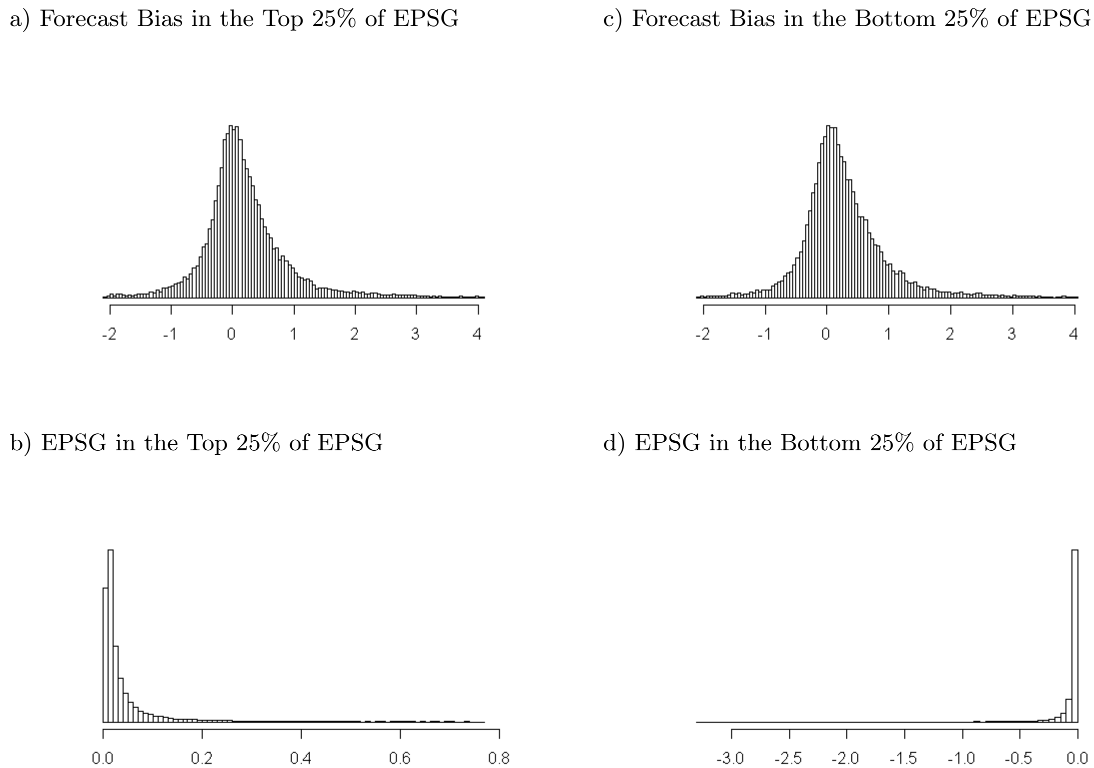

Figure 5: Histograms of Forecast Bias and EPS Growth. *Forecast Bias* and *EPS Growth* are calculated as $y_{i,t} = \frac{TP_{i,t-4} - P_{i,t}}{P_{i,t-4}}$ and $EPSG_{i,t} = \frac{EPS_{i,t} - EPS_{i,t-1}}{P_{i,t}}$ respectively.

There are no indications of Abarbanell and Lehavy's (2003) remark If I partition my sample by the set of cases in the top 25%, the bottom 25% and the observations in the middle of $EPSG$ (see table 2). Both the median and the mean of optimism in each group are positive, the percentages of optimistic forecasts are all around 60% and the ratios of pessimistic to optimistic forecasts are all between 0.52 and 0.72. In contrast, Abarbanell and Lehavy (2003) found, for a skewed distribution of optimism in consensus EPS forecasts, that the median of optimism given negative (positive) earnings changes, were positive (negative), the percentages of optimistic forecasts were 50% (34%, a difference of 16 pp) and the ratios of the number of pessimistic to the number of optimistic forecasts were 0.81 (1.83, the double for positive earnings changes).

4 Empirical Strategy

4.1 Model

I specify the following model:

$$y_{i,t} = c_i + \sum_{j=1}^{4} \rho_j y_{i,t-j} + \boldsymbol{x}_{i,t-5}\boldsymbol{\delta} + \boldsymbol{w}_{i,t-4}\boldsymbol{\gamma} + \lambda_t + u_{i,t} \tag{1}$$

where c_i is a firm-level unobserved effect, λ_t is a time effect common to all firms, $u_{i,t}$ is the error term with $t = 1, ..., T$ and $i = 1, ..., N$ and the other variables are defined as above. The vector of explanatory variables $\boldsymbol{x}_{i,t-5}$ of dimension 1x17 is composed by $EPSG_{i,t-5}$, $D_{i,t-5}$, $S^{LL}_{i,t-5}$, $S^{LM}_{i,t-5}$, $S^{LH}_{i,t-5}$, $S^{HL}_{i,t-5}$, $S^{HM}_{i,t-5}$ and $S^{HH}_{i,t-5}$ as well as by their interactions. It also includes $Size_{i,t-5}$ and the cross-standardized squared error (CSE) at $t-5$ since at t past inaccuracy is observable only from $t-5$[14]. The vector $\boldsymbol{w}_{i,t-4}$ of 1x2 includes $\Delta Cvrg_{i,t-4}$ and $\Delta BNH_{i,t-4}$ which are not firm characteristics but are variables associated to the informational environment. The vectors of parameters $\boldsymbol{\delta}$ and $\boldsymbol{\gamma}$ are of dimensions 17x1 and 2x1 respectively.

In equation 1, statistically positive values of the parameters on the interactions $EPSG_{i,t-5}(D_{i,t-5}S^{HL}_{i,t-5})$, $EPSG_{i,t-5}(D_{i,t-5}S^{HM}_{i,t-5})$ and $EPSG_{i,t-5}(D_{i,t-5}S^{HH}_{i,t-5})$ would show that analysts bias their forecasts in the direction of a high contradictory signal for different levels of intensity. Let δ_1, δ_2 and δ_3 be such parameters. Statistically negative or zero values of δ_1, δ_2 and δ_3 are consistent with confirmatory bias. Whether or not the strength of the signal countervails the presence of confirmatory bias can be known from the differences between the parameters. Values of the estimates such that $\delta_1 \leq \delta_2 < \delta_3$ or such that $\delta_1 < \delta_2 \leq \delta_3$ would indicate that, as the strength of the high signal increases, analysts bias their forecasts in the direction of the signal to a greater extent, notwithstanding their pessimistic prior. Together, analysts' overreaction to high signals and underreaction to low signals, is consistent with systematic optimism (Easterwood and Nutt, 1999). Also, increasing overreaction upon the intensity of signals is consistent with the model of trading incentives of Beyer and Guttman (2011). Finally, underreaction to high contradictory signals is consistent with confirmation bias (Pouget et al., 2017).

4.2 Identification

As explained in section 3, $EPSG_{i,t-5}$ and its deciles are not affected by analysts' forecasts at t. In addition, since $D_{i,t-5}$, $CSE_{i,t-5}$ and $Size_{i,t-5}$ are included at $t-5$, they can be considered exogenous in equation 1. That is, the vector $\boldsymbol{x}_{i,t-5}$ is exogenous. In contrast, it is very likely that there is feedback

[14]Notice that the squared error at $t-5$ is $SE_{i,t-5} = \left[\dfrac{TP_{i,t-9} - P_{i,t-5}}{P_{i,t-9}}\right]^2$

between optimism (which contains target prices at $t-4$) and analysts' coverage ($\Delta Cvrg_{i,t-4}$) and news seeking ($\Delta BNH_{i,t-4}$). Thus, the vector $\boldsymbol{w}_{i,t-4}$ is not exogenous in equation 1. Nevertheless, it is reasonable to say that $\boldsymbol{w}_{i,t-4}$ is sequentially exogenous in the sense that forecasts at $t-4$ do not affect the coverage or news seeking before $t-4$. I will use this to estimate the parameters.

In equation 1, the random effects assumption of independence between the regressors and the unobserved term is invalid. Additionally, as Nickell (1981) showed, the fixed effects estimator of ρ_1 is biased and inconsistent for a fixed T and $N \to \infty$ since the within-transformed lagged dependent variable and the within-transformed error are correlated. Thus, I use a difference transformation of equation 1 to eliminate the unobserved c_i:

$$\Delta y_{i,t} = \sum_{j=1}^{4} \rho_j \Delta y_{i,t-j} + \Delta \boldsymbol{x}_{i,t-5}\boldsymbol{\delta} + \Delta \boldsymbol{w}_{i,t-4}\boldsymbol{\gamma} + \Delta\lambda_t + \Delta u_{i,t} \tag{2}$$

where $\Delta y_{i,t} = y_{i,t} - y_{i,t-1}$ and the parameter vector of interest $\boldsymbol{\delta}$ is the same of equation 1. That is, estimating equation 2 gives the parameters of equation 1. In equation 2, $\Delta u_{i,t}$ and $\Delta y_{i,t-1}$ are, by construction, correlated, i.e. $\Delta y_{i,t-1}$ brings an endogeneity problem so ordinary least squares estimators are inconsistent. Nevertheless, with $u_{i,t}$ that are $i.d.d$ we have that $\mathbb{E}[(u_{i,t} - u_{i,t-1})(y_{i,t-2})] = 0$ which suggests that we can use an instrumental variables approach.

As proposed by Arellano and Bond (1991)[15], all lags of y from $t-2$ are potential instruments for $\Delta y_{i,t-1}$ that solve the endogeneity problem in equation 2. In addition, for $\boldsymbol{w}_{i,t-4}$ we have $\mathbb{E}[(u_{i,t} - u_{i,t-1})(w_{i,t-6})] = 0$ and I can use all lags of $\boldsymbol{w}_{i,t}$ from $t-6$ as potential instruments for $\Delta \boldsymbol{w}_{i,t-4}$. From this set of potential valid instruments, I must choose a number of them that brings an overidentified model in order to test their validity. The validity of these instruments, nonetheless, do require that the error terms $u_{i,t}$ of equation 1 are not serially correlated, that is, it requires $\mathbb{E}[\Delta u_{i,t} \Delta u_{i,t-2}] = 0$ for which I use the Arellano and Bond's (1991) m-statistic to test the second-order residual serial correlation coefficient, and Sargan test of over-identifying restrictions. Finally, the exogeneity of the signals allows us to have consistent estimators of their corresponding parameters in equation 2 without using its lagged values as instruments and to give them a causality interpretation.

As in Arellano and Bond (1991), the potential valid instruments increase as t increases. For instance,

[15] I do not make use of the orthogonal deviations proposed by Arellano and Bover (1995) to eliminate c_i because I can expect that ρ_1 does not approach to 1. Although, individually, stock prices and target prices may be integrated of order one, notice that $y_{i,t}$ can be expressed as the difference between $\frac{TP_{i,t}}{P_t}$ and $\frac{P_{i,t+4}}{P_t}$ both of which are growth rates and a linear combination of two $I(0)$ variables is $I(0)$. In this regard, Brav and Lehavy (2003) found that the target price-to-stock price ratio seems graphically stationary and that target and stock prices are cointegrated.

at $t = 6$ the moment conditions are:

$$\mathbb{E}[(u_{i,6} - u_{i,5})(y_{i,4})] = 0$$

$$\mathbb{E}[(u_{i,6} - u_{i,5})(y_{i,3})] = 0$$

$$\mathbb{E}[(u_{i,6} - u_{i,5})(y_{i,2})] = 0$$

$$\mathbb{E}[(u_{i,6} - u_{i,5})(y_{i,1})] = 0$$

$$\mathbb{E}[(u_{i,6} - u_{i,5})(y_{i,0})] = 0$$

and therefore, for $\Delta y_{i,6}$ I can use some or all the instruments from the set $\{y_{i,4}, y_{i,3}, ..., y_{i,0}\}$. For $t = 7$ the moment conditions are

$$\mathbb{E}[(u_{i,7} - u_{i,6})(y_{i,5})] = 0$$

$$\mathbb{E}[(u_{i,7} - u_{i,6})(y_{i,4})] = 0$$

$$\vdots$$

$$\mathbb{E}[(u_{i,7} - u_{i,6})(y_{i,0})] = 0$$

and the set of potential valid instruments for $\Delta y_{i,7}$ is therefore $\{y_{i,5}, y_{i,4}, ..., y_{i,0}\}$. Similarly, for each $t \geq 6$ the instruments for $\Delta \boldsymbol{w}_{i,t-4}$ are the lags of $\boldsymbol{w}_{i,t}$ from $t-6$. This variable is instrumented since the forecast bias $y_{i,t}$ is constructed using the price forecast issued at $t-4$ which, as explained in the beginning of this section, is correlated with $\Delta \boldsymbol{w}_{i,t-4}$. Finally, $\Delta \boldsymbol{x}_{i,t-5}$ is used as its own instrument.

To develop the estimators, I express equation 1 as

$$y_i = c_i + X_i \boldsymbol{\beta} + u_i \tag{3}$$

and equation 2 as

$$\Delta y_i = \Delta X_i \boldsymbol{\beta} + \Delta u_i \tag{4}$$

where $\Delta X_i \equiv (\Delta y_{i,-1}, \Delta y_{i,-2}, \Delta y_{i,-3}, \Delta y_{i,-4}, \Delta \boldsymbol{x}_{i,-5}, \Delta \boldsymbol{w}_{i,-4}, d)$, d is a time dummy and $\boldsymbol{\beta}$ is the vector of parameters $(\rho_1, \rho_2, \rho_3, \rho_4, \boldsymbol{\delta}, \boldsymbol{\gamma}, \lambda)'$. Notice that the vector $\boldsymbol{\beta}$ of equation 4 is the same as the vector in equation 3 so that I am estimating the parameters of the equation in levels through the equation in differences. Remembering that $\boldsymbol{w}_{i,t-4}$ is instrumented using its lags from $t-6$, let

$$\Delta u_i = \begin{bmatrix} \Delta u_{i,6} \\ \vdots \\ \Delta u_{i,T} \end{bmatrix}$$

and let the block diagonal matrix Z_i be the instrument matrix:

$$\begin{bmatrix} [y_{i,0},...,y_{i,4},\boldsymbol{w}_{i,0},\boldsymbol{\Delta x}_{i,1},d_6] & 0 & \dots & 0 \\ 0 & [y_{i,0},...,y_{i,5},\boldsymbol{w}_{i,0},\boldsymbol{w}_{i,1},\boldsymbol{\Delta x}_{i,2},d_7] & & 0 \\ \vdots & & \ddots & 0 \\ 0 & \dots & 0 & [y_{i,0},...,y_{i,T-2},\boldsymbol{w}_{i,0},...,\boldsymbol{w}_{i,T-6},\boldsymbol{\Delta x}_{i,T-5},d_T] \end{bmatrix}$$

Therefore, the set of moment conditions can be expressed as $\mathbb{E}[Z_i'\Delta u_i] = \mathbb{E}[Z_i'(\Delta y_i - \Delta X_i\boldsymbol{\beta})] = 0$ and the GMM estimators of the parameters can be found by solving:

$$\min_{\boldsymbol{\beta}} \left[\sum_{i=1}^{N}[Z_i'(\Delta y_i - \Delta X_i\boldsymbol{\beta})\right]' A \left[\sum_{i=1}^{N}[Z_i'(\Delta y_i - \Delta X_i\boldsymbol{\beta})\right]$$

where A is the weighting matrix of the moments, which must satisfy $A = \mathbb{E}[Z_i'\Delta u_i\Delta u_i'Z_i]^{-1}$ so that we get the most efficient estimator. Notice that with error terms in levels that are *i.i.d.* we have that

$$\mathbb{E}[\Delta u_i\Delta u_i'] = \sigma_u^2 G = \sigma_u^2 \begin{bmatrix} 2 & -1 & 0 & \dots \\ -1 & 2 & \ddots & 0 \\ 0 & \ddots & \ddots & -1 \\ \vdots & 0 & -1 & 2 \end{bmatrix}$$

Thus, it is possible to first solve for $\boldsymbol{\beta}$ utilizing $\hat{A} = [\sum_{i=1}^{N} Z_i'GZ_i]^{-1}$ and estimate $\Delta\hat{u}_i$. Afterwards, we can estimate A as

$$A^* = [\sum_{i=1}^{N} Z_i'\Delta\hat{u}_i\Delta\hat{u}_i'Z_i]^{-1}$$

Therefore, the GMM estimator can be computed as:

$$\boldsymbol{\beta}_{GMM} = (\Delta X'ZA^*Z'\Delta X)^{-1}(\Delta X'ZA^*Z'\Delta y)$$

$$= \left[\left(\sum_{i=1}^{N}\Delta X_i'Z_i\right) A^* \left(\sum_{i=1}^{N} Z_i'\Delta X_i\right)\right]^{-1} \left[\left(\sum_{i=1}^{N}\Delta X_i'Z_i\right) A^* \left(\sum_{i=1}^{N} Z_i'\Delta y_i\right)\right]$$

5 Results

In table 3, I report the results from a regression that shows the basic relation between signals and forecast bias where column (1) shows the results of a specification with two autoregressive terms and column (2) includes one autoregressive term. Although both specifications show that the instruments are valid according to the Sargan test, the inclusion of two autoregressive terms augments the probability that there is no second-order serial correlation of the residuals (see the m-statistics), i.e. that the instruments are valid. This first regression shows a coefficient on $EPSG_{i,t-5}$ significantly positive, indicating overreaction consistent with DeBondt and Thaler (1990) and that $y_{i,t}$ is autocorrelated with an estimate such that $0 < \rho < 1$ which does not meet the classical rational expectations hypothesis since the bias is to some extent predictable from past observed biases and public information[16].

Table 3: Panel Regression of Forecast Bias on Earnings Per Share Growth

The dependent variable $y_{i,t}$ is calculated as $\frac{TP_{i,t-4}-P_{i,t}}{P_{i,t-4}}$; $TP_{i,t-4}$ is the consensus target price on stock i for the next 4 quarters; the signal $EPSG_{i,t-5}$ is calculated as $\frac{EPS_{i,t-5}-EPS_{i,t-6}}{P_{i,t-6}}$. The control variables are the following: $CSE_{i,t-5}$ equals the standardized value of $\left[\frac{TP_{i,t-9}-P_{i,t-5}}{P_{i,t-9}}\right]^2$; $Size_{i,t-5}$ corresponds to the log of market capitalization; $\Delta Cvrg_{i,t-4}$ equals the first differences of the number of analysts' recommendations; and $\Delta BNH_{i,t-4}$ equals the first differences of the quarterly average of Bloomberg's $News\ Heat - Daily\ Max\ Readership$. In both specifications there are 5 more instruments than regressors. The instruments used for $\Delta Cvrg_{i,t-4}$ and $\Delta BNH_{i,t-4}$ are their lags from $t-6$ to $t-8$. The instruments for $y_{i,t-1}$ are the lags from $t-2$ to $t-4$ in column (1) and from $t-2$ to $t-3$ in column (2). The instruments for the other variables are the first differences of themselves.***, ** and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively. Robust standard errors in parenthesis.

Varible	(1)	(2)
$y_{i,t-1}$	0.6806***	0.6311***
	(0.0315)	(0.0267)
$y_{i,t-3}$	0.0311***	—
	(0.0098)	—
$EPSG_{i,t-5}$	0.1032***	0.0932***
	(0.0318)	(0.0289)
Controls	yes	yes
N	70252	71414
(Sargan) $\chi^2(5)$	8.0540	6.6235
(p-value)	(0.1533)	(0.2502)
First-order m-statistic	-11.0217	-12.6965
(p-value)	(0.0000)	(0.0000)
Second-order m-statistic	-0.2153	-1.8137
(p-value)	(0.8295)	(0.0697)

Although not reported, the coefficient on coverage changes is significant and negative, which is consistent with the research that show that stocks with higher analyst following have more accurate analysts' reports (Merkley, Michaely and Pacelli, 2017; Wieland 2011; Hong et al., 2000; Mikhail et al., 1997). The estimate of the parameter on $\Delta BNH_{i,t-4}$ is negative (although not significant), sign that is consistent with the idea that more informed investors have more precise signals which induces analysts to issue more accurate and less optimistic reports. For instance, Fischer and Stocken (2010) theoretically show that, as investors receive a more precise signal, analysts make more precise forecasts in order to increase the investors' responsiveness and gain credibility which suggests that variables that capture informed trading may serve as a control for reputational incentives. In addition, $CSE_{i,t-5}$ is statistically negative consistent with analysts that, after knowing their inaccuracy relative to the analysts that follow other stocks, try to correct their past relative inaccuracy in line with Butler and Saraoglu (1999). The statistically positive coefficient on $Size_{i,t-5}$ is in line with Hayes (1998), who theoretically proposes that firm size incentivize analysts to follow the stock whenever they have favorable views about it.

[16] Traditionally, rational forecasts are considered to have forecast errors with an unconditional mean of zero (unbiasedness), a zero mean conditional on current and past values of the forecasted variable (efficiency), and zero correlation with other variables in the information set (Ackert and Hunter, 1995; Eastwood and Nutt, 1999; Lim, 2001; Keane and Runkle, 1998; Abarbanell and Bernard, 1992).

In table 4 I report the estimates of equation 1 using the signal dummies $S^L_{i,t-5}$ and $S^H_{i,t-5}$ which take the value of one for signals that are less or equal than the third decile and greater or equal than the seventh decile respectively. Also $D_{i,t-5}$ takes the value of one for $y_{i,t-5} < 0$. Columns (1), (3), (5) and (7) include controls and columns (2), (4), (6) and (8) do not include the endogenous controls. Columns (1) and (2) show the estimates of the model that includes the signals $EPSG_{i,t-5}$ and the dummies without interactions. Columns (3) and (4) also include $D_{i,t-5}$ interacted with $S^L_{i,t-5}$, $S^H_{i,t-5}$ and $EPSG_{i,t-5}$. Columns (5) and (6) add high ($EPSG_{i,t-5}S^H_{i,t-5}$) and low signals ($EPSG_{i,t-5}S^L_{i,t-5}$), and columns (7) and (8) add high and low signals interacted with $D_{i,t-5}$. As seen in columns (7) and (8), the negative estimates on $EPSG_{i,t-5}(D_{i,t-5}S^{HL}_{i,t-5})$ are consistent with confirmation bias (see figure 6). Given the observed pessimism at the time of observing a past signal ($D_{i,t-5} = 1$), analysts underreact to high (contradictory) signals. The negative estimates on $EPSG_{i,t-5}(D_{i,t-5}S^{LH}_{i,t-5})$ show that analysts underreact to low signals, consistent with systematic optimism (Easterwood and Nutt, 1999). In addition, the positive estimates on $S^{HL}_{i,t-5}$ show that the average forecast bias is positive (optimistic) and statistically different for those stocks with a high signal compared to the forecast bias on the stocks with signals in the middle. The negative estimates on $D_{i,t-5}S^{LH}_{i,t-5}$ show that the average forecast bias is negative (pessimistic) whenever the signal was low, and it is statistically different with respect to those stocks with signals in the middle.

Table 4: Panel Regression of Forecast Bias on Low, High and High Contradictory Signals. Past Pessimism in Stock Prices as Prior.

The dependent variable $y_{i,t}$ is calculated as $\frac{TP_{i,t-4}-P_{i,t}}{P_{i,t-4}}$; $TP_{i,t-4}$ is the consensus target price on stock i for the next 4 quarters; the signal $EPSG_{i,t-5}$ is calculated as $\frac{EPS_{i,t-5}-EPS_{i,t-6}}{P_{i,t-6}}$. The dummy $S^L_{i,t-5}$ takes the value of one whenever $EPSG_{i,t-5}$ is lower or equal than the 3rd cross-sectional decile. The dummy $S^H_{i,t-5}$ takes the value of one whenever $EPSG_{i,t-5}$ is higher or equal than the 7th cross-sectional decile. The dummy $D_{i,t-5}$ takes the value of one for $y_{i,t-5} < 0$. All specifications include $Size_{i,t-5}$ and $CSE_{i,t-5}$ which are exogenous to $u_{i,t}$. In the specifications that include the non-exogenous controls (columns (1), (3), (5) and (7)) there are 5 more instruments than regressors and the specifications without these controls have one more instruments than regressors. The instruments for $y_{i,t-1}$ are its the lags from $t-2$ to $t-4$. The instruments used for $\Delta Cvrg_{i,t-4}$ and $\Delta BNH_{i,t-4}$ are their lags from $t-6$ to $t-8$. The instruments for the other variables are the first differences of themselves. ***, ** and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively. Robust standard errors in parenthesis.

Varible	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$y_{i,t-1}$	0.7168***	0.6886***	0.7172***	0.6888***	0.7232***	0.6930***	0.7240***	0.6932***
	(0.0332)	(0.0268)	(0.0332)	(0.0268)	(0.0336)	(0.0269)	(0.0336)	(0.0269)
$y_{i,t-3}$	0.0446***	0.0377***	0.0445***	0.0376***	0.0443***	0.0371***	0.0443***	0.0370***
	(0.0112)	(0.0010)	(0.0112)	(0.0010)	(0.0112)	(0.0099)	(0.0112)	(0.0100)
$EPSG_{i,t-5}$	0.0522	0.0509	0.0560	0.0543	0.3162	0.3010	−1.2238	−0.9614
	(0.0358)	(0.0332)	(0.0390)	(0.0360)	(0.7536)	(0.6389)	(1.0784)	(0.9240)
$D_{i,t-5}$	−0.0095**	−0.0078**	−0.0023	−0.0014	−0.0033	−0.0022	−0.0048	−0.0033
	(0.0044)	(0.0038)	(0.0048)	(0.0041)	(0.0049)	(0.0041)	(0.0050)	(0.0042)
$S^L_{i,t-5}$	−0.0081**	−0.0078**	−0.0017	−0.0019	−0.0030	−0.0031	−0.0038	−0.0039
	(0.0038)	(0.0034)	(0.0053)	(0.0047)	(0.0054)	(0.0048)	(0.0055)	(0.0048)
$S^H_{i,t-5}$	0.0159***	0.0146***	0.0207***	0.0187***	0.0151***	0.0134***	0.0141**	0.0124**
	(0.0039)	(0.0035)	(0.0054)	(0.0049)	(0.0055)	(0.0050)	(0.0055)	(0.0050)
$D_{i,t-5}S^L_{i,t-5}$			−0.0166**	−0.0153**	−0.0178**	−0.0163***	−0.0145**	−0.0129**
			(0.0068)	(0.0059)	(0.0070)	(0.0059)	(0.0073)	(0.0062)
$D_{i,t-5}S^H_{i,t-5}$			−0.0114	−0.0098	−0.0084	−0.0069	−0.0046	−0.0031
			(0.0070)	(0.0062)	(0.0071)	(0.0062)	(0.0074)	(0.0064)
$D_{i,t-5}EPSG_{i,t-5}$			−0.0293	−0.0208	−0.077	−0.0645	3.8521***	3.1644***
			(0.0844)	(0.0728)	(0.0852)	(0.0736)	(1.4306)	(1.2059)
$EPSG_{i,t-5}S^L_{i,t-5}$					−0.3938	−0.3748	1.1412	0.8816
					(0.7535)	(0.6394)	(1.0774)	(0.9238)
$EPSG_{i,t-5}S^H_{i,t-5}$					−0.0208	−0.0199	1.5300	1.2551
					(0.7574)	(0.6411)	(1.0829)	(0.9264)
$EPSG_{i,t-5}(D_{i,t-5}S^L_{i,t-5})$							−3.8454***	−3.1259***
							(1.4418)	(1.2092)
$EPSG_{i,t-5}(D_{i,t-5}S^H_{i,t-5})$							−4.0393***	−3.3579***
							(1.4387)	(1.2119)
Controls	Yes	No	Yes	No	Yes	No	Yes	No
N	66966	66966	66966	66966	66966	66966	66966	66966
(Sargan) χ^2	7.0558	0.4759	6.9770	0.4974	7.1498	0.4741	7.0761	0.4934
(p-value)	(0.2165)	(0.4903)	(0.2223)	(0.4806)	(0.2097)	(0.4911)	(0.2150)	(0.4824)
First-order m-statistic	-10.3798	-21.7398	-10.3496	-21.7398	-10.0674	-21.7772	-10.0137	-21.7726
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Second-order m-statistic	0.3062	0.4104	0.2724	0.3861	0.3046	0.4163	0.2843	0.3930
(p-value)	(0.7594)	(0.6815)	(0.7853)	(0.6994)	(0.7607)	(0.6772)	(0.7762)	(0.6943)

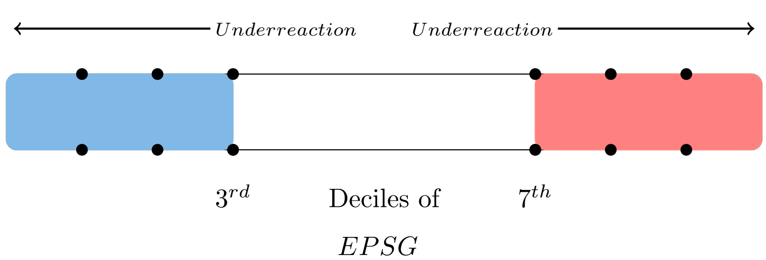

Figure 6: Results on High and Low Signals Interacted with $D_{i,t-5}$

In order to verify if the intensity of the high signals counteract the effects of confirmation bias, I calculate the interactions disaggregating high and low signals by deciles. I show the results in table 5. The negative estimates on $EPSG_{i,t-5}(D_{i,t-5}S^{HL}_{i;t-5})$ and the positive estimates on $EPSG_{i,t-5}(D_{i,t-5}S^{HH}_{i,t-5})$ indicate that, given a pessimistic prior ($D_{i,t-5} = 1$), analysts underreact to high signals consistent with confirmation bias (see figure 7), but overreact when the signal is above the ninth decile which is consistent with the model of Beyer and Guttman (2011). In both regressions, with and without controls, the estimates are nondecreasing functions of the signal. As shown in columns (7) and (8), the estimates on the high contradictory signals increase as we go from the seventh decile to the ninth decile. For instance, in the specification with controls of column (7), the coefficient on $EPSG_{i,t-5}(D_{i,t-5}S^{HL}_{i;t-5})$ is statistically negative, the one on $EPSG_{i,t-5}(D_{i,t-5}S^{HM}_{i;t-5})$ is statistically zero and the estimate on $EPSG_{i,t-5}(D_{i,t-5}S^{HH}_{i;t-5})$ is statistically positive. That is, as the strength of the high contradictory signal increases, the parameters go from statistically negative to statistically positive. The negative estimate (seventh decile) and the zero estimate (eighth decile) indicate that, given their pessimistic prior, analysts do not bias their forecasts in the direction of the signal, consistent with Pouget's et al. (2017) findings on confirmation bias. The fact that the values of the estimates are increasing in the deciles show that the strength of the high contradictory signal counteracts the effects of confirmation bias as expected from Beyer and Guttman (2011). The statistically positive estimate on $EPSG_{i,t-5}(D_{i,t-5}S^{HH}_{i;t-5})$ show that analysts bias their forecast in the direction of the signals above the ninth decile, notwithstanding their pessimistic prior. With respect to low signals, the estimates show that analysts underreact to these (negative estimates on $EPSG_{i,t-5}(D_{i,t-5}S^{LH}_{i,t-5})$) consistent with systematic optimism except for sufficiently low signals consistent with Beyer and Guttman (2011). Specifically, in both columns (7) and (8) the estimates go from statistically negative to statistically zero and in the regression with controls, the estimates increase as the signal lowers.

Table 5: Panel Regression of Forecast Bias on High Contradictory Signals Grouped by Deciles. Past Pessimism in Stock Prices as Prior.

The dependent variable $y_{i,t}$ is calculated as $\frac{TP_{i,t-4}-P_{i,t}}{P_{i,t-4}}$; $TP_{i,t-4}$ is the consensus target price on stock i for the next 4 quarters; the signal $EPSG_{i,t-5}$ is calculated as $\frac{EPS_{i,t-5}-EPS_{i,t-6}}{P_{i,t-6}}$. The dummies $S^{LH}_{i,t-5}$, $S^{LM}_{i,t-5}$ and $S^{LL}_{i,t-5}$ take the value of one whenever $EPSG_{i,t-5}$ is lower or equal than the 3rd, 2nd and 1st cross-sectional deciles respectively. The dummies $S^{HL}_{i,t-5}$, $S^{HM}_{i,t-5}$ and $S^{HH}_{i,t-5}$ take the value of one whenever $EPSG_{i,t-5}$ is higher or equal than the 7th, 8th and 9th cross-sectional deciles respectively. The dummy $D_{i,t-5}$ takes the value of one for $y_{i,t-5} < 0$. All specifications include $Size_{i,t-5}$ and $CSE_{i,t-5}$ which are exogenous. In the specifications that include the non-exogenous controls (columns (1), (3), (5) and (7)) there are 5 more instruments than regressors and the specifications without these controls have one more instruments than regressors. The instruments for $y_{i,t-1}$ are its the lags from $t-2$ to $t-4$. The instruments used for $\Delta Cvrg_{i,t-4}$ and $\Delta BNH_{i,t-4}$ are their lags from $t-6$ to $t-8$. The instruments for the other variables are the first differences of themselves. ***, ** and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively. Robust standard errors in parenthesis.

Varible	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$y_{i,t-1}$	0.7168^{***}	0.6886^{***}	0.7172^{***}	0.6888^{***}	0.7232^{***}	0.6930^{***}	0.7238^{***}	0.6929^{***}
	(0.0332)	(0.0268)	(0.0332)	(0.0268)	(0.0336)	(0.0269)	(0.0337)	(0.0269)
$y_{i,t-3}$	0.0446^{***}	0.0377^{***}	0.0445^{***}	0.0376^{***}	0.0443^{***}	0.0371^{***}	0.0442^{***}	0.0369^{***}
	(0.0112)	(0.0010)	(0.0112)	(0.0010)	(0.0112)	(0.0099)	(0.0112)	(0.0099)
$EPSG_{i,t-5}$	0.0522	0.0509	0.0560	0.0543	0.3162	0.3010	-1.2301	-0.9643
	(0.0358)	(0.0332)	(0.0390)	(0.0360)	(0.7536)	(0.6389)	(1.0801)	(0.9239)
$D_{i,t-5}$	-0.0095^{**}	-0.0078^{**}	-0.0023	-0.0014	-0.0033	-0.0022	-0.0046	-0.0033
	(0.0044)	(0.0038)	(0.0048)	(0.0041)	(0.0049)	(0.0041)	(0.0050)	(0.0042)
$S^{LH}_{i,t-5}$	-0.0081^{**}	-0.0078^{**}	-0.0017	-0.0019	-0.0030	-0.0031	-0.0039	-0.0039
	(0.0038)	(0.0034)	(0.0053)	(0.0047)	(0.0054)	(0.0048)	(0.0055)	(0.0048)
$S^{HL}_{i,t-5}$	0.0159^{***}	0.0146^{***}	0.0207^{***}	0.0187^{***}	0.0151^{***}	0.0134^{***}	0.0140^{**}	0.0124^{**}
	(0.0039)	(0.0035)	(0.0054)	(0.0049)	(0.0055)	(0.0050)	(0.0056)	(0.0050)
$D_{i,t-5}S^{LH}_{i,t-5}$			-0.0166^{**}	-0.0153^{**}	-0.0178^{**}	-0.0163^{***}	-0.0134	-0.0116
			(0.0068)	(0.0059)	(0.0070)	(0.0059)	(0.0095)	(0.0084)
$D_{i,t-5}S^{HL}_{i,t-5}$			-0.0114	-0.0098	-0.0084	-0.0069	0.0085	0.0092
			(0.0070)	(0.0062)	(0.0071)	(0.0062)	(0.0113)	(0.0097)
$D_{i,t-5}EPSG_{i,t-5}$			-0.0293	-0.0208	-0.077	-0.0645	3.8447^{***}	3.1541^{***}
			(0.0844)	(0.0728)	(0.0852)	(0.0736)	(1.4305)	(1.2046)
$EPSG_{i,t-5}S^{LH}_{i,t-5}$					-0.3938	-0.3748	1.1477	0.8845
					(0.7535)	(0.6394)	(1.0791)	(0.9237)
$EPSG_{i,t-5}S^{HL}_{i,t-5}$					-0.0208	-0.0199	1.5363	1.2579
					(0.7574)	(0.6411)	(1.0846)	(0.9263)
$EPSG_{i,t-5}(D_{i,t-5}S^{LL}_{i,t-5})$							-0.0782	-0.1271
							(0.5189)	(0.4707)
$EPSG_{i,t-5}(D_{i,t-5}S^{LM}_{i,t-5})$							-0.1563	-0.0362
							(1.0403)	(0.8987)
$EPSG_{i,t-5}(D_{i,t-5}S^{LH}_{i,t-5})$							-3.5990^{*}	-2.9476^{*}
							(1.8950)	(1.6303)
$EPSG_{i,t-5}(D_{i,t-5}S^{HL}_{i,t-5})$							-5.6271^{***}	-5.1155^{***}
							(1.9495)	(1.6470)
$EPSG_{i,t-5}(D_{i,t-5}S^{HM}_{i,t-5})$							0.3704	0.8009
							(0.9680)	(0.7636)
$EPSG_{i,t-5}(D_{i,t-5}S^{HH}_{i,t-5})$							1.1764^{*}	0.9165
							(0.6971)	(0.6103)
Controls	Yes	No	Yes	No	Yes	No	Yes	No
N	66966	66966	66966	66966	66966	66966	66966	66966
(Sargan) χ^2	7.0558	0.4759	6.9770	0.4974	7.1498	0.4741	7.0700	0.5120
(p-value)	(0.2165)	(0.4903)	(0.2223)	(0.4806)	(0.2097)	(0.4911)	(0.2155)	(0.4743)
First-order m-statistic	-10.3798	-21.7398	-10.3496	-21.7398	-10.0674	-21.7772	-9.9550	-21.7800
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Second-order m-statistic	0.3062	0.4104	0.2724	0.3861	0.3046	0.4163	0.2653	0.3754
(p-value)	(0.7594)	(0.6815)	(0.7853)	(0.6994)	(0.7607)	(0.6772)	(0.7908)	(0.7073)

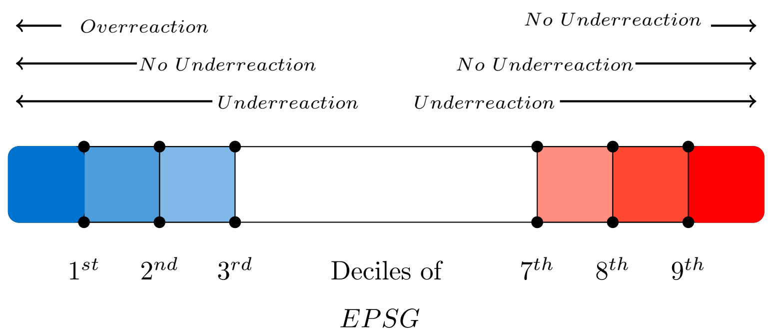

Figure 7: Results on High and Low Signals by Deciles Interacted with D

Overall, these results connect the theoretical implications of Beyer and Guttman (2011), with the empirical and theoretical results of Pouget et al. (2017) on confirmation bias. Specifically, analysts' forecasts are related to prior pessimistic beliefs and high signals as expected from confirmation bias, nonetheless, the effects of confirmation bias is counteracted by sufficiently strong high signals as we would expect from rational analysts as in Beyer and Guttman (2011).

Although not reported, the results of all controls were similar as those of table 3 in terms of significance and sign for both specifications. These results point out that forecast accuracy improves with higher analyst coverage, that firm size is positively associated to favorable views about the stock and that analysts partially correct their past relative inaccuracy. Additionally, the negative relation between the news seeking at Bloomberg Terminals and optimism suggests that variables that capture informed trading may serve as a control for reputational incentives (see e.g. Fischer and Stocken, 2010)

5.1 Robustness Check

As a robustness check, I now use the negative forecast bias in Corporate Profits as a proxy for prior beliefs in line with the practice of financial analysts of using aggregate Earnings Per Share or the Corporate Profits from the National Income and Product Accounts to predict movements in stock markets e.g. using Shiller's Cyclically Adjusted Price-Earnings Ratio (CAPE) . As Siegel (2016) found, the forecasting ability of the CAPE model improves when using Corporate Profits instead of reported GAAP[17] earnings. Therefore, $D_{i,t-5}$ takes the value of one whenever the difference between the forecast (issued at $t-6$ for $t-5$) and its realized value (at $t-5$) is less than zero.

The results, in table 6, are similar to those obtained before. For $D_{i,t-5} = 1$, analysts underreact to high contradictory signals as well as to low signals. Also, the average forecast bias is optimistic for those

[17]GAAP stands for "generally accepted accounting principles."

stocks with a high signal and statistically different than the forecast bias on the stocks with signals in the middle. The average forecast bias is pessimistic whenever the signal was low, and it is statistically different with respect to those stocks with signals in the middle.

Table 6: Panel Regression of Forecast Bias on Low, High and High Contradictory Signals. Past Pessimism in Corporate Profits as Prior.

The dependent variable $y_{i,t}$ is calculated as $\frac{TP_{i,t-4}-P_{i,t}}{P_{i,t-4}}$; $TP_{i,t-4}$ is the consensus target price on stock i for the next 4 quarters; the signal $EPSG_{i,t-5}$ is calculated as $\frac{EPS_{i,t-5}-EPS_{i,t-6}}{P_{i,t-6}}$. The dummy $S^{LH}_{i,t-5}$ takes the value of one whenever $EPSG_{i,t-5}$ is lower or equal than the 3rd cross-sectional decile. The dummy $S^{HL}_{i,t-5}$ takes the value of one whenever $EPSG_{i,t-5}$ is higher or equal than the 7th cross-sectional decile. The dummy $D_{i,t-5}$ takes the value of one whenever the consensus forecast on Corporate Profits issued at $t-6$ is less than the actual Corporate Profits at $t-5$. All specifications include $Size_{i,t-5}$ and $CSE_{i,t-5}$ which are exogenous to $y_{i,t}$. In the specifications that include the non-exogenous controls (columns (1), (3), (5) and (7)) there are 5 more instruments than regressors and the specifications without these controls have one more instruments than regressors. The instruments for $y_{i,t-1}$ are its the lags from $t-2$ to $t-4$. The instruments used for $\Delta Cvrg_{i,t-4}$ and $\Delta BNH_{i,t-4}$ are their lags from $t-6$ to $t-8$. The instruments for the other variables are the first differences of themselves. ***, ** and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively. Robust standard errors in parenthesis.

Varible	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$y_{i,t-1}$	0.6775^{***}	0.7224^{***}	0.6787^{***}	0.7229^{***}	0.6836^{***}	0.7262^{***}	0.6840^{***}	0.7263^{***}
	(0.0313)	(0.0212)	(0.0314)	(0.0212)	(0.0317)	(0.0212)	(0.0317)	(0.0212)
$y_{i,t-3}$	0.0311^{***}	0.0356^{***}	0.0311^{***}	0.0356^{***}	0.0309^{***}	0.0352^{***}	0.0310^{***}	0.0352^{***}
	(0.0097)	(0.0094)	(0.0097)	(0.0094)	(0.0097)	(0.0093)	(0.0097)	(0.0093)
$EPSG_{i,t-5}$	0.0485	0.0415	0.0782^{*}	0.0614	0.2593	0.1319	-0.9495	-1.0560
	(0.0343)	(0.0334)	(0.0472)	(0.0452)	(0.7319)	(0.6550)	(1.1340)	(1.0117)
$D_{i,t-5}$	-0.0280	0.0975^{**}	-0.0339	0.1029^{***}	-0.0347	0.1016^{***}	-0.0365	0.1010^{***}
	(0.0988)	(0.0387)	(0.0998)	(0.0388)	(0.0998)	(0.0388)	(0.1005)	(0.0388)
$S^{L}_{i,t-5}$	-0.0096^{***}	-0.0124^{***}	-0.0036	-0.0056	-0.0050	-0.0070	-0.0049	-0.0069
	(0.0037)	(0.0034)	(0.0052)	(0.0049)	(0.0052)	(0.0049)	(0.0053)	(0.0050)
$S^{H}_{i,t-5}$	0.0153^{***}	0.0106^{***}	0.0183^{***}	0.0142^{***}	0.0137^{***}	0.0097^{**}	0.0138^{***}	0.0098^{**}
	(0.0037)	(0.0035)	(0.0051)	(0.0048)	(0.0052)	(0.0049)	(0.0053)	(0.0050)
$D_{i,t-5}S^{L}_{i,t-5}$			-0.0132^{*}	-0.0148^{**}	-0.0130^{*}	-0.0146^{**}	-0.0121	-0.0138^{*}
			(0.0071)	(0.0066)	(0.0071)	(0.0066)	(0.0077)	(0.0070)
$D_{i,t-5}S^{H}_{i,t-5}$			-0.0058	-0.0074	-0.0049	-0.0066	-0.0039	-0.0058
			(0.0072)	(0.0067)	(0.0073)	(0.0067)	(0.0073)	(0.0067)
$D_{i,t-5}EPSG_{i,t-5}$			-0.0746	-0.0499	-0.0833	-0.0566	2.5352	2.5034^{*}
			(0.0970)	(0.0898)	(0.0976)	(0.0900)	(1.5466)	(1.3648)
$EPSG_{i,t-5}S^{L}_{i,t-5}$					-0.3025	-0.1893	0.9080	1.0006
					(0.7319)	(0.6549)	(1.1343)	(1.0119)
$EPSG_{i,t-5}S^{H}_{i,t-5}$					0.0285	0.1325	1.2351	1.3169
					(0.7339)	(0.6572)	(1.1393)	(1.0169)
$EPSG_{i,t-5}(D_{i,t-5}S^{L}_{i,t-5})$							-2.6228^{*}	-2.5649^{*}
							(1.5515)	(1.3681)
$EPSG_{i,t-5}(D_{i,t-5}S^{H}_{i,t-5})$							-2.6140^{*}	-2.5523^{*}
							(1.5538)	(1.3693)
Controls	Yes	No	Yes	No	Yes	No	Yes	No
N	70252	70941	70252	70941	70252	70941	70252	70941
(Sargan) χ^2	8.0680	0.0063	8.0239	0.0047	8.1240	0.0070	8.1156	0.0076
(p-value)	(0.1525)	(0.9367)	(0.1549)	(0.9452)	(0.1495)	(0.9350)	(0.1500)	(0.9304)
First-order m-statistic	-11.0414	-24.5654	-10.8990	-24.5680	-10.6283	-24.6111	-10.6097	-24.6105
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Second-order m-statistic	-0.2203	0.9647	-0.2224	0.9655	-0.1774	0.9920	-0.1745	1.0005
(p-value)	(0.8256)	(0.3347)	(0.8240)	(0.3343)	(0.8592)	(0.3212)	(0.8615)	(0.3171)

The results of disaggregating the signals by deciles are in table 7. In both regressions with and without controls, the estimates on high contradictory signals are nondecreasing with respect to the intensity of the signal, although are not statistically significant. With respect to low signals, the corresponding estimates go from statistically negative to statistically positive. In the regression with controls, the estimates increase as the signal lowers.

Table 7: Panel Regression of Forecast Bias on High Contradictory Signals Grouped by Deciles. Past Pessimism in Corporate Profits as Prior.

The dependent variable $y_{i,t}$ is calculated as $\frac{TP_{i,t-4}-P_{i,t}}{P_{i,t-4}}$; $TP_{i,t-4}$ is the consensus target price on stock i for the next 4 quarters; the signal $EPSG_{i,t-5}$ is calculated as $\frac{EPS_{i,t-5}-EPS_{i,t-6}}{P_{i,t-6}}$. The dummies $S^{LH}_{i,t-5}$, $S^{LM}_{i,t-5}$ and $S^{LL}_{i,t-5}$ take the value of one whenever $EPSG_{i,t-5}$ is lower or equal than the 3rd, 2nd and 1st cross-sectional deciles respectively. The dummies $S^{HL}_{i,t-5}$, $S^{HM}_{i,t-5}$ and $S^{HH}_{i,t-5}$ take the value of one whenever $EPSG_{i,t-5}$ is higher or equal than the 7th, 8th and 9th cross-sectional deciles respectively. The dummy $D_{i,t-5}$ takes the value of one whenever the consensus forecast on Corporate Profits issued at $t-6$ is less than the actual Corporate Profits at $t-5$. All specifications include $Size_{i,t-5}$ and $CSE_{i,t-5}$ which are exogenous. In the specifications that include the non-exogenous controls (columns (1), (3), (5) and (7)) there are 5 more instruments than regressors and the specifications without these controls have one more instruments than regressors. The instruments for $y_{i,t-1}$ are its the lags from $t-2$ to $t-4$. The instruments used for $\Delta Cvrg_{i,t-4}$ and $\Delta BNH_{i,t-4}$ are their lags from $t-6$ to $t-8$. The instruments for the other variables are the first differences of themselves. ***, ** and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively. Robust standard errors in parenthesis.

Varible	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$y_{i,t-1}$	0.6775***	0.7224***	0.6787***	0.7229***	0.6836***	0.7262***	0.6859***	0.7269***
	(0.0313)	(0.0212)	(0.0314)	(0.0212)	(0.0317)	(0.0212)	(0.0319)	(0.0212)
$y_{i,t-3}$	0.0311***	0.0356***	0.0311***	0.0356***	0.0309***	0.0352***	0.0309***	0.0352***
	(0.0097)	(0.0094)	(0.0097)	(0.0094)	(0.0097)	(0.0093)	(0.0097)	(0.0093)
$EPSG_{i,t-5}$	0.0485	0.0415	0.0782*	0.0614	0.2593	0.1319	−0.9591	−1.0581
	(0.0343)	(0.0334)	(0.0472)	(0.0452)	(0.7319)	(0.6550)	(1.1370)	(1.0114)
$D_{i,t-5}$	−0.0280	0.0975**	−0.0339	0.1029***	−0.0347	0.1016***	−0.0390	0.1019***
	(0.0988)	(0.0387)	(0.0998)	(0.0388)	(0.0998)	(0.0388)	(0.1008)	(0.0388)
$S^{LH}_{i,t-5}$	−0.0096***	−0.0124***	−0.0036	−0.0056	−0.0050	−0.0070	−0.0054	−0.0075
	(0.0037)	(0.0034)	(0.0052)	(0.0049)	(0.0052)	(0.0049)	(0.0053)	(0.0050)
$S^{HL}_{i,t-5}$	0.0153***	0.0106***	0.0183***	0.0142***	0.0137***	0.0097**	0.0135**	0.0095*
	(0.0037)	(0.0035)	(0.0051)	(0.0048)	(0.0052)	(0.0049)	(0.0053)	(0.0050)
$D_{i,t-5}S^{LH}_{i,t-5}$			−0.0132*	−0.0148**	−0.0130*	−0.0146**	−0.0291***	−0.0290***
			(0.0071)	(0.0066)	(0.0071)	(0.0066)	(0.0109)	(0.0101)
$D_{i,t-5}S^{HL}_{i,t-5}$			−0.0058	−0.0074	−0.0049	−0.0066	−0.0021	−0.0092
			(0.0072)	(0.0067)	(0.0073)	(0.0067)	(0.0101)	(0.0092)
$D_{i,t-5}EPSG_{i,t-5}$			−0.0746	−0.0499	−0.0833	−0.0566	2.4906	2.4872*
			(0.0970)	(0.0898)	(0.0976)	(0.0900)	(1.5501)	(1.3656)
$EPSG_{i,t-5}S^{LH}_{i,t-5}$					−0.3025	−0.1893	0.9178	1.0022
					(0.7319)	(0.6549)	(1.1373)	(1.0116)
$EPSG_{i,t-5}S^{HL}_{i,t-5}$					0.0285	0.1325	1.2385	1.3133
					(0.7339)	(0.6572)	(1.1422)	(1.0166)
$EPSG_{i,t-5}(D_{i,t-5}S^{LL}_{i,t-5})$							1.5260**	1.3124**
							(0.6020)	(0.5424)
$EPSG_{i,t-5}(D_{i,t-5}S^{LM}_{i,t-5})$							1.8070	1.8638*
							(1.1194)	(1.0568)
$EPSG_{i,t-5}(D_{i,t-5}S^{LH}_{i,t-5})$							−5.9489***	−5.7569***
							(2.1191)	(1.8895)
$EPSG_{i,t-5}(D_{i,t-5}S^{HL}_{i,t-5})$							−2.1517	−1.4759
							(1.8235)	(1.6332)
$EPSG_{i,t-5}(D_{i,t-5}S^{HM}_{i,t-5})$							−0.9154	−1.1275
							(0.8432)	(0.7446)
$EPSG_{i,t-5}(D_{i,t-5}S^{HH}_{i,t-5})$							0.5007	0.0858
							(0.4678)	(0.4366)
Controls	Yes	No	Yes	No	Yes	No	Yes	No
N	70252	70941	70252	70941	70252	70941	70252	70941
(Sargan) χ^2	8.0680	0.0063	8.0239	0.0047	8.1240	0.0070	7.9669	0.0126
(p-value)	(0.1525)	(0.9367)	(0.1549)	(0.9452)	(0.1495)	(0.9350)	(0.1581)	(0.9106)
First-order m-statistic	-11.0414	-24.5654	-10.8990	-24.5680	-10.6283	-24.6111	-10.5142	-24.6369
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Second-order m-statistic	-0.2203	0.9647	-0.2224	0.9655	-0.1774	0.9920	-0.1764	1.0275
(p-value)	(0.8256)	(0.3347)	(0.8240)	(0.3343)	(0.8592)	(0.3212)	(0.86)	(0.3042)

6 Conclusions

In this research I study whether the signal strength counteracts the effects of confirmation bias in sell-side analysts' stock price forecasts when these signals are high and contradictory. There is evidence in favor of underreaction to high contradictory signals in line with Pouget et al. (2017), except for signals above the ninth decile for which analysts overreact. In addition, analysts underreact to low signals except for signals below the second decile. Theoretically and following Beyer and Guttman (2011), if analysts bias their forecasts in accordance to the direction and intensity of the signals, is because they expect to increase the trading volume of the stocks they cover. The fact that analysts bias their forecasts monotonically with the intensity of the signal might be explained by the presence of trading incentives.

Additionally, I find that analysts' forecast bias is positively autocorrelated. The results from the control variables also show that optimism decreases with higher analyst coverage, that firm size is positively associated to favorable views about the stock price, that analysts partially correct their past relative inaccuracy and that informed trading may be negatively related to optimism.

For further research, an interesting objective is to capture the effects of analysts' expected trading volume on forecast bias for different levels of signals. In particular, analysts' expectations on trading volume are not observable nor is the data on trading volume exogenous to the forecast bias. Therefore, a next step requires finding the methodology or proxy that captures analysts' expectations on trading volume. In addition, the identification of the level of confirmation bias as well as the internal validity of the results showed in this research could be improved in an experimental setting in which the forecasts of purely Bayesian agents, with no trading incentives or confirmation bias, can be observed and in which prior beliefs and contradictory signals can be measured in a cleaner manner, although sacrificing external validity.

Appendix

Table 8: Cross-Sectional Distributions of EPS Growth

The column $z - score$ $(3rd)$ shows the standardized value of the 3th decile of EPS Growth for the cross-sectional distribution at each quarter, and the column $z - score$ $(7th)$ shows the standardized value of the 7th decile. $Kurtosis$ is the fourth standardized moment minus 3, and $Skewness$ is the third standardized moment.

Date	Mean	S.D.	3th Decile	z-score (3rd)	7th Decile	z-score (7th)	Kurtosis	Skewness
2006-06-30	0.006	0.425	−0.002	−0.019	0.004	−0.005	2,318.185	44.219
2006-09-29	0.010	0.213	−0.003	−0.059	0.003	−0.029	641.239	22.547
2006-12-29	0.004	0.132	−0.004	−0.061	0.004	−0.004	467.300	17.194
2007-03-30	−0.005	0.261	−0.004	0.004	0.003	0.031	795.939	−22.587
2007-06-29	0.004	0.125	−0.002	−0.046	0.005	0.005	362.405	4.758
2007-09-28	0.001	0.263	−0.003	−0.017	0.003	0.007	1,828.280	36.886
2007-12-31	0.0003	0.211	−0.004	−0.022	0.003	0.015	448.802	1.981
2008-03-31	0.016	0.341	−0.005	−0.062	0.004	−0.036	1,030.631	28.520
2008-06-30	0.002	0.200	−0.003	−0.026	0.006	0.016	360.903	−5.908
2008-09-30	0.001	0.450	−0.006	−0.015	0.004	0.005	1,764.046	36.940
2008-12-31	−0.064	2.071	−0.014	0.024	0.002	0.032	2,638.528	−50.492
2009-03-31	0.379	15.035	−0.006	−0.026	0.012	−0.024	2,740.020	52.247
2009-06-30	0.067	1.614	−0.004	−0.044	0.010	−0.035	2,249.096	45.571
2009-09-30	0.022	0.917	−0.002	−0.026	0.009	−0.014	1,374.135	32.409
2009-12-31	−0.003	0.341	−0.005	−0.007	0.006	0.025	338.807	−11.199
2010-03-31	0.007	0.684	−0.004	−0.017	0.006	−0.002	588.470	2.591
2010-06-30	0.036	1.115	−0.002	−0.034	0.007	−0.026	1,472.658	36.352
2010-09-30	−0.023	1.206	−0.003	0.016	0.006	0.023	2,351.513	−47.506
2010-12-31	0.001	0.419	−0.005	−0.013	0.005	0.010	425.421	−2.719
2011-03-31	0.004	0.580	−0.005	−0.014	0.005	0.002	972.196	2.762
2011-06-30	0.003	0.179	−0.002	−0.028	0.005	0.015	422.642	−2.422
2011-09-30	−0.014	0.755	−0.003	0.015	0.005	0.025	2,345.710	−47.769
2011-12-30	−0.057	2.944	−0.007	0.017	0.004	0.021	2,417.493	−48.982
2012-03-30	0.023	3.483	−0.004	−0.008	0.006	−0.005	1,436.331	22.120
2012-06-29	−0.014	1.313	−0.003	0.009	0.005	0.015	2,076.744	−42.784
2012-09-28	0.001	0.282	−0.004	−0.017	0.004	0.011	544.679	4.771
2012-12-31	−0.002	0.364	−0.005	−0.007	0.004	0.018	642.109	−5.154
2013-03-28	−0.0003	0.539	−0.004	−0.007	0.005	0.010	975.542	−4.814
2013-06-28	0.009	0.138	−0.002	−0.079	0.005	−0.028	264.846	13.658
2013-09-30	−0.024	1.493	−0.003	0.014	0.004	0.019	2,181.122	−45.875
2013-12-31	0.010	1.004	−0.004	−0.014	0.003	−0.007	1,911.371	40.966
2014-03-31	0.013	0.372	−0.004	−0.046	0.003	−0.027	1,191.037	32.927
2014-06-30	−0.861	31.867	−0.001	0.027	0.005	0.027	1,756.798	−40.912
2014-09-30	0.941	44.771	−0.002	−0.021	0.004	−0.021	2,284.957	47.822
2014-12-31	−0.009	0.390	−0.005	0.011	0.003	0.031	990.839	−27.337
2015-03-31	−0.0001	0.138	−0.005	−0.035	0.003	0.023	221.669	−4.908
2015-06-30	0.001	0.113	−0.002	−0.024	0.004	0.030	299.644	5.248
2015-09-30	−0.050	2.345	−0.003	0.020	0.003	0.023	2,213.986	−47.005
2015-12-31	0.053	2.921	−0.005	−0.020	0.004	−0.017	2,144.598	45.955
2016-03-31	0.019	0.685	−0.005	−0.035	0.004	−0.023	1,227.180	28.097
2016-06-30	0.008	0.308	−0.001	−0.031	0.006	−0.008	938.433	16.955
2016-09-30	0.005	0.212	−0.003	−0.038	0.004	−0.005	363.691	4.439
2016-12-30	0.001	0.170	−0.005	−0.036	0.003	0.011	406.175	15.840

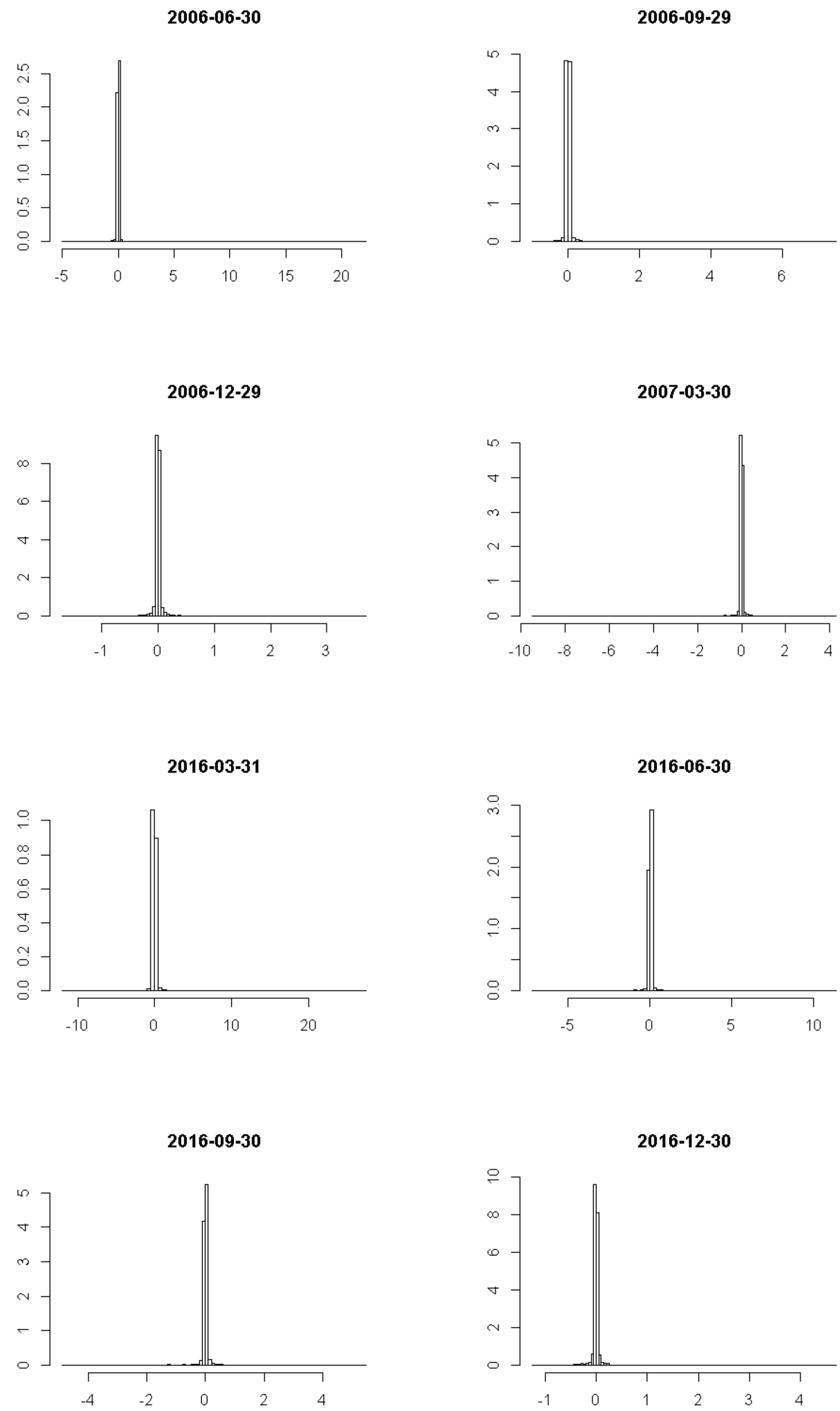

Figure 8: Cross-Sectionals Distributions for Quarters 2006Q2, 2006Q3, 2006Q4, 2007Q1, 2016Q1,2016Q2, 2016Q3 and 2016Q4.

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