Analysts and Anomalies[Ψ]

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Abstract

Analysts' price targets and recommendations contradict stock return anomaly variables. Analysts' one-year return forecasts are 31% for anomaly-longs and 44% for anomaly-shorts. Similarly, analysts issue more favorable recommendations for anomaly-shorts than anomaly-longs. We find similar results among all-star analysts. Our findings imply that investors who follow actionable, analyst information contribute to mispricing.

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Financial firms spend more than $4 billion annually on sell-side analyst research.[1] The information produced includes earnings and revenue forecasts, stock recommendations, and future stock price targets. Revenue and earnings forecasts communicate a firm's financial prospects. The brunt of academic research on analysts focuses on forecasts (for example, Bradshaw, 2011, and Kothari, So, and Verdi, 2016). Unlike financial forecasts, stock recommendations and future stock price targets provide direct, actionable information for investors. Recommendations, described by Schipper (1991), as the "ultimate analyst judgement" explicitly guide investors to either buy, hold, or sell a stock. Target prices scaled by the current market prices provide investors with a clear estimate of expected stock returns.

While stock price targets and recommendations reflect analysts' views on future stock returns, there is considerable evidence that many cross-sectional variables predict stock returns. This research goes back to at least Ball and Brown (1968) and Blume and Husic (1973), and shows that simple cross-sectional sorts based on easy-to-observe characteristics such as earnings surprises (Foster, Olsen, and Shevlin, 1984), sales growth (Lakonishok, Shleifer, and Vishny, 1994), share issues (Loughran and Ritter, 1995), and recent past returns (Jegadeesh and Titman, 1993) forecast stock returns.

We ask two questions: (i) Do "actionables" (recommendations and target price return forecasts) reflect the information in the large number of anomaly

[1] This was during the year 2014, according to the article "Banks Forced to Shake Up Analyst Research Business", Wall Street Journal, February 9, 2015.

variables studied in the academic literature? (ii) Do investors who follow analysts' actionables contribute to market efficiency or inefficiency?

Using an index of 125 anomaly variables from accounting, economics, and finance journals over the past 40 years, we find that analysts offer price targets and recommendations that predict returns in the *opposite direction* as anomaly variables. Analysts forecast higher (lower) stock returns and offer more (less) favorable recommendations for stocks that anomaly variables suggest should be sold (bought). This finding continues to hold when we focus on *Institutional Investor* "all-star" analysts, firms with increases in analyst coverage, and firms that do not embark on investment banking activity in the subsequent year. Our sample consists of 125 anomalies extends the 97-anomaly sample used in McLean and Pontiff (2016) and Engelberg, McLean, and Pontiff (2017). Those studies provide evidence that the return predictability stemming from anomalies is, at least partially, the result of mispricing. The evidence in this paper therefore suggests that investors who invest in accordance with analysts' suggestions contribute to this mispricing.

We create an anomaly index that reflects all 125 of our anomaly variables and sort stocks into anomaly-long and anomaly-short portfolios. We use the one-year median analyst price target to construct a one-year stock return forecast for analysts. Stocks in the bottom quintile of the anomaly index (anomaly-sells) have a mean one-year return forecast of 44%, while stocks in the top quintile (anomaly-buys) have a mean one-year return forecast of 31%. We confirm these results in a multivariate regression that includes standard control variables from the analysts' literature.

We also consider analysts' recommendations (e.g. "buy" or "strong sell") and find the same tendency. Stocks for which anomaly signals predict higher returns have less favorable recommendations as compared to stocks for which anomaly signals forecast lower returns. The difference in average recommendation (ranges from 5=strong buy to 1=strong sell) between stocks in the top quintile of the anomaly index and the bottom quintile of the anomaly index is statistically significant, but economically much smaller than the difference in return forecasts, as the variation in mean recommendations is smaller than the variation in return forecasts. The recommendation difference is negative and insignificant in portfolio sorts, and negative and significant in regressions that include control variables.

We assign each of our 125 anomalies to one of five groups to better understand whether our findings vary across different types of anomalies. The groupings are the four groupings used in McLean and Pontiff (2016) and Engelberg, McLean, and Pontiff (2017), plus a new category, *Opinion*, which contains variables based on the trades and holdings of insiders and institutions. With respect to price targets, our main result holds in all 5 anomaly categories: analysts forecast higher returns for anomaly-shorts than for anomaly-longs. With respect to recommendations, there is a good deal of variance, as analysts get it right in 3 groups, and wrong in 2 groups.

To better understand if analysts are making predictable mistakes we create a variable, *Mistakes*, which is equal to the analysts' forecasted stock return minus the realized stock return. We find that the anomaly index predicts lower values of *Mistakes*, showing that analysts' return forecasts are too low for anomaly-longs and too high for anomaly-shorts. Moreover, we find that the anomaly index forecasts changes in analysts' price targets. Stocks for which the anomaly index forecasts higher returns subsequently have increases in price targets. We find this effect for lags of up to 18 months, i.e., the anomaly index today can predict increases in price targets over the next month and continuing on for the next 18 months. This suggests that the "mistakes" analysts make today by being at odds with anomaly variables are corrected over the following year and a half. These results hold for all 5 groups of anomaly variables.

Over time many anomaly variables have become widely known, and we find that analysts have incorporated more of this information into their recommendations and price targets. However, even during the later years of our sample we still find a negative relation between the anomaly index and return forecasts and the anomaly index and analysts' recommendations. Thus, analysts today are still overlooking a good deal of valuable, anomaly-related information.

In the final part of our paper we study the relations between analyst actionables, the anomaly index, and future stock returns. We find that analysts' return forecasts predict stock returns, *but in the wrong direction*. This effect has not been shown previously, and it is both statistically and economically larger than the effect that changes in recommendations has on stocks returns. Previous studies find a positive relation between changes in price targets and announcement day returns, and a post-announcement drift that follows the price target change. We also find a positive relation between price target changes and future stock returns, although the effect is not statistically significant. Our specification includes a larger set of controls as compared to previous studies.

We also find that including analyst actionables in a regression with the anomaly index has little impact on the index's ability to predict returns, so the useful information in the anomaly index is largely orthogonal to the information in the analyst actionables. Like previous studies, we find that recommendations do not predict returns, but that changes in recommendations predict stock returns in the direction intended by the analyst.

Our paper builds on several literatures. First, it's related to studies linking analysts to anomalies. Engelberg, McLean, and Pontiff (2017) show that anomaly variables predict earnings forecast errors. Unlike earnings forecasts, analyst "actionables" (recommendations and price targets) provide a clear message of how investors should act, as it is not clear how an investor should act based on an earnings forecast. Engelberg, McLean, and Pontiff (2017) do not study analyst recommendations or price targets. Our paper shows that relation between anomaly variables and analysts' actionables is not a manifestation of an earnings forecast effect, as we control for earnings forecasts in our main tests. The paper most similar to ours is Jegadeesh, Kim, Krische, and Lee (2004), who study how analyst recommendations (but not return forecasts) relate to 12 anomaly variables. Their findings are neutral; analyst recommendations agree with 6 of the anomaly variables and go against the other 6. Grinblatt, Jostava, and Philipov (2016) find that stocks high levels of uncertainty (e.g., high idiosyncratic volatility) tend to have biased earnings forecasts. Bradshaw (2004) finds that analysts' recommendations are either uncorrelated or negatively correlated with Frankel and Lee's (1998) residual income model, which is shown to predict stock returns.

Our paper is related to a literature that studies how sophisticated investors use anomaly strategies. McLean and Pontiff (2016) find that short sellers tend to target stocks in anomaly-short portfolios, and that this effect increases after a paper has been published. Lewellen (2011) finds that institutional investors fail to take advantage of anomalies when forming their portfolios. Edelen, Ince, and Kadlec (2016) suggest that institutions may contribute to anomalies, as they find that in the year prior to portfolio formation institutional demand is typically on the wrong side of anomaly portfolios. Calluzzo, Moneta, and Topaloglu (2017) find that institutions, especially hedge funds, do follow anomaly strategies, but only after an anomaly is highlighted in an academic publication.

We also contribute to a literature that asks whether analyst information is useful in predicting stock returns. Our contribution to this literature is to show that return forecasts based on median price targets predict returns in the opposite direction intended by analysts, an effect that has not been documented previously. We also show that analysts' information about future returns and anomaly variable information about future returns are largely orthogonal. Papers linking analyst actionable analyst information to stock returns include Elton, Gruber, and Grossman (1986), Cowles (1993), Stickel (1995) Womack (1996), Barber, Lehavy, McNichols, and Trueman (2001), Brav and Lehavy (2003), Asquith, Mikhail, and Au (2005), Jegadeesh et al. (2004), Da and Schaumburg (2011) and Bradshaw, Huang, and Tan. (2014). This literature finds that sell recommendations predict lower returns, but buys do *not* predict higher returns.[2] This literature also finds that changes in recommendations, changes in price targets, and newly initiated targets and recommendations all predict returns in the direction intended by the analyst. We are the first study to document predictability that goes in the *opposite* direction as intended by the analysts, implying that the investors who follow analyst price target forecasts make markets *less* efficient.

Finally, our paper is related to a literature that examines analysts' role in the existence of anomaly returns. Abarbanell and Bernard (1993) find that analysts underreact to the information in earnings announcements and that this underreaction can explain part of the returns in post-earnings announcement drift. Dechow and Sloan (1997) find that the value-growth anomaly might be, in part, explained by stocks not living up to the lofty earnings growth that analysts expect. Bradshaw, Richardson, and Sloan (2004) show that external finance predicts analyst earnings forecast errors, target price-return forecast errors, and lower stock returns. We show that analyst price targets and recommendation are in the opposite direction of an index based on 125 anomaly variables, implying that investors who follow analysts' actionables contribute to anomaly-based mispricing.

1. Sample, Data, and Descriptive Statistics

Our sample is based on median 12-month price targets and consensus recommendations from IBES, and 125 anomaly variables, 96 of which are studied in

[2] Altinkilinc and Hansen (2009) and Altinkilinc, Balashov, and Hansen (2013) argue that most changes in recommendations are simply responses to public news, which is what explains the stock price reaction. Altinkilinc, Hansen, and Ye (2016) argue that the post-change in recommendation drift has attenuated in recent years due to more efficient arbitrage.

McLean and Pontiff (2016) and McLean, Pontiff, and Engelberg (2017). These 125 anomalies are drawn from studies published in peer-reviewed finance, accounting, and economics journals. Each anomaly variable is shown to predict the cross-section of stock returns.

Table 1 provides descriptive statistics for our sample. We exclude stocks for which we cannot calculate an anomaly index value (*Net*) and stocks for which we do not have stock price value in CRSP.[3] Our price target data begin in 1999 and end in 2016. We construct a return forecast variable by taking the log of the median 12-month price forecast and subtracting from the log of the current stock price. The resulting variable has a mean of 0.34 and a standard deviation of 0.83. This average analyst target return forecast is much higher than most return estimates, as has been documented by Bradshaw et al. (2014), who use international data to show that analyst price targets are 25% to 30% too optimistic.

We construct a second expected return measure, which accounts for expected dividends. We use dividends from the past year to reflect expected dividends for the coming year. We trim both forecast variables by omitting forecasts that either exceed 5, or are less than -5. We then winsorize both forecast variables at the top and bottom 1% of the respective samples.

With respect to recommendations, we have 920,440 observations with at least one recommendation. Or recommendation data begin in 1994 and end in 2016. We construct the mean recommendation variable such that 5 is a "strong buy" and 1

[3] In a previous version of the paper we also excluded stocks with prices less than $5. Excluding such stocks lowers the mean of our main variable – analysts' target based return – considerably because analysts forecast particularly large returns for extremely low-priced stocks. Our main results hold both with and without this price filter.

is a "strong sell." Our sample is constructed at the stock-level, the unit of observation is *not* at the analyst-level, and each observation reflects the mean recommendation for a particular stock. Table 1 shows that the mean of these mean recommendations is 3.77, revealing that on average, analysts' recommendations have an upward bias (otherwise the mean would be 3). Mean recommendations do vary, however the variation is much smaller as compared to expected returns; the standard deviation of the mean recommendation is 0.68. The average number of recommendations is 5.20.

To create the anomaly variables, stocks are sorted each month on each of the anomaly-characteristics. We define the long and short side of each anomaly strategy as the extreme quintiles produced by the sorts. Some of our anomalies are indicator variables (e.g, credit rating downgrades). For these cases, there is only a long or short side, based on the binary value of the indicator. We remake the anomaly portfolios each month. We begin our anomaly variables in 1994, the first year for which we have recommendation data.

We refer to our anomaly index as *Net*; it is the difference between the number of long and short anomaly portfolios that a stock belongs to in given month. As an example, a *Net* value of 10 in month *t* means that a stock belongs to 10 more anomaly-long portfolios than anomaly-short portfolios in month *t*. We form long and short anomaly portfolios each month for each anomaly by sorting stocks into quintiles. *Net* has a mean value of -0.22, and minimum and maximum values of -51 and 41 respectively.

We also create anomaly variables for 5 different anomaly groups. This builds on McLean and Pontiff (2016) and McLean, Pontiff, and Engelberg (2017), who categorize anomalies into 4 different types: (i) *Event*; (ii) *Market*; (iii) *Valuation*; and (iv) *Fundamentals*. The categorization is based on the information needed to construct the anomaly variable. We create a fifth anomaly group, which we refer to as *Opinion*, which consists of anomalies that reflect the holdings and trades of insiders and institutional investors. As with *Net*, we create the 5 anomaly-group variables by summing up the long and short portfolio memberships within each of the 5 groups.

Event anomalies are based on events within the firm, external events that affect the firm, and changes in firm-performance. Examples of *Event* anomalies include share issues, earnings surprises, and unexpected increases in R&D spending. *Market* anomalies are anomalies that can be constructed using only financial data, such as volume, prices, returns and shares outstanding. Momentum, long-term reversal, and market value of equity are included in our sample of market anomalies.

Valuation anomalies are ratios, where one of the numbers reflects a market value and the other reflects fundamentals. Examples of valuation anomalies include sales-to-price and market-to-book. *Fundamental* anomalies are constructed with financial statement data and nothing else. Leverage, taxes, and accruals are fundamental anomalies.

2. Main Results

2.1. Do Analysts Use the Information in Anomaly Variables?

2.1.1. Univariate Tests

In this section of the paper we present our main findings. The information reflected in anomalies is publicly available and has been shown to predict cross-sectional stock returns. We ask whether analysts incorporate such information when making their price forecasts and recommendations. We begin by sorting stocks into quintiles based on values of the different anomaly variables, and testing for differences in return forecasts and recommendations across the quintiles. If analysts' price forecasts and recommendations capture the information contained in anomaly variables, then stocks with high values of *Net* should have higher return forecasts and more favorable recommendations than stocks with low values of *Net.*

We report the findings from these tests in Table 2. Panels A and B report the results for return forecasts without and with dividends, while Panel C reports the results for recommendations. Figures 1 and 2 put the results from Table 2 in a nutshell. Figure 1 displays the return forecasts by *Net* quintile, while Figure 2 displays the mean recommendations by *Net* quintile. In Figure 1, we see that the return forecasts are significantly higher for the anomaly-shorts as compared to the other quintiles. In Figure 2, we see that the anomaly-shorts have the most favorable recommendations and the anomaly-longs have the least favorable.

The first column in Panel A of Table 2 shows that anomaly-shorts have higher return forecasts than anomaly-longs. The average return forecast is 0.439 for anomaly-shorts and 0.313 for anomaly-longs. The difference, -0.130, is statistically significant (t-statistic = 2.68).

Looking across the columns we find similar effects for *Event*, *Fundamental Valuation*, and *Opinion* anomalies. For all four groups, the shorts have higher return forecasts than the longs, and return forecasts decrease across the anomaly quintiles. The differences range from -0.189 to -0.103, and all of the differences are statistically significant.

With respect to *Market* anomalies, analysts do a better job. The mean return forecast for the longs is 0.432, the mean return forecast for the shorts is 0.332, and the difference, 0.101, is positive (*t*-statistic = 2.13). This contradicts that notion that analysts are experts at understanding firm fundamentals--the only thing they seem to not get wrong with respect to anomalies are variables that do not contain any accounting information.

Panel B presents the results for return forecasts that include dividends. The results are basically identical to those in Panel A, so we skip the discussion and move on to discuss the recommendation results in Panel C.

The results reported in the first column of Panel C show that anomaly-longs (stocks with high *Net* values) have lower recommendations than anomaly-shorts (stocks with low *Net* values), although the difference is not statistically significant. Analyst recommendations therefore do not reflect anomaly variables. The mean recommendation for anomaly-longs is 3.74, while the mean recommendation for anomaly-shorts is 3.76.

The next 5 columns in Table 2 report separate results for the 5 different anomaly groups. The results show that *Event* and *Valuation* anomalies drive the recommendation results, as for these anomalies recommendations are more favorable for anomaly-shorts than for anomaly-longs. Both of these differences are statistically significant. The largest difference (-0.10) is for *Event* anomalies. The difference shows that analyst recommendations are 2.6% lower for the longs as compared to the shorts. However, in both cases the mean recommendation is approximately 4, which is a "buy" recommendation. The difference with *Opinion* anomalies is also negative, but insignificant. The differences for *Fundamental*, and *Market* anomalies are both positive and significant, so analysts appear to get these right.

2.1.1. Regression Evidence

Table 3 reports regression evidence of whether analyst return forecasts and recommendations incorporate the information in anomaly variables. We report results for return forecasts in Panel A and for recommendations in Panel B. Throughout the rest of the paper we use only return forecasts without expected dividends, although in untabulated results we find that that the two return forecast variables produce virtually identical findings.

The results in Panel A of Table 3 mirror the univariate findings in Panel A of Table 2. The regressions include time fixed effects, the number of analysts offering targets, whether there is only a single price target, and the standard deviation of the price targets scaled by the mean price target. We also use the forecasted earnings-to-price ratio, i.e., the forecasted earnings over the subsequent year scaled by current price, as a control variable. We include this because it is already known that anomalies are related to biases in earnings forecasts (see McLean, Pontiff, and Engelberg, 2017). To make the coefficients easier to read the dependent variable (return forecast) is multiplied by 100. Standard errors are clustered on the firm level.

In the first column, the *Net* coefficient is -0.423 and statistically significant. What this shows is that a stock with a *Net* value of -5 has a return forecast that is higher by about 4.2% than a stock with a *Net* value of 5, which is sizeable difference. If analysts paid attention to anomaly variables then we would expect the *Ne*t coefficient to be positive.

Looking across the columns in Panel A, we see that analyst return forecasts are also in the wrong direction for all five of the anomaly groups, although the coefficient is insignificant for the *Market* anomaly group. The results here are essentially the same results that we reported in the univariate sorts in Table 2.

With respect to the control variables, return forecasts are shown to be lower for stocks with fewer analysts offering price targets, but higher for stocks with only a single analyst offering a target. The price target standard deviation coefficient is positive and significant, showing that return forecasts are higher for stocks with greater variance in price targets. Surprisingly, stocks with higher forecasted earnings tend to have lower forecasted stock returns.

Panel B reports the results for mean recommendations. In the first column, the *Net* coefficient is -0.004 and statistically significant. Thus, a stock with a *Net* value of -5 has a mean recommendation that is higher by 0.004 than a stock with a *Net* value of 5. The mean recommendation is 3.77, so like those in Panel C of Table 2 this difference is not large economically, however it is in the wrong direction, further confirming that analysts ignore anomaly variables when issuing advice.

The results in Panel B show that analyst recommendations are in the wrong direction with respect to *Event* and *Valuation* anomalies. The largest effect is for *Valuation* anomalies. The coefficient is -0.028. Table 1 shows that *Valuation* has a standard deviation of 2.55, so a 1 standard deviation increase in *Valuation* leads to a -0.071 decrease in mean recommendation. The mean of the mean recommendations is 3.77, so this reflects a 1.9% lower mean recommendation.

Like in Table 2, analyst recommendations are in the right direction for *Fundamental and Market* anomalies, although the coefficients and economic magnitudes are very small. The coefficient for *Opinion* is negative and insignificant.

The coefficients for the number of recommendations, the standard deviation of the recommendations, and whether there is only a single analyst offering a recommendation are all negative and statistically significant. Hence, firms with more analyst coverage, firms with more dispersion in recommendations, and firms that only have a single analyst offering a recommendation tend to have less favorable recommendations. The coefficient for the forecasted earnings-to-price ratio is positive and significant, showing that stocks with higher earnings forecasts have more favorable recommendations.

2.3. Robustness

Table 4 repeats the analysis in Table 3, but explores the results in different samples, formed on either analyst- or firm-characteristics.

Panel A focuses on return forecasts. In regression 1, we consider firms with increases in analyst coverage. Lee and So (2017) argue that analysts are constrained, and so the decision to initiate coverage on a stock is associated with an increase of resources devoted to analyzing the firm. As such, we expect the negative relation between *Net* and analyst actionables to be smaller or even positive for firms with increases in coverage. For regression 1, we limit the sample to firms that are in the top decile for percentage change in the number of analysts issuing price targets. The *Net* coefficient in regression 1 of Panel A is -0.790 (t-statistic = 7.48), which is more negative than the full-sample result reported in Panel A of Table 3. This finding runs counter to the explanation that the mismatch between analyst actionables and analyst forecast returns is the result of limited analyst attention and resources.

Perhaps highly acclaimed analysts are more likely to do a better job utilizing information from anomaly variables. For example, Clarke, Khorana, Patel, and Rau (2007) argue that analysts determined by *Institutional Investor* magazine to be "All-Stars" might be more adept than the typical analysts. In regression 2, we limit the sample to price targets issued by these analysts. An All-Star analyst is defined as an analyst who was denoted by the magazine as being an All-Star or a runner-up to being an All-Star in the previous November's issue of the magazine or in a November issue before last November. The *Net* coefficient in regression 2 is closer to zero than the Table 3 estimate although, at -0.331, the null hypothesis is still comfortably rejected. So even All-Star analysts' price targets conflict with the information anomaly variables, even if they do somewhat better than other analysts.

Some argue that analysts have worse incentives to provide accurate actionables when faced with potential investment banking business. For example, Lin and McNichols (1998) find that analysts that are affiliated with the firm's investment bank make more positive recommendations. Other research questions how accurate affiliation with investment banks can be assigned (see, for example, Bradshaw, Ertimur, and O'Brien, 2017).

In regression 3, we limit the sample to firms that are more *unlikely* to hire an investment bank in the following year. We define these firms as firms which, in the subsequent year, did *not* do any of the following: (i) are in the top quintile for use of external finance, according to the measure of Bradshaw, Richardson, and Sloan (2006); (ii) acquired another firm; (iii) spun off a firm. In regression 3, which only includes firms that did not use banking over the subsequent year, *Net* has a coefficient of -0.411, similar to what we find in the full-sample regression in Table 3. Hence, the negative relation between *Net* and analysts' return forecasts does not seem to be driven by biases that arise from investment banking opportunities. Contrary to what we expect, anomaly information is still ignored in the forecast returns of firms that do not use banking services in the subsequent year.

Panel B reports the same analysis as Panel A, except the dependent variable is recommendation. The results are remarkably similar; Firms with larger increases in analyst covered tend to have a more negative relation between *Net* and recommendation level, all-star analysts do a worse job incorporating information from *Net* into their recommendations, and recommendations issues on firms with future investment banking activity have a minor and insignificant negative relation with *Net*.

2.3. Analysts' Mistakes and Stock Return Anomalies

The results thus far suggest that analysts may be making predictable mistakes, as their forecasts are at odds with the stock return predictions of anomaly variables. To better understand if this is the case, we create a variable, *Mistakes*, which is the difference between the return forecast divided by 12 minus the realized monthly stock return in month *t*, the first month of the forecast period (recall that the return forecast is based on a 12-month price target):

$$Mistakes = Return\ Forecast - Return\ Realized$$

A negative (positive) value of *Mistakes* means that the return forecast was too low (high). For readability, we multiply the *Mistakes* variable by 100 before estimating the regressions.

Table 5 shows that *Net* does indeed predicts mistakes in return forecasts. The *Net* slope coefficient is -0.132 (*t*-statistic = 8.76). This means that for firms with higher values of *Net,* analysts' return forecasts are more pessimistic relative to realized returns than firms with lower values of *Net*. The results are economically meaningful. For example, for firms with values of *Net* that vary by 10, the estimated *Mistake* varies by –1.32%,

The next five columns replace *Net* with anomaly variables constructed using the anomaly groups. The anomaly variables' coefficients range from -0.168

to -0.275, and all are statistically significant. The results therefore show that all types of anomalies (including *Opinion* anomalies) forecast analysts' mistakes, with similar economic magnitude. Note that the standard deviations are smaller for the anomaly-type variables than for *Net*, which explains why the coefficients are usually larger (in absolute value).

The results also show that *Mistakes* are higher (lower) for stocks with higher (lower) mean recommendations. This means that price targets are too high for stocks with more favorable recommendations. This makes sense, and suggests that if analysts are overly optimistic when they issue price targets then the same bias is present with recommendations. The single target dummy and the standard deviation of price targets both forecast higher values of *Mistakes* as well, so price targets are too high for firms with only 1 analyst issuing a target, and for firms that have more disagreement among the analysts that follow it. In contrast, changes in recommendation forecast lower values of *Mistakes*, as does the number of analysts issuing price targets.

2.3. Can Anomalies Predict Changes in Price Targets and Recommendations?

In the previous sections, we show that analysts tend to be at odds with the information in anomaly variables. Anomalies predict stock returns, so one could argue that it's a mistake for analysts to overlook or be in disagreement with the public information that anomaly variables are based on. In this section of the paper we ask whether anomaly variables can predict changes in analyst price targets and recommendations. If anomaly variables do predict changes in price targets and recommendations, then this shows that analysts initially overlook the information captured in anomalies, but then subsequently and predictably update.

We report the results from these tests in Tables 6 and 7. We use *Net* to predict monthly changes in price targets in Table 6 and monthly changes in recommendations in Table 7. We use *Net* lagged at 1, 3, 6, 12, and 18 months to forecast the changes. Like the previous tables, our standard errors are clustered on firm and we include time fixed effects. We include the same control variables as those used in Table 5 along with the median price target (Panel A) and mean recommendation (Panel B).

The dependent variable in Panel A is the change in log price target (log target (t+1) – log target (t)) multiplied by 100. In the first regression reported in Panel A of Table 6, *Net* is lagged one month. The coefficient for *Net* is 0.064 and is statistically significant. This means if a firm has a *Net* value of 10, then its median price target increases by about .64% in the next month. Table 1 shows that the mean monthly change in price target is zero, so this is a meaningful effect. Regressions 2-5 repeat these tests using *Net* lagged from 3, 6, 12, and 18 months. All of the coefficients are positive and statistically significant, so even after 18 months analysts are still responding to the public information that is reflected in anomaly variables. The coefficients are also monotonically decreasing as the number of lags increase.

With respect to the control variables, we see that price targets tend to subsequently increase when the initial price target is higher, and decrease when there is a single target, and when the standard deviation of targets is greater.

Panel B reports the results for different anomaly types. The coefficients are positive and significant for *Event*, *Fundamental*, *Valuation*, and *Market* anomalies, and negative and significant for *Opinion* anomalies. Analysts update their price targets with respect to the information in most anomaly variable, but not *Opinion* anomalies.

Table 7 reports the results for recommendations. Panel A reports the results for *Net* and *Net* at various lags. Like the results with price targets, the *Net* coefficient is positive and significant across specifications, except for the 18-month lag, where *Net* is positive but insignificant. The dependent variable here is simply the change in mean recommendation. In regression 1, the *Net* coefficient is 0.009. *Net* has a standard deviation of 9.29, so a one standard deviation increase in *Net* leads to a 0.084 increase in mean recommendation. As we mention earlier, there is much less variation in average recommendations (they all tend to hover around 4 or "buy") so it is not surprising to find economically smaller results here.

In Panel B, we explore the effects for the different anomaly types. The coefficients are positive and significant for all of the groups, with the exception of *Valuation*, which has a negative and significant coefficient. Hence, analysts update their recommendations with respect to the information in *Event*, *Fundamental*, *Market*, and *Opinion* anomalies, but seem to double down on their bad recommendations for value and growth stocks.

2.4. Analysts and Anomalies over Time

In this section of the paper we ask whether analyst price targets and recommendations have improved over time with respect to anomalies. We estimate time effects via the same regression framework as that used in Table 3, only we interact the anomaly variables with *Time*, which is equal to 1/100 during the first month of our sample, increases by 1/100 each month, and is equal to 2.07 during the last month of our price target sample, and equal to 2.76 in the last month of our recommendation sample, which begins earlier (in 1994 vs 1999) due to data availability. The regressions include month fixed effects, so we do not include *Time* in the regressions.

We report results for return forecasts in Panel A and recommendations in Panel B of Table 8. In column 1 of Panel A the interaction between *Time* and *Net* is positive and significant, showing that analysts have improved over time with respect to making expected return forecasts that are not at odds with *Net*. The coefficient for *Net* is -2.413 and the interaction coefficient if 0.411. *Time* ranges from 0.01 to 2.07 in this specification, so during the first month of our sample the overall *Net* coefficient (*Net* + *Net* * *Time*) is -2.413 during the first month, and during the final month it is -1.562, which is closer to neutral, but still quite negative.

Looking across the columns, we find similar effects for *Event*, *Market*, *Valuation,* and *Opinion* anomalies. In each case, the coefficient for the anomaly variable is negative and significant and the interaction is positive and significant, showing that analysts have improved over time with all 4 of these groups. With *Fundamental* anomalies, there is no significant change over time.

In Panel B, we report the results for recommendations. In the first column the coefficient for *Net* is -0.008 and the coefficient for *Net***Time* is 0.001. This means that during the first month of our sample, in which *Time* is equal to 1/100, the overall coefficient for *Net* (*Net* + *Net***Time*) is -0.008. During the last month of our sample *Time* has a value of 2.76, so the overall *Net* coefficient is -0.005, which is an improvement, but still in the wrong direction.

Looking across the columns in Panel B, we see that the analyst recommendations have gotten worse over time with *Event*, *Fundamental*, and *Opinion* anomalies, and much better with *Market* and *Valuation* anomalies. Analysts also worsened over time with respect to price targets and Fundamental anomalies, although that effect was not statistically significant.

2.5. Analysts, Anomalies, and Stock Returns

The results so far show that analysts' price targets and recommendations overlook and are often at odds with the information embedded in anomaly variables. It still could be the case that price forecasts and recommendations contain other information that outweighs the anomaly-conflicts. We test this hypothesis in this section of the paper. We study how different analyst variables predict future stock returns, after controlling for the information in anomaly variables.

The dependent variable in this section of the paper is monthly stock return multiplied by 100. The independent variables are based on the various analyst variables used in the previous tables and the anomaly variable *Net*. We use the mean recommendation variable, and also generate a "Buy" dummy variable that is equal to 1 if the mean recommendation is 4 or more, and zero otherwise, and a "Sell" dummy variable that is equal to 1 if the mean recommendation is 3 or less and zero otherwise. In all regressions we begin our sample in1999, the first year that we have target price data, so that we can compare the coefficients across specifications.

Our estimation allows us to compare the return-predictability of different analyst measures. As we mention in the Introduction, previous literature generally finds that sell recommendations predict lower returns, while changes in recommendations, changes in price targets, and newly announced price targets are associated with contemporaneous returns and a post-announcement drift that go in the direction intended by the analyst, e.g., an increase in recommendation portends higher stock returns.

We report these results in Table 9. The return forecast variable is at odds with analysts' intentions. We consider return forecasts that are lagged for 1 month (the variable is designed to predict returns one year ahead), although in unreported tests we lag the variable 12 months and get the same results. In all specifications, the expected return coefficient is negative and statistically significant. As an example, in column 8, which is our most complete specification, the coefficient is -0.786. Hence, a one standard deviation increase in target-based return forecasts leads to a 0.652% lower monthly stock return.

Like previous studies, we find that recommendation levels do not predict stocks returns, but that the change in recommendation is positive in all specifications, which is consistent with what previous studies find.

Unsurprisingly the *Net* coefficient is consistently positive and significant. In column 8 the *Net* coefficient is 0.051, showing that a one standard deviation increase in *Net* leads to a 0.47% increase in monthly return. Surprisingly, this is smaller than the effect with the return forecast variable. We see that the *Net* coefficient is pretty stable across specifications, so it seems that the information in *Net* is largely orthogonal to the information found in the analyst variables.

Table 10 repeats the specifications in Table 9, but uses only all-star analysts to make the recommendations and return forecast variables. The return forecast variable is negative in all specifications. It is insignificant in regression 1, which does not have control variables, but significant in regressions 7 and 8, which include the controls. The coefficient is -0.927 in regression, which is lower than the same coefficient reported in regression 8 of Table 9, so all-star price targets are actually worse than those issued by other analysts.

3. Conclusion

In this paper, we study several relations between analyst "actionables", which include return forecasts and recommendations, and stock return anomalies. We find that anomaly-shorts have, on average, higher return forecasts and more favorable recommendations than anomaly-longs. There is far more variation in price targets than in recommendations and our results are stronger, both economically and statistically, with return forecasts than with recommendations. If anomaly variables signal mispricing, our findings imply that investors who follow analysts' suggestions contribute to anomaly mispricing.

To better understand if analysts are making predictable mistakes we create a variable, *Mistakes*, which is the difference between the forecasted and the realized stock returns. We find that anomaly-buys forecast negative values of *Mistakes*, while anomaly-sells forecast positive values of *Mistakes*. This means that analysts' forecasts are too high (low) for anomaly-buys (anomaly-sells). Consistent with the idea that analysts overlook the public information captured by anomaly variables, anomaly variables predict changes in price targets; anomaly-longs subsequently have increases in price targets whereas anomaly-shorts have decreases. This predictability is robust and significant at lags up to 18 months.

Return forecasts and recommendations have both improved over time with respect to anomaly variables. Towards the end of our sample both return forecasts and recommendations are roughly neutral with respect to anomaly variables. Put differently, price targets and recommendations still do not reflect the information in anomaly variables, but at least they are not so strongly at odds with anomaly variables towards the end of our sample period.

Finally, we find that stocks for which analysts expect to have higher returns subsequently have lower returns. This result paints a different picture of analysts' role in mispricing than previous studies, which find that changes in recommendations and changes in price targets predict returns in the direction intended by the analysts. While our other findings suggest that investors who follow analyst actionables contribute to anomaly-variable mispricing, these results show that investors who follow target return forecasts create mispricing that is not explained by previously-documented anomaly variables.

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Figure 1: Analysts' Return forecasts by Anomaly Portfolio

In this figure, we compute the mean return forecasts, which are based on analysts' 12-month price targets, for portfolios that are based on monthly sorts of the comprehensive anomaly variable, *Net*. *Net* is the difference between the number of long and short anomaly portfolios that a stock is in for month *t*. We use 125 different anomalies.

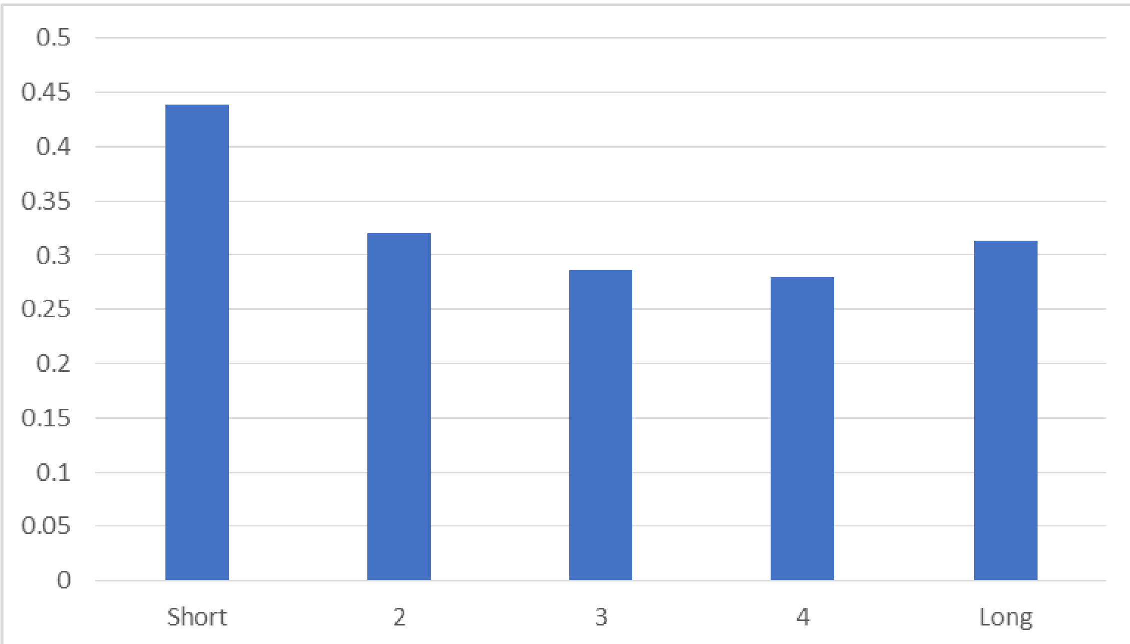

Figure 2: Analysts' Recommendations by Anomaly Portfolio

In this figure, we summarize the mean recommendation for portfolios that are based on monthly sorts of the comprehensive anomaly variable, *Net*. *Net* is the difference between the number of long and short anomaly portfolios that a stock is in for month *t*. We use 125 different anomalies.

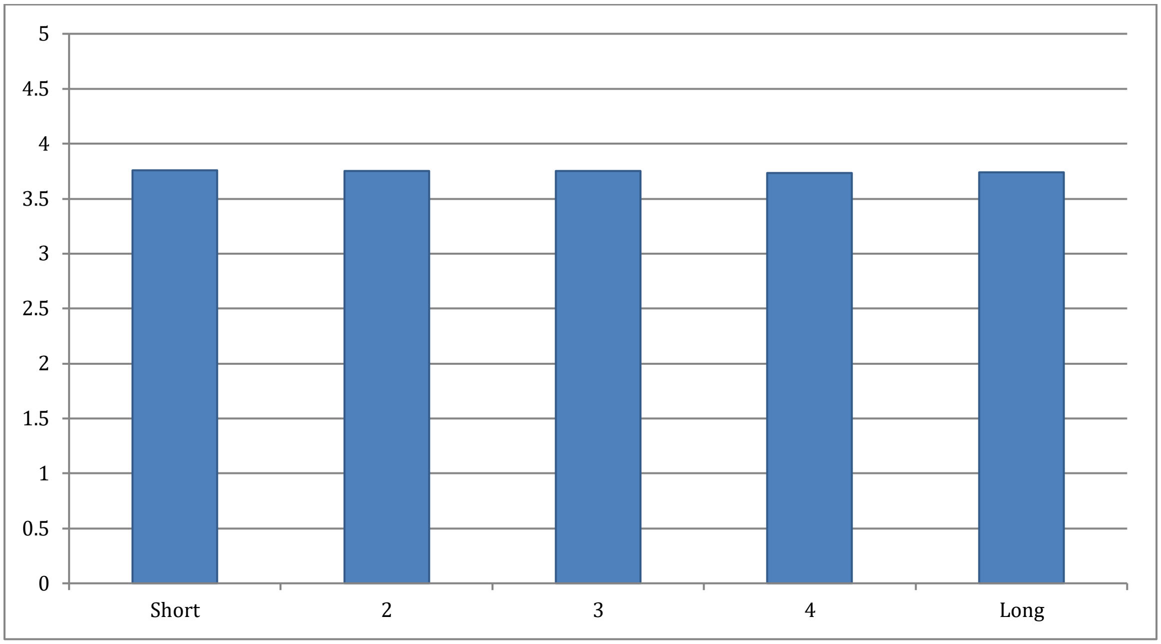

Table 1: Summary Statistics

This table reports summary statistics for the main variables used in this study. For. Ret. is the 12-month return forecast based on the median 12-month price forecast. We take the median based on forecasts issued over the last 11 months, suing only the most recent forecast for each analyst. For. Ret. Dy. is the 12-month return forecast based on the median 12-month price forecast plus the expected dividends, which are equal to last year's total dividends. Num. Target is the number of analysts providing a price target. Std. Dev. Target is the standard deviation of the price targets scaled by the mean price target. Std. Dev. Target is equal to 0 for firms with only 1 price target. Single Target is a dummy equal to 1 if the firm only has a single analyst making issuing a target, and 0 if there are multiple analysts issuing targets. Target Chg. is the monthly difference in the log of the price targets, multiplied by 100. Mean Rec. is the mean analyst recommendation. We construct the Mean Rec. variable such that 5 reflects a strong buy and 1 reflects a strong sell. Rec. Change is the monthly change in the log of the mean recommendations, multiplied by 100. Num. Recs is the number of analysts offering recommendations. Std. Dev. Recs. is the standard deviation of the analysts' recommendations. Std. Dev. Recs. is equal to zero for firms with only one recommendation. E/P Ratio is the average annual earnings forecast divided by the current stock price. Net is the difference between the number of long and short anomaly portfolios (based on quintiles) that a stock is in for month t. We use 96 anomalies from McLean and Pontiff (2016). We also perform sorts on anomaly variables that are limited to specific anomaly types. To conduct this exercise, we split our anomalies into the five groups: (i) Event; (ii) Market; (iii) Valuation; (iv) Fundamentals; and (v.) Opinion. Event anomalies are those based on corporate events or changes in performance. Examples of event anomalies are share issues, changes in financial analyst recommendations, and unexpected increases in R&D spending. Market anomalies are anomalies that can be constructed using only financial data, such as volume, prices, returns and shares outstanding. Momentum, long-term reversal, and market value of equity (size) are included in our sample of market anomalies. Valuation anomalies are ratios, where one of the numbers reflects a market value and the other reflects fundamentals. Examples of valuation anomalies include sales-to-price and market-to-book. Fundamental anomalies are those that are constructed with financial statement data and nothing else. Leverage, taxes, and accruals are fundamental anomalies. Opinion anomalies reflect the opinions of institutional investors and insiders. Insider buys and the level of institutional ownership are examples of opinion anomalies. Our recommendation data begin in 1994 and our price target data begin in 1999. Both datasets end in 2016.

Table 1: (Continued)

Variable	Observations	Mean	Std. Dev.	Min	Max
For. Ret.	645,244	0.34	0.83	-1.37	3.86
For. Ret. Dy.	645,244	0.34	0.83	-1.78	4.25
Num. Target	652,182	6.93	6.49	1.00	59.00
Std. Dev. Target	546,312	0.19	0.18	0.00	1.11
Single Target	645,244	0.16	0.37	0.00	1.00
Trgt. Chng.	641,638	-0.23	8.42	-40.55	28.77
Mean Rec.	920,440	3.77	0.68	1.00	5.00
Rec. Chng.	900,386	-0.25	5.66	-24.12	22.31
Num. Rec	920,440	5.20	4.76	1.00	54.00
Std. Dev. Rec.	732,206	0.73	0.39	0.00	2.83
Single Rec.	920,440	0.20	0.40	0.00	1.00
E/P Ratio	1,016,884	0.01	.016	-1.01	0.20
Net	1,433,026	-0.22	9.29	-51.00	41.00
Event	1,433,026	-0.16	3.62	-18.00	16.00
Fundamental	1,433,026	0.00	3.58	-19.00	16.00
Market	1,433,026	-0.18	4.03	-20.00	16.00
Valuation	1,433,026	0.12	2.55	-11.00	12.00
Opinion	1,433,026	-0.22	9.29	-51.00	41.00

Table 2: Return forecasts and Recommendations Across Anomaly Quintiles

In this table, we summarize target-based return forecasts and mean recommendations for portfolios based on monthly sorts of the anomaly variable, Net. Net is the difference between the number of long and short anomaly portfolios that a stock is in for month t. We use 125 different anomalies. We also perform sorts on anomaly variables that are limited to specific anomaly types. To conduct this exercise, we split our anomalies into the five groups: (i) Event; (ii) Market; (iii) Valuation; (iv) Fundamentals; and (v) Opinion. These variables are defined in Table 1. The standard errors are computed using the method of Newey and West (1987) with 12 lags.

Panel A: Return forecasts

Anomaly Quintile	Net	Event	Fundamental	Market	Valuation	Opinion
1 (Short)	0.439	0.434	0.435	0.332	0.386	0.429
2	0.321	0.373	0.338	0.294	0.361	0.387
3	0.286	0.317	0.315	0.324	0.334	0.344
4	0.279	0.251	0.310	0.355	0.292	0.302
5 (Long)	0.313	0.287	0.284	0.432	0.286	0.240
Long - Short	-0.130	-0.148	-0.151	0.101	-0.103	-0.189
t-statistic	(2.68)	(3.71)	(4.71)	(2.13)	(2.92)	(6.27)

Panel B: Return forecasts Including Dividends

Anomaly Quintile	Net	Event	Fundamental	Market	Valuation	Opinion
1 (Short)	0.440	0.435	0.436	0.332	0.386	0.430
2	0.322	0.374	0.339	0.295	0.362	0.388
3	0.287	0.317	0.315	0.325	0.334	0.345
4	0.280	0.252	0.311	0.356	0.293	0.303
5 (Long)	0.314	0.288	0.285	0.433	0.287	0.241
Long - Short	-0.130	-0.147	-0.151	0.101	-0.102	-0.189
t-statistic	(2.67)	(3.69)	(4.71)	(2.13)	(2.90)	(6.26)

Table 2: (Continued)

Panel C: Mean Recommendations

Anomaly Quintile	**Net**	**Event**	**Fundamental**	**Market**	**Valuation**	**Opinion**
1 (Short)	3.760	3.805	3.715	3.701	3.791	3.748
2	3.752	3.788	3.728	3.743	3.763	3.749
3	3.749	3.752	3.758	3.764	3.774	3.747
4	3.732	3.694	3.776	3.778	3.709	3.748
5 (Long)	3.741	3.681	3.774	3.789	3.676	3.748
Long - Short	-0.004	-0.100	0.038	0.111	-0.097	-0.012
t-statistic	(0.20)	(6.34)	(2.05)	(3.31)	(3.64)	(1.00)

Table 3. Return Forecasts, Recommendations, and Anomaly Variables: Regression Evidence

This table reports the results from a regression of target-based return forecasts (Panel A – the forecast is multiplied by 100)) and mean recommendations (Panel B) on various anomaly variables and controls. *Net* is the difference between the number of long and short anomaly portfolios that a stock is in for month *t*. We use 125 different anomalies. We also conduct regressions with anomaly variables based on specific anomaly types. To conduct this exercise, we split our anomalies into the five groups: (i) Event; (ii) Market; (iii) Valuation; (iv) Fundamentals; and (v) Opinion. These variables are defined in Table 1. In Panel A we include the number of analysts forecasting price targets, whether the firm only has one analyst forecasting its price target, the standard deviation of price targets, and the forecasted earnings to current price ratio as control variables. In Panel B we include the number of analysts making recommendations, whether the firm only has a single analyst making a recommendation, the forecasted earnings to current price ratio, and the standard deviation of the recommendations as control variables. The regressions have time fixed effects and standard errors are clustered on the firm. *, **, and *** stars denote statistical significance at the 10%, 5%, and 1% level.

Panel A: Return forecasts

	(1) Net	(2) Event	(3) Fundamental	(4) Market	(5) Valuation	(6) Opinion
Net Group	-0.423	-1.170	-0.682	-0.062	-0.432	-0.496
	(7.38)***	(10.72)***	(4.58)***	(0.59)	(1.94)*	(2.53)**
Number of Targets	25.059	24.711	24.426	24.321	24.531	24.211
	(16.71)***	(16.57)***	(16.34)***	(16.26)***	(16.33)***	(16.23)***
Single Target	70.243	70.922	72.124	72.555	72.910	72.655
	(20.92)***	(21.22)***	(21.51)***	(21.49)***	(21.82)***	(21.81)***
Std. Dev. Target	-168.580	-171.109	-170.772	-172.018	-170.837	-171.363
	(38.46)***	(39.06)***	(38.94)***	(39.18)***	(39.24)***	(38.89)***
E_{t+1}/P_t *Ratio*	-1.223	-1.107	-1.098	-1.091	-1.111	-1.072
	(12.34)***	(11.43)***	(11.41)***	(11.20)***	(11.26)***	(11.13)***
Observations	624,193	624,193	624,193	624,193	624,193	624,193

Table 3: (Continued)

Panel B: Recommendations

	(1) Net	(2) Event	(3) Fundamental	(4) Market	(5) Valuation	(6) Opinion
Net Group	-0.004	-0.015	0.005	0.002	-0.028	-0.001
	(14.43)***	(23.60)***	(6.11)***	(3.67)***	(25.32)***	(1.38)
Number of Recs	-0.013	-0.012	-0.011	-0.011	-0.014	-0.011
	(21.72)***	(20.37)***	(19.16)***	(17.84)***	(23.57)***	(19.32)***
Single Rec.	-0.039	-0.038	-0.050	-0.052	-0.038	-0.050
	(4.46)***	(4.36)***	(5.74)***	(5.91)***	(4.29)***	(5.64)***
Std. Dev. Rec.	-0.104	-0.100	-0.102	-0.102	-0.103	-0.102
	(15.15)***	(14.65)***	(14.83)***	(14.90)***	(15.09)***	(14.96)***
E/P Ratio	0.354	0.331	0.300	0.306	0.393	0.313
	(19.31)***	(18.28)***	(16.18)***	(16.68)***	(21.51)***	(16.98)***
Observations	883,662	883,662	883,662	883,662	883,662	883,662

Table 4. Robustness: Return Forecasts, Recommendations, and Anomaly Variables

This table reports the results from a regression of target-based return forecasts (Panel A – the forecast is multiplied by 100)) and mean recommendations (Panel B) on *Net* and controls. We estimate these regressions in three different subsamples. In regression 1 in both panels, we limit the sample to firm-month observations which are in the top decile for percentage increase in the number of analysts issuing price targets (Panel A) and recommendations (Panel B). In regression 2, we limit the sample to forecasts and recommendations issued by All-Star analysts. In regression 3 in both panels, we limit the sample to observations that over the subsequent year did *not* do any of the following: (i) are in the top quintile for net external finance; (ii) acquired another firm; (iii) spun off a firm; i.e. these are firms that did *not* engage in banking business in year t+1. *, **, and *** stars denote statistical significance at the 10%, 5%, and 1% level.

Panel A: Return Forecasts			
	Top Decile for Increase in Number of Targets	**All-Star Analysts**	**No Banking in Year t+1**
Net	-0.790	-0.331	-0.411
	(7.48)***	(6.56)***	(6.21)***
Number of Targets	-1.926	0.391	-1.226
	(7.39)***	(3.58)***	(10.90)***
Single Target		33.874	26.822
		(6.50)***	(15.27)***
Std. Dev. Target	92.682	86.137	77.215
	(15.98)***	(10.61)***	(19.06)***
E/P	-206.367	-111.432	-202.846
	(24.87)***	(15.96)***	(32.67)***
Observations	61,983	195,230	474,253

Table 4 (Continued)

Panel B: Recommendations			
	Top Decile for Increase in Number of Targets	**All-Star Analysts**	**No Banking in Year t+1**
Net	-0.005	-0.006	-0.004
	(9.78)***	(10.65)***	(14.10)***
Number of Recs	-0.010	0.003	-0.013
	(10.77)***	(2.70)***	(19.96)***
Single Rec.		-0.160	-0.051
		(5.51)***	(5.14)***
Std. Dev. Rec.	-0.125	-0.182	-0.128
	(9.74)***	(10.71)***	(16.56)***
E/P Ratio	0.233	0.473	0.261
	(7.13)***	(12.17)***	(10.84)***
Observations	111,937	272,440	688,455

Table 5: Analysts' *Mistakes* and Stock Return Anomalies

The dependent variable in these regressions is the analysts' return forecast "mistakes". *Mistakes* is defined as the return forecast minus the realized return. To compute *Mistakes* we divide next year's return forecast by 12, and from this subtract month *t+1*'s realized stock return. The difference is the *Mistake* for month *t*. We multiply *Mistakes* by 100 to improve readability. *Mistakes* is regressed on lagged variables that are measured at time *t*. *Net*, is the difference between the number of long and short anomaly portfolios that a stock is in for month *t*. We use 125 different anomalies. We also conduct regressions with anomaly variables based on specific anomaly types. To conduct this exercise, we split our anomalies into the five groups: (i) Event; (ii) Market; (iii) Valuation; (iv) Fundamentals; and (v) Opinion. These variables are defined in Table 1. We include the number of analysts issuing price targets whether the firm only has a single analyst issuing a target, and the standard deviation of the price targets as control variables. The regressions have time fixed effects and standard errors are clustered on the time. *, **, and *** stars denote statistical significance at the 10%, 5%, and 1% level.

Table 5: (Continued)

	(1) **Net**	(2) **Event**	(3) **Fundamental**	(4) **Market**	(5) **Valuation**	(6) **Opinion**
Net Group	-0.132	-0.207	-0.168	-0.170	-0.272	-0.275
	(8.76)***	(8.90)***	(7.33)***	(4.53)***	(6.06)***	(5.28)***
Mean Rec.	0.908	0.911	1.018	1.024	0.915	0.997
	(6.92)***	(6.83)***	(7.50)***	(7.46)***	(7.20)***	(7.37)***
Change in Rec.	-2.884	-2.750	-2.656	-2.913	-2.993	-2.828
	(4.27)***	(4.07)***	(3.95)***	(4.24)***	(4.40)***	(4.16)***
Number of Targets	-0.159	-0.123	-0.121	-0.154	-0.137	-0.113
	(14.25)***	(11.81)***	(11.81)***	(12.33)***	(12.79)***	(11.08)***
Single Target	3.794	3.717	3.685	3.786	3.765	3.613
	(10.62)***	(10.53)***	(10.51)***	(10.45)***	(10.55)***	(10.51)***
Std. Dev. Target	10.532	11.331	11.517	11.126	11.529	11.567
	(7.12)***	(7.36)***	(7.38)***	(7.48)***	(7.46)***	(7.47)***
Observations	591,553	591,553	591,553	591,553	591,553	591,553

Table 6: Can Anomalies Predict Changes in Analysts' Price Targets?

In this table the dependent variable is the monthly change in price target. It is regressed on lagged values of *Net*. We use lags of 1, 3, 6, 12, and 18 months. *Net* is the difference between the number of long and short anomaly portfolios that a stock is in for month *t*. We use 125 different anomalies. We also conduct regressions with anomaly variables based on specific anomaly types in Panel B. To conduct this exercise, we split our anomalies into the five groups: (i) Event; (ii) Market; (iii) Valuation; (iv) Fundamentals; and (v) Opinion. These variables are defined in Table 1. We include the median price target, the number of analysts forecasting price targets, whether the firm only has one analyst forecasting its price target, and the standard deviation of price targets as control variables. The regressions have time fixed effects and standard errors are clustered on the firm. *, **, and *** stars denote statistical significance at the 10%, 5%, and 1% level.

Panel A: *Net* at various Lags

	(1)	(2)	(3)	(4)	(5)
Median Target	0.000	0.000	0.000	0.000	0.000
	(2.65)***	(2.02)**	(1.39)	(0.40)	(0.09)
Number of Targets	0.021	0.018	0.014	0.005	-0.000
	(9.13)***	(7.87)***	(6.33)***	(2.42)**	(0.00)
Single Target	-0.865	-0.852	-0.835	-0.812	-0.794
	(22.01)***	(21.81)***	(21.26)***	(20.50)***	(19.88)***
Std. Dev. Target	-4.877	-4.975	-5.124	-5.374	-5.283
	(43.33)***	(44.23)***	(45.43)***	(46.73)***	(44.69)***
Net_1	0.064				
	(39.28)***				
Net_3		0.053			
		(32.72)***			
Net_6			0.041		
			(25.04)***		
Net_12				0.017	
				(10.69)***	
Net_18					0.007
					(4.11)***
Observations	634,950	634,299	626,734	609,536	591,924

Table 6: (Continued)

Panel B: Different Anomaly Types

	(1) Event	(2) Fundamental	(3) Market	(4) Valuation	(5) Opinion
Median Target	0.000	0.000	0.000	0.000	0.000
	(0.64)	(1.36)	(1.29)	(0.29)	(0.17)
Number of Targets	0.003	0.003	0.034	0.002	0.001
	(1.17)	(1.53)	(14.79)**	(0.77)	(0.39)
Single Target	-0.813	-0.791	-0.901	-0.792	-0.790
	(20.92)***	(20.30)***	(22.83)**	(20.34)**	(20.29)**
Std. Dev. Targets	-5.271	-5.252	-4.848	-5.421	-5.449
	(47.11)***	(46.76)***	(43.25)**	(48.35)**	(48.58)**
Net Group _1	0.090	0.112	0.155	0.017	-0.020
	(25.21)***	(29.98)***	(39.66)**	(3.27)**	(2.67)**
Observations	634,950	634,950	634,950	634,950	634,950

Table 7: Can Anomalies Predict Changes in Recommendations?

In this table the dependent variable is the monthly change in mean recommendation. It is regressed on lagged values of *Net*. We use lags of 1, 3, 6, 12, and 18 months. *Net* is the difference between the number of long and short anomaly portfolios that a stock is in for month *t*. We use 125 different anomalies. We also conduct regressions with anomaly variables based on specific anomaly types in Panel B. To conduct this exercise, we split our anomalies into the five groups: (i) Event; (ii) Market; (iii) Valuation; (iv) Fundamentals; and (v) Opinion. These variables are defined in Table 1. We include the mean recommendation, number of recommendations, whether the firm only has a single analyst making a recommendation, and the standard deviation of the recommendations as control variables. The regressions have time fixed effects and standard errors are clustered on the firm. *, **, and *** stars denote statistical significance at the 10%, 5%, and 1% level.

Panel A: Net at various lags

	(1)	(2)	(3)	(4)	(5)
Mean Rec.	-1.469	-1.466	-1.469	-1.487	-1.491
	(120.03)***	(120.06)***	(119.15)***	(117.57)***	(114.81)***
Number of Recs.	-0.002	-0.002	-0.002	-0.002	-0.005
	(1.64)	(1.35)	(1.18)	(1.53)	(3.45)***
Single Rec.	-0.027	-0.028	-0.015	0.006	0.011
	(1.25)	(1.28)	(0.71)	(0.25)	(0.48)
Std. Dev. Rec.	-0.335	-0.334	-0.327	-0.323	-0.296
	(15.27)***	(15.25)***	(14.78)***	(14.24)***	(12.76)***
Net_1	0.009				
	(12.67)***				
Net_3		0.010			
		(13.36)***			
Net_6			0.008		
			(11.17)***		
Net_12				0.005	
				(6.66)***	
Net_18					0.001
					(1.50)
Observations	900,386	899,418	885,509	852,471	818,918

Table 7: (Continued)

Panel B: Different Anomaly Types

	(1) **Event**	**(2)** **Fundamental**	**(3)** **Market**	**(4)** **Valuation**	**(5)** **Opinion**
Mean Rec.	-1.469	-1.477	-1.476	-1.482	-1.473
	(119.79)***	(120.29)***	(120.82)***	(120.72)***	(120.78)***
Number of Recs.	-0.006	-0.005	0.003	-0.009	-0.006
	(4.03)***	(3.81)***	(2.29)**	(5.98)***	(4.48)***
Single Rec.	-0.011	-0.008	-0.048	0.007	-0.003
	(0.53)	(0.36)	(2.19)**	(0.34)	(0.14)
Std. Dev. Rec.	-0.338	-0.333	-0.328	-0.337	-0.337
	(15.42)***	(15.21)***	(14.97)***	(15.39)***	(15.38)***
Net Group_1	0.010	0.022	0.033	-0.028	0.010
	(5.91)***	(12.44)***	(18.86)***	(11.21)***	(2.70)***
Observations	811,342	811,342	811,342	811,342	811,342

Table 8: Analysts and Anomalies over Time

This table reports the results from a regression of target-based Return forecasts (Panel A) and mean recommendations (Panel B) on various anomaly variables and controls. *Net* is the difference between the number of long and short anomaly portfolios that a stock is in for month *t*. We use 96 anomalies from McLean and Pontiff (2016). We interact the anomaly variables with *Time*, which is equal to 1/100 during the first month of our sample and increases by 1/100 each month. We also use anomaly variables that are limited to a specific anomaly type. We use 125 different anomalies. We also conduct regressions with anomaly variables based on specific anomaly types. To conduct this exercise, we split our anomalies into the five groups: (i) Event; (ii) Market; (iii) Valuation; (iv) Fundamentals; and (v) Opinion. These variables are defined in Table 1. In Panel A we include the number of analysts forecasting price targets, whether the firm only has one analyst forecasting its price target, and the standard deviation of targets as control variables. In Panel B we include the number of analysts making recommendations, whether the firm only has a single analyst making a recommendation, and the standard deviation of the recommendations as control variables. The regressions have time fixed effects and standard errors are clustered on the firm. *, **, and *** stars denote statistical significance at the 10%, 5%, and 1% level.

Panel A: Target-Based Return forecasts

	(1) Net	(2) Event	(3) Fundamental	(4) Market	(5) Valuation	(6) Opinion
Net Group	-2.413	-4.523	-0.394	-3.434	-6.714	-13.723
	(8.33)***	(7.28)***	(0.53)	(5.46)***	(5.97)***	(12.13)***
*Time * Net Group*	0.411	0.846	-0.294	0.821	1.209	3.042
	(5.31)***	(5.15)***	(1.54)	(4.89)***	(4.09)***	(10.42)***
Number of Targets	-1.940	-1.694	-1.691	-1.722	-1.817	-1.617
	(17.98)***	(16.50)***	(16.51)***	(16.24)**8	(17.06)***	(15.88)***
Single Target	44.592	43.655	43.208	43.947	44.227	42.348
	(25.94)***	(25.50)***	(25.24)***	(25.40)***	(25.66)***	(24.82)***
Std. Dev. Targets	128.187	134.058	134.714	134.678	135.040	134.674
	(34.57)***	(35.94)***	(36.02)***	(35.95)***	(36.76)***	(36.47)***
Observations	645,244	645,244	645,244	645,244	645,244	645,244

Panel B: Recommendations

	(1) Net	(2) Event	(3) Fundamental	(4) Market	(5) Valuation	(6) Opinion
Net Group	-0.008	0.003	0.037	-0.056	-0.062	0.019
	(5.18)***	(0.89)	(8.60)***	(16.15)***	(9.94)***	(2.94)***
*Time * Net Group*	0.001	-0.005	-0.010	0.016	0.011	-0.007
	(2.36)**	(4.57)***	(8.33)***	(16.35)***	(6.18)***	(3.81)***
Number of Recs.	-0.011	-0.010	-0.009	-0.009	-0.011	-0.009
	(17.05)***	(15.20)***	(14.08)***	(14.23)***	(17.84)***	(14.24)***
Single Rec.	0.043	0.042	0.036	0.033	0.041	0.035
	(4.52)***	(4.39)***	(3.77)***	(3.46)***	(4.31)***	(3.70)***
Std. Dev. Recs.	-0.595	-0.578	-0.552	-0.569	-0.575	-0.557
	(37.79)***	(37.39)***	(35.40)***	(36.53)***	(37.50)***	(35.84)***
Observations	612,112	612,112	612,112	612,112	612,112	612,112

Table 9: Analysts, Anomalies, and Cross-Sectional Stock Returns

This table reports the results from regressions of monthly stock returns on lagged values of target-based return forecasts, recommendations, and the anomaly variable *Net*. The variables are defined in Table 1. We also include the lagged change in median price target, the lagged change in mean recommendation, the dummy variable "Buy" equal to 1 if the mean recommendation is 4 or higher, the dummy variable "Sell" equal to 1 if the mean recommendation is less than 3 and zero otherwise, the number of targets, the standard deviations of the price targets and mean recommendations, and the anomaly variable *Net*. The regressions have time fixed effects and the standard errors are clustered on time. To better facilitate interpretation the dependent variable is multiplied by 100 before estimating the regressions. So that the coefficients can be compared across specifications, we begin the sample in 1999, the first year for which we have target price data. Standard errors are clustered on time. *, **, and *** stars denote statistical significance at the 10%, 5%, and 1% level.

Table 9: (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Return Forecast	-0.680			-0.629		-0.658	-0.842	-0.786
	(2.26)**			(2.16)**		(2.16)**	(3.15)***	(3.04)***
Mean Rec.		-0.080			-0.061	-0.062		
		(0.82)			(0.62)	(0.47)		
Net			0.073	0.052	0.064	0.050		0.051
			(7.00)***	(4.27)***	(5.41)**	(4.07)***		(4.87)***
Target Chg.							1.792	1.314
							(1.65)*	(1.21)
Rec. Chg.							1.147	1.009
							(2.29)**	(2.06)**
Buy							-0.122	-0.089
							(0.84)	(0.62)
Sell							-0.066	-0.116
							(0.42)	(0.76)
Num. of Targets							-0.026	-0.009
							(2.49)**	(0.94)
Single Target							0.507	0.427
							(1.97)*	(1.62)
Std. Dev. Targets							1.707	2.053
							(1.41)	(1.75)*
Observations	632,117	904,120	1,417,854	632,117	904,120	593,973	578,321	578,321

Table 10: All-Star Analysts, Anomalies, and Cross-Sectional Stock Returns

This table reports the results from regressions of monthly stock returns on lagged values of all-star analysts' target-based return forecasts, recommendations, and the anomaly variable *Net*. The variables are defined in Table 1. We also include the lagged change in median price target, the lagged change in mean recommendation, the dummy variable "Buy" equal to 1 if the mean recommendation is 4 or higher, the dummy variable "Sell" equal to 1 if the mean recommendation is less than 3 and zero otherwise, the number of targets, the standard deviations of the price targets and mean recommendations, and the anomaly variable *Net*. The regressions have time fixed effects and the standard errors are clustered on time. To better facilitate interpretation the dependent variable is multiplied by 100 before estimating the regressions. So that the coefficients can be compared across specifications, we begin the sample in 1999, the first year for which we have target price data. Standard errors are clustered on time. *, **, and *** stars denote statistical significance at the 10%, 5%, and 1% level.

Table 10 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Return Forecast (AS)	-0.760			-0.688		-0.673	-0.979	-0.927
	(1.52)			(1.43)		(1.35)	(2.39)**	(2.32)**
Mean Rec. (AS)		-0.125			-0.081	-0.230		
		(1.22)			(0.79)	(1.56)		
Net			0.073	0.055	0.059	0.054		0.062
			(7.00)***	(2.93)**8	(3.50)***	(2.66)***		(3.66)***
Target Chg. (AS)							1.033	0.557
							(0.77)	(0.41)
Rec. Chg. (AS)							-0.108	-0.229
							(0.19)	(0.41)
Buy (AS)							-0.287	-0.232
							(1.55)	(1.29)
Sell (AS)							-0.163	-0.232
							(0.78)	(1.14)
Num. of Targets							-0.035	-0.018
							(2.41)**	(1.29)
Single Target							0.880	0.800
							(1.26)	(1.14)
Std. Dev. Targets							3.030	3.546
							(1.40)	(1.70)
Observations	194,493	271,684	1,417,854	194,493	271,684	153,335	146,554	146,554