Analysts and Anomalies[Ψ]

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Abstract

Analysts' price targets and recommendations contradict stock return anomaly variables. Forecasted returns based on price targets are higher (lower) among stocks that anomaly variables suggest will have lower (higher) returns. Analysts' one-year forecasted returns are 14% for anomaly-longs and 24% for anomaly-shorts. Similarly, analysts issue more favorable recommendations for anomaly-shorts than anomaly-longs. Analysts' ex-post mistakes, which we calculate as the forecasted return less the realized return, can be predicted with anomaly variables. Our findings show that investors who follow analysts may contribute to mispricing.

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There is considerable evidence of cross-sectional return predictability. 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 abnormal returns. In aggregate, financial firms spend more than $4 billion annually on sell-side research.[1] The question in this paper is simple: does analyst advice reflect the large number of anomaly variables studied in the academic literature?

Our answer is "no." Using 96 anomaly variables from accounting, economics, and finance journals over the past 40 years, we find that analysts offer price targets and recommendations in the *opposite direction* as anomalies. Analysts forecast higher (lower) stock returns and offer more (less) favorable recommendations to stocks that anomaly variables suggest should be sold (bought). McLean and Pontiff (2016) and Engelberg, McLean, and Pontiff (2017) argue that the return predictability stemming from these 96 predictors 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 begin by calculating each stock's net exposure (*Net*) to 96 different stock return anomaly variables as the number of long-anomaly portfolio memberships minus the number of short-anomaly portfolio memberships (this follows Engelberg, McLean, and Pontiff (2017)). We use the one-year median price target to estimate a

[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.

one-year stock return forecast. We sort stocks into quintiles based on *Net,* and find a negative, monotonic relationship between *Net* and forecasted returns. Stocks in the bottom quintile of *Net* (anomaly-sells) have a mean one-year forecasted return of 24%, while stocks in the top quintile of *Net* (anomaly-buys) have a mean one-year forecasted return of 14%.

We confirm these results in a multivariate regression that includes standard control variables from the analysts' literature and time fixed effects. The coefficient for *Net* in this regression is -0.628 (t-stat = 9.88). This suggests that for stocks with an additional 10 long-anomaly portfolio memberships, analysts forecast returns over the subsequent year to be 6.28 percentage points *lower*. Such forecasts conflict with the anomaly literature, which shows forecasted returns for these stocks should be *higher*.

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 *Net* and the bottom quintile of *Net* is 2% (*t*-stat 4.08). This is economically smaller than the difference in forecasted returns, however the variation in mean recommendations is also smaller than the variation in return forecasts.

We break our 96 anomalies into four groups to better understand whether our findings vary across different types of anomalies. The groupings come from McLean and Pontiff (2016) and Engelberg, McLean, and Pontiff (2017). We find our main result in 3 of the 4 anomaly categories. The exception is among "market" anomalies, (e.g., momentum and idiosyncratic risk), which are based only on stock return, price, and volume data. We find that analysts return forecasts and recommendations are correlated in the right direction (more favorable for longs, less favorable for shorts) with market anomaly signals. This is perhaps surprising, as analysts are supposed to be experts in firms' fundamentals, yet they perform best with anomalies that are not based on accounting data.

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 *Net* 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 *Net* forecasts changes in analysts' price targets. Stocks for which *Net* forecasts higher returns subsequently have increases in price targets. We find this effect for lags of up to 18 months, i.e., *Net* 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 eventually and predictably corrected over the following year and a half. We find these results for all 4 groups of anomaly variables, including market anomalies. This shows that although analysts do a better job at capturing the information in market anomalies, they do not incorporate this information fully.

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 over time. If we regress forecasted returns or recommendations on *Net* and *Net* interacted with a time trend, we find a positive and significant coefficient on the interaction term suggesting that the negative correlation between *Net* and analysts' views has weakened over our sample. However, even during the later years of our sample we still find negative or at best neutral relations between *Net* and forecasted returns and *Net* 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 variables, the anomaly variable *Net*, and future stock returns. We find that including analyst variables in a regression with *Net* has little impact on *Net*'s ability to predict returns, so the useful information in *Net* is largely orthogonal to the information in the analyst variables. Like previous studies, we find that buy recommendations do not predict returns, sell recommendations predict lower returns, and positive (negative) changes in recommendations predict higher (lower) stock returns.

We find that analysts' return forecasts predict stock returns, *but in the wrong direction*. To the best of our knowledge, 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 does not include the announcement day return, and includes a larger set of controls as compared to previous studies.

Our paper builds on several literatures. First, it's related to studies showing how sophisticated investors use anomaly strategies. The paper most similar to ours is Jegadeesh, Kim, Krische, and Lee (2004), who study how analyst recommendations (but not forecasted returns) relate to 12 anomaly variables. Their findings are neutral; analyst recommendations agree with 6 of the anomaly variables and go against the other 6. 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 also related to a literature that studies how institutional 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 Kadelc (2015) 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 (2015) argue that institutions do follow anomaly strategies, but only after an anomaly is highlighted in an academic publication.

We also build on a literature that asks whether analyst information is useful in predicting future returns. Our contribution to this literature is to show that analysts' information about future returns and anomaly variable information about future returns are largely orthogonal. We also 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. Papers linking analyst variables 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. There is, however, some disagreement over some of these effects. 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 really explains the stock price reaction. Altinkilinc, Hansen, and Ye (2016) argue that the post change in recommendations drift has attenuated in recent years due to more efficient arbitrage.

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. We show that analyst price targets and recommendation are in the opposite direction of anomaly variables, which suggests that analysts could be contributing to anomaly-based mispricing.

1. Sample and Data

Our sample is based on median 12-month price targets and consensus recommendations from IBES, and 96 anomaly variables that are studied in McLean and Pontiff (2016). These 96 anomalies are drawn from 80 studies published in peer-reviewed finance, accounting, and economics journals. Each anomaly variable is shown to predict the cross-section of stock returns. All of the anomaly variables can be constructed with data from CRSP, Compustat, or IBES. McLean and Pontiff (2016) study 97 anomalies, however one of the anomalies are based on changes in analysts' recommendations, so we remove it our sample, leaving us with 96 predictive variables.

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 anomaly-characteristic sorts. 14 of our 96 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. As in McLean and Pontiff (2016), the sample selection for each anomaly follows the original study. So if a study only uses NYSE firms, then we only create that anomaly variable for NYSE firms.

We conduct all of our tests during the period 1994-2014, which is the period for which we have analysts' data. We also exclude stocks with prices under $5. These low-priced stocks are excluded from many of the anomaly studies to begin with, and low-priced stocks are less likely to have analyst coverage.

1.1. Variables and Sample Descriptive Statistics

Table 1 provides some descriptive statistics for our sample. We exclude stocks with prices under $5 and stocks for which we cannot calculate a *Net* value. We have a total of 862,891 firm-month observations with one or more analyst recommendation. We construct a forecasted return 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 value of 0.139 and a standard deviation of 0.602. 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 optimistic by 25 to 30%.

We also 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. The mean for this second expected returns variable is 0.143 and its standard deviation is 0.575. 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 construct the mean recommendation variable such that 5 is a "strong buy" and 1 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 3.81, 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 0.64. The average number of recommendations is 7.12.

The variable *Net* 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*. As we mention earlier, we form long and short anomaly portfolios each month for each anomaly by sorting stocks into quintiles. *Net* has a mean value of -0.81, and minimum and maximum values of -39 and 30 respectively.

We also create anomaly variables for 4 different anomaly groups. McLean and Pontiff (2016) 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. As with *Net*, we create the 4 anomaly-group variables by summing up the long and short portfolio memberships within each of the 4 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 forecasted returns 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 forecasted returns 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 forecasted returns without and with dividends, while Panel C reports the results for recommendations. In the first column in Panel A, we see that anomaly-shorts have higher forecasted returns than anomaly-longs. The average forecasted return is 0.228 for anomaly-shorts and 0.112 for anomaly-longs. The difference, -0.116, is statistically significant (t-statistic = 3.20).

Looking across the columns we find similar effects for *Event*, *Fundamental* and *Valuation* anomalies. For all three groups, the shorts have higher forecasted returns than the longs, and forecasted returns decrease monotonically over the anomaly quintiles. The differences in returns are -0.078, -0.154, and -0.068 for the *Event*, *Fundamental*, and *Valuation* anomalies respectively, and all three differences are statistically significant.

With respect to *Market* anomalies, analysts seem to get these "right." The mean forecasted return for the longs is 0.188, the mean forecasted return for the shorts is 0.124, and the difference, 0.063, is statistically significant (*t*-statistic = 2.00). This is perhaps surprising, as analysts are supposed to be experts in analyzing firm fundamentals, yet the only thing they seem to get right with respect to anomalies is with variables that do not contain any accounting information.

Panel B contains the results for forecasted returns that include dividends. The results are basically identical to those in Panel A, so we skip the discussion and move on to discuss 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). Analyst recommendations therefore do not reflect and in fact conflict with anomaly variables. This result is consistent with the result with forecasted returns. The mean recommendation for anomaly-longs is 3.76, while the mean recommendation for anomaly-shorts is 3.83. The difference is statistically significant and reflects a 2% lower mean recommendation for anomaly-longs as compared to anomaly shorts.

The next 4 columns in Table 2 report separate results for the 4 different anomaly types. The results show that for *Event*, *Fundamental*, and *Valuation* anomalies analysts' recommendations are more favorable for anomaly-shorts than for anomaly-longs. All three of these differences are statistically significant. The largest difference (-0.12) is for *Valuation* anomalies. The difference shows that analyst recommendations are 3.2% lower for the longs as compared to the shorts. However, in both cases the mean recommendation is approximately 4, which is a "buy" recommendation. As with forecasted returns the mean recommendation, for *Market* anomalies is higher for the longs. The mean recommendation for the longs is 3.84, and for the shorts it is 3.77.

Figures 1 and 2 put the results from Table 2 in a nutshell. Figure 1 displays the forecasted returns by *Net* quintile, while Figure 2 displays the mean recommendations for the 5 different *Net* quintiles. In Figure 1 we see that the forecasted returns are significantly higher for the anomaly-shorts as compared to the other quintiles. In Figure 2 we see that the anomaly-shorts have better recommendations than the anomaly-longs.

2.1.1. Regression Evidence

Table 3 reports regression evidence of whether analyst forecasted returns and recommendations incorporate the information in anomaly variables. We report results for forecasted returns in Panel A and recommendations in Panel B.

Throughout the rest of the paper we only use forecasted returns without expected dividends, although in untabulated results we find that that the two forecasted return 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. To make the coefficients easier to read the dependent variable (forecasted return) is multiplied by 100. Standard errors are clustered on the firm level.

In the first column the *Net* coefficient is -0.628 and statistically significant. What this shows is that a stock with a *Net* value of -10 has a forecasted return that is higher by about 13% than a stock with a *Net* value of 10, which is sizeable difference. Again, 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 forecasted returns are also in the wrong direction for *Event*, *Fundamental*, and *Valuation* anomalies, whereas forecasted returns are in the right direction for *Market* anomalies. These are the same results that we reported in the univariate sorts in Table 2.

With respect to the control variables, forecasted returns are shown to be higher for stocks with fewer analysts offering price targets and higher for stocks with only a single analyst offering a target. Hence, when there are fewer analysts the analysts tend to be more bullish. The price target standard deviation coefficient is positive and significant, showing that forecasted returns are also higher for stocks with greater variance in price targets.

Panel B reports the results for mean recommendations. In the first column the *Net* coefficient is -0.007 and statistically significant. What this shows is that a stock with a *Net* value of -10 would have a mean recommendation that is higher by 0.014 than a stock with a *Net* value of 10. The mean recommendation is 3.80, 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 offering opinions.

Looking across the columns in Table 2, we see that analyst recommendations are also in the wrong direction with respect to *Event*, *Fundamental*, 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 1.81, so a 1 standard deviation increase in *Valuation* leads to a -0.051 decrease in mean recommendation. The mean of the mean recommendations is 3.81, so this reflects a 1.3% lower mean recommendation.

Like in Table 2, analyst forecasts are in the right direction for *Market* anomalies. The coefficient for *Market* is 0.004, showing that a one standard deviation increase in *Market* leads to a 0.9% higher mean recommendation, which is a small effect, i.e., both the longs and shorts for *Market* have mean recommendations that are close to 3.81, the mean recommendation value.

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, and firms that only have a single analyst offering a recommendation tend to have less favorable recommendations.

2.2. 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 forecasted return divided by 12 minus the realized monthly stock return in month *t*, the first month of the forecast period:

$$\textit{Mistakes} = \textit{Return Forecast} - \textit{Return Realized}$$

Recall that forecasted return is based on a 12-month price target. 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.

We report these results in Table 4 of the paper. It shows that *Net* does indeed predict mistakes in return forecasts. The *Net* coefficient is -0.110 (*t*-statistic = 4.39). This means that if a firm has a positive value of *Net*, its realized stock return tends to be lower than its forecasted return. In contrast, if a firm has a negative value of *Net*, forecasted return is higher than its realized return. The results are economically meaningful. As an example, for a firm with a *Net* value of 10, the estimated *Mistake* is -1.10%, which is an economically meaningful amount.

The next four columns replace *Net* with anomaly variables constructed using the *Event*, *Fundamental*, *Market*, and *Valuation* sample of anomalies. The anomaly variables' coefficients range from -0.101 to -0.186, and all are statistically significant. The results therefore show that all types of anomalies (including *Market* 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 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. Do Anomalies Predict Changes in Price Targets and Recommendations?

In the previous sections we show that overall analysts tend to be at odds with the information in anomaly variables. Anomalies predict stock returns, so one could argue that it is a mistake for analysts to overlook and in fact 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 5 and 6. We use *Net* to predict monthly changes in price targets in Table 5 and monthly changes in mean recommendations in Table 6. 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 4 along with the median price target (Panel A) and mean recommendation (Panel B).

The dependent variable in Table 5 is the change in price target (log target (t+1) – log target (t)) multiplied by 100. In the first regression reported in Panel A of Table 5 *Net* is lagged one month. The coefficient for *Net* is 0.088 and is statistically significant. This means if a firm has a *Net* value of 10, then its median price target increases by 0.88% in the next month. Table 1 shows that the mean monthly change in price target is only 0.2%, so this is a sizeable 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 decrease when the initial price target is higher, when there is a single target, and when the standard deviation of targets is greater.

Panel B reports the results for the different anomaly types. The results are robust across all four of the anomaly groups. Hence, analysts overlook information in all types of anomalies when offering price targets. This is even true for market anomalies, which in Tables 2 and 3 we showed are correlated in the right direction with forecasted returns. The results here and with the *Mistakes* variable in Table 5 suggest that analysts are still overlooking as good deal of the information in *Market* anomalies.

Table 6 reports the results for recommendations. Panel A reports the results for *Net* and *Net* at various lags. In contrast to the results with price targets, the Net coefficient is insignificant across all specifications. 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 weaker results here. Indeed, Table 1 shows that the mean change in recommendation is only -0.01.

In Panel B we explore the effects for the different anomaly types. Here the results are mixed. The coefficients for *Market* and *Event* are positive and significant, whereas the coefficients for *Fundamenta*l and *Valuation* are negative and significant. Hence, the effects tend to cancel out, which explains why the *Net* coefficient is insignificant in Panel A. The largest coefficient in economic terms is for *Valuation*. This coefficient is -0.164. *Valuation* has a standard deviation of 1.81, so a one standard deviation increase leads to a decrease in mean recommendation of -0.30, or a little less than 1% (the mean of the mean recommendations is 3.81). Like the other results with recommendations, the economic significance here is small.

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 1.80 during the last month of our sample. The regressions include month fixed effects, so we do not include *Time* in the regressions.

We report results for forecasted returns in Panel A and recommendations in Panel B of Table 7. 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 -1.474 and the interaction coefficient if 0.804. Time ranges from 1/100 to 1.80, so during the first month of our sample the overall *Net* coefficient *Net* (*Net* + *Net* * *Time*) is -1.466 and during the final month it is -0.034 or basically neutral.

Looking across the columns, we find similar effects for *Event*, *Fundamental*, and *Valuation* 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 3 of these anomaly types.

With *Market* anomalies, the results show the opposite. As in Table 3, the anomaly coefficient is positive and significant, and the time interaction is negative and significant. This means that analysts have gotten worse with respect to market anomalies over time. In this regression, the coefficient for the anomaly variable is 2.115 and the interaction is -1.698. The overall coefficient during the last month of our sample is therefore equal to -0.945. So in the end, analysts reverse, and get *Market* anomalies wrong.

In Panel B we report the results for recommendations. In regression 1 the coefficient for *Net* is -0.019 and the coefficient for *Net* * *Time* is 0.008. 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 -0.019. During the last month of our sample *Time* has a value of 2.4 (we have a longer time series for recommendations than for price targets), so the overall *Net* coefficient is about 0. The results therefore show that analysts had a slight tendency to recommend anomaly-shorts in the past, but no longer do so.

Looking across the columns in Table 7, we see that the improvement in analyst recommendations with respect to anomaly variables is driven completely by *Valuation* anomalies. As we explain earlier, *Valuation* anomalies are based on variables for which price is scaled by an accounting variable, such as book value, sales, or earnings. What the results show is that during the earlier part of our sample analysts were giving more favorable recommendations (analysts almost never issue sells recommendations) to highly valued stocks that are more likely to raise capital, which are also stocks that have low expected returns. Over time, analysts increasingly give more similar recommendations to stocks with high and low expected returns based on these variables. It is interesting to note that stocks with low expected returns based on the *Valuation* anomaly variable are also the stocks that are likely to provide the most investment banking business.

With respect to *Fundamental* anomalies, the results show that analyst recommendations have gotten worse over time, although the effect is marginal (*t*-statistic = -1.84). *Fundamental* anomalies include accruals, leverage, and other variables that are made solely with accounting information. Among other things analysts are supposed to be experts at dissecting financial statements, so it is perhaps surprising that analysts have gotten worse with respect to this information over time. The time trend coefficient for *Market* anomalies is positive but insignificant, and the coefficient for *Market* is positive and significant, as it is in Table 3. Hence, analyst recommendations have always tended to be slightly on the right side of *Market* based anomalies, which include several momentum and reversal variables, along with other variables based on price and trading volume.

2.5. Analysts, Anomalies, and Stock Returns

The results so far show that analysts overlook and are often at odds with anomaly variables. Yet 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, while 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 to generate a "Buy" dummy variable that is equal to 1 if the mean recommendation is 4 or more, and zero otherwise. We also create a "Sell" dummy variable that is equal to 1 if the mean recommendation is 3 or less and zero otherwise.

Our estimation allows us to compare the return-predictability of different analyst measures. As we mention in the Introduction, this 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 announcement day returns and a post-announcement drift that go in the direction intended by the analyst.

We report these results in Table 8. Like previous studies, we find that buy recommendations do not predict stocks returns, while sell recommendations and changes in recommendations do predict returns in the direction intended by the analyst. The change in price target is positive in all specifications, which is consistent with what previous studies find, but insignificant. In regression 1, the change in recommendation coefficient is 0.379, showing that, consistent with analysts' intentions, a one standard deviation increase in the change in recommendation is associated with a 0.102% increase in next month's stock return. The magnitude of this result drops slightly when *Net* is included as an independent variable.

The results using the forecasted return variable are at odds with analysts' intentions. We consider forecasted returns that are lagged for 1 month and 12 months (the variable is designed to predict returns one year ahead). In all specifications the expected return coefficient is negative and statistically significant. As an example, in regression 4, in which the expected return variable is lagged 12 months, the coefficient is -1.035. Hence, a one standard deviation increase in target-based forecasted returns leads to a 0.66% lower monthly stock return. This is a sizeable effect and to the best of our knowledge it has not been shown previously. The standard deviation of the price targets coefficient is also negative and statistically significant in 3 of the 4 specifications. To the best of our knowledge this also has not been shown previously.

The *Net* coefficient is consistently positive and significant. In regression 5 the *Net* coefficient is 0.054, showing that a one standard deviation increase in *Net* leads to a 0.260 increase in monthly return. Surprisingly, this is smaller than the effect with the forecasted return variable. The slope coefficient on *Net* decays only slightly when other independent variables are added to the regression. Thus, the information in *Net* is largely orthogonal to the useful information in recommendation changes and target-forecasted returns.

3. Conclusion

In this paper we study several relations between analysts' forecasted returns, analysts' recommendations, and stock return anomalies. We find that analyst forecasted returns and recommendations tend to conflict with anomaly variables;

anomaly-shorts have, on average, have higher forecasted returns 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 forecasted returns than with recommendations. If anomaly variables are the outcome of 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 indeed 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.

Forecasted returns and recommendations have both improved over time with respect to anomaly variables. Towards the end of our sample both forecasted returns 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 forecasted returns predict lower stock returns. Stocks for which analysts expect to have high returns actually have low returns. This builds on previous studies, which show that changes in recommendations and price targets and sell recommendation predict returns in the direction intended by the analysts. We also find that the information that these analyst variables provide for future stock returns is largely orthogonal to the information in our comprehensive stock return anomaly variable, *Net.* Our earlier findings told us that investors who follow analysts contribute to anomaly-variable mispricing. These findings tell us investors who follow analyst recommendation changes and sell recommendations, mitigate non-anomaly mispricing, while investors who follow target forecasted returns exacerbate mispricing.

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Figure 1: Analysts' Forecasted Returns by Anomaly Portfolio

In this table we compute the mean forecasted returns, 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 96 anomalies from McLean and Pontiff (2016).

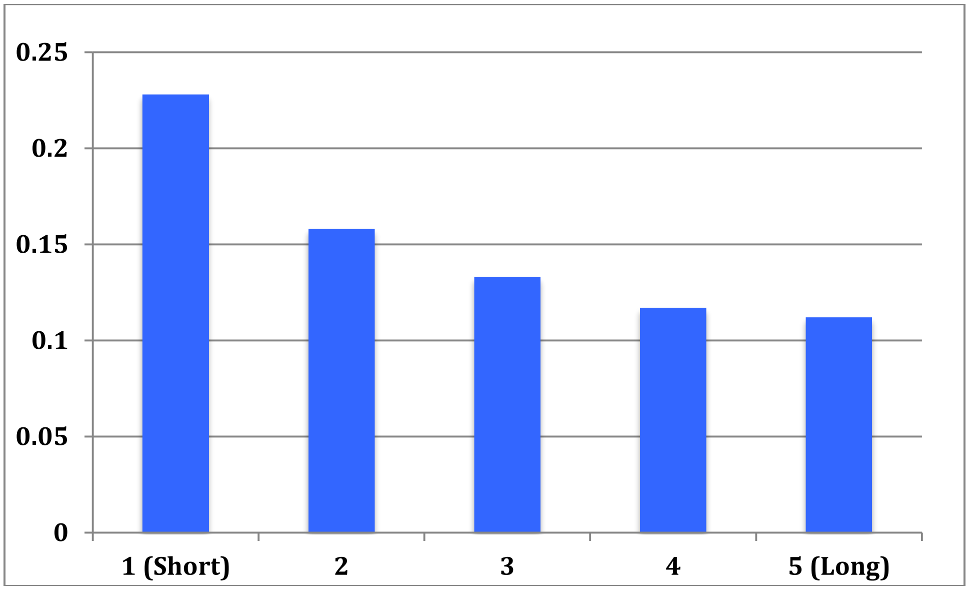

Figure 2: Analysts' Recommendations by Anomaly Portfolio

In this table 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 96 anomalies from McLean and Pontiff (2016).

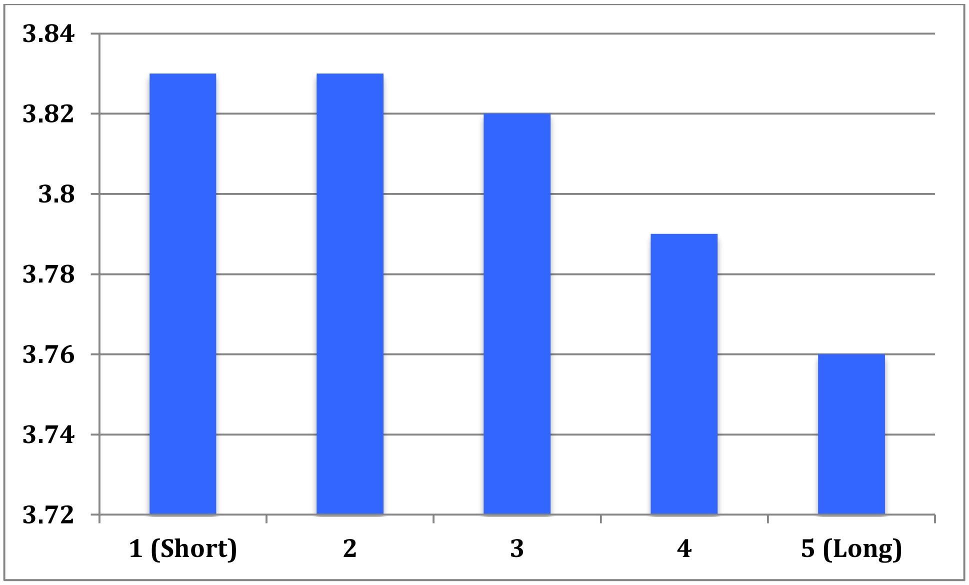

Table 1: Summary Statistics

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. *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. *Target Chg*. is the monthly change in median price target. *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 mean recommendation. *Num. Recs* is the number of analysts making 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. *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 four groups created in McLean and Pontiff (2016): (i) Event; (ii) Market; (iii) Valuation; and (iv) Fundamentals. 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. The sample period is 1994-2014.

Table 1: (Continued)

Variable	Observations	Mean	Std. Dev.	Min	Max
For. Ret.	561, 285	0.139	0.602	-1.538	2.845
For. Ret. Dy.	509,403	0.143	0.575	-1.489	2.739
Num. Target	561,285	6.136	5.293	1	50
Std. Dev. Target	561,287	0.121	0111	0	0.578
Target Chg.	552,617	0.002	0.089	-0.419	0.318
Mean Rec.	964,865	3.81	0.64	1	5
Rec. Chg.	953,736	-0.01	0.27	-4	4
Num. Rec	964,865	7.12	6.49	1	58
Std. Dev. Rec.	964,865	0.63	0.42	0	2.83
Net	1,451,437	-0.81	4.81	-39	30
Event	1,451,437	-0.37	1.94	-13	13
Fundamental	1,451,437	0.09	1.72	-11	11
Market	1,451,437	-0.34	2.46	-15	13
Valuation	1,451,437	0.03	1.81	-10	10

Table 2: Forecasted Returns and Recommendations Across Anomaly Quintiles

In this table we summarize target-based forecasted returns 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 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 four groups created in McLean and Pontiff (2016): (i) Event; (ii) Market; (iii) Valuation; and (iv) Fundamentals. These variables are defined in Table 1. The standard errors are computed using the method of Newey and West (1987) with 12 lags. The sample period is 1994-2014.

Panel A: Forecasted Returns

Anomaly Quintile	Net	Event	Fundamental	Market	Valuation
1 (Short)	0.228	0.173	0.225	0.124	0.174
2	0.158	0.155	0.154	0.105	0.136
3	0.133	0.144	0.149	0.124	0.158
4	0.117	0.120	0.090	0.148	0.116
5 (Long)	0.112	0.095	0.071	0.188	0.105
Long - Short	-0.116	-0.078	-0.154	0.063	-0.068
t-statistic	(3.20)	(4.23)	(4.49)	(2.00)	(1.66)

Panel B: Forecasted Returns Including Dividends

Anomaly Quintile	Net	Event	Fundamental	Market	Valuation
1 (Short)	0.238	0.185	0.245	0.151	0.185
2	0.180	0.178	0.174	0.105	0.157
3	0.127	0.154	0.147	0.124	0.135
4	0.140	0.128	0.092	0.148	0.129
5 (Long)	0.138	0.121	0.089	0.187	0.129
Long - Short	-0.106	-0.071	-0.156	0.050	-0.049
t-statistic	(2.91)	(4.18)	(4.56)	(1.83)	(1.51)

Table 2: (Continued)

Panel C: Mean Recommendations

Anomaly Quintile	**Net**	**Event**	**Fundamental**	**Market**	**Valuation**
1 (Short)	3.83	3.83	3.81	3.77	3.85
2	3.83	3.81	3.84	3.80	3.84
3	3.82	3.81	3.86	3.83	3.87
4	3.79	3.80	3.80	3.83	3.78
5 (Long)	3.76	3.80	3.77	3.84	3.72
Long - Short	-0.076	-0.030	-0.045	0.069	-0.125
t-statistic	(4.06)	(2.87)	(3.53)	(5.33)	(4.37)

Table 3. Forecasted Returns, Recommendations, and Anomaly Variables: Regression Evidence

This table reports the results from a regression of target-based forecasted returns (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 also conduct regressions with anomaly variables based on specific anomaly types. We split our anomalies into the four groups created in McLean and Pontiff (2016): (i) Event; (ii) Market; (iii) Valuation; and (iv) Fundamentals. 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 price 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. The sample period is 1994-2014.

Panel A: Forecasted Returns

	(1) **Net**	**(2)** **Event**	**(3)** **Fundamental**	**(4)** **Market**	**(5)** **Valuation**
Anomaly Variable	-0.628	-0.790	-1.817	0.427	-1.032
	(9.61)***	(6.73)***	(9.62)***	(3.99)***	(4.50)***
Number of Targets	-0.814	-0.703	-0.677	-0.638	-0.762
	(7.12)***	(6.24)***	(6.03)***	(5.64)***	(6.65)***
Single Target	12.332	12.246	11.847	11.961	12.306
	(9.13)***	(9.14)***	(8.86)***	(8.94)***	(9.09)***
Std. Dev. Target	76.697	80.557	76.656	81.738	79.944
	(17.30)***	(17.98)***	(17.49)***	(18.24)***	(18.03)***
Observations	561,287	561,287	561,287	561,287	561,287

Table 3: (Continued)

Table B: Recommendations

	(1) Net	(2) Event	(3) Fundamental	(4) Market	(5) Valuation
Anomaly Variable	-0.007	-0.007	-0.010	0.004	-0.028
	(13.74)***	(6.33)***	(7.21)***	(3.72)***	(17.68)***
Number of Recs	-0.007	-0.006	-0.006	-0.006	-0.007
	(13.09)***	(11.44)***	(11.29)***	(9.99)***	(13.42)***
Single Rec.	-0.098	-0.104	-0.105	-0.107	-0.098
	(5.05)***	(5.38)***	(5.47)***	(5.54)***	(5.07)***
Std. Dev. Rec.	-0.152	-0.15	-0.152	-0.15	-0.151
	(15.80)***	(15.52)***	(15.71)***	(15.42)***	(15.67)***
Observations	953,736	953,736	953,736	953,736	953,736

Table 4: Analysts' *Mistakes* and Stock Return Anomalies

The dependent variable in these regressions is the analysts' return forecast "mistake". *Mistake* is defined as the return forecast minus the realized return. To compute *Mistake* 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*. *Mistake* 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 96 anomalies from McLean and Pontiff (2016). We also split our anomalies into the four groups created in McLean and Pontiff (2016): (i) Event; (ii) Market; (iii) Valuation; and (iv) Fundamentals and create a different *Net* variable for each group. 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. The sample period is 1994-2014.

Table 4: (Continued)

	(1) Net	(2) Event	(3) Fundamental	(4) Market	(5) Valuation
Anomaly Variable	-0.110	-0.123	-0.186	-0.101	-0.171
	(6.83)***	(6.78)***	(5.96)***	(2.92)***	(3.52)***
Mean Rec.	1.002	1.034	1.012	1.070	1.013
	(6.89)***	(6.91)***	(6.98)***	(7.22)***	(7.18)***
Change in Rec.	-0.539	-0.556	-0.587	-0.624	-0.580
	(4.02)***	(4.01)***	(4.22)***	(4.41)***	(4.28)***
Number of Targets	-0.062	-0.042	-0.039	-0.055	-0.052
	(5.86)***	(3.82)***	(3.54)***	(5.33)***	(4.76)***
Single Target	1.563	1.550	1.497	1.548	1.559
	(6.11)***	(6.11)***	(6.01)***	(6.13)***	(6.01)***
Std. Dev. Target	10.497	11.221	10.848	11.310	11.091
	(6.48)***	(6.59)***	(6.59)***	(6.63)***	(6.73)***
Observations	558,405	550,641	550,641	550,641	550,641

Table 5: 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 96 anomalies from McLean and Pontiff (2016). In Panel B we split our anomalies into the four groups created in McLean and Pontiff (2016): (i) Event; (ii) Market; (iii) Valuation; and (iv) Fundamentals. 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. The sample period is 1994-2014.

Panel A: *Net* at various Lags

	(1)	(2)	(3)	(4)	(5)
Median Target	-0.004	-0.004	-0.004	-0.004	-0.004
	(4.27)***	(4.48)***	(4.59)***	(4.77)***	(4.73)***
Number of Targets	0.005	0.001	-0.002	-0.010	-0.015
	(1.12)	(0.14)	(0.47)	(2.01)**	(2.78)***
Single Target	-0.624	-0.609	-0.604	-0.599	-0.614
	(6.63)***	(6.41)***	(6.28)***	(6.02)***	(6.14)***
Std. Dev. Target	-4.681	-4.911	-5.104	-5.352	-5.556
	(6.16)***	(6.37)***	(6.53)***	(6.64)***	(6.98)***
Net	0.088				
	(13.20)***				
Net_3		0.061			
		(10.50)***			
Net_6			0.044		
			(7.42)***		
Net_12				0.017	
				(3.16)***	
Net_18					0.011
					(2.07)**
Observations	552,619	551,812	539,668	507,154	474,456

Table 5: (Continued)

Panel B: Different Anomaly Types

	(1) Event	(2) Fundamental	(3) Market	(4) Valuation
Anomaly Var.	0.127	0.054	0.152	0.136
	(12.44)***	(5.00)***	(12.75)***	(7.74)***
Median Target	-0.004	-0.004	-0.004	-0.004*
	(4.72)***	(4.85)***	(4.28)***	(4.77)**
Number of Targets	-0.010	-0.012	0.009	-0.002
	(1.92)*	(2.20)**	(1.82)*	(0.51)
Single Target	-0.617	-0.581	-0.621	-0.619
	(6.49)***	(6.15)***	(6.62)***	(6.46)***
Std. Dev. Targets	-5.202	-5.200	-5.231	-5.146
	(6.58)***	(6.66)***	(6.69)***	(6.60)***
Observations	552,619	552,619	552,619	552,619

Table 6: 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 96 anomalies from McLean and Pontiff (2016). In Panel B we split our anomalies into the four groups created in McLean and Pontiff (2016): (i) Event; (ii) Market; (iii) Valuation; and (iv) Fundamentals. 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. The sample period is 1994-2014.

Panel A: Net at various lags

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Mean Rec.	-9.396	-9.306	-9.332	-9.548	-9.775
	(22.04)***	(21.76)***	(21.19)***	(20.39)***	(19.56)***
Number of Recs.	-0.055	-0.049	-0.044	-0.038	-0.036
	(7.10)***	(6.38)***	(5.74)***	(4.81)***	(4.70)***
Single Rec.	0.465	0.416	0.450	0.605	0.728
	(0.71)	(0.63)	(0.66)	(0.83)	(0.94)
Std. Dev. Rec.	0.081	0.084	0.142	0.259	0.429
	(0.63)	(0.64)	(1.09)	(1.91)	(3.05)**
Net	-0.015				
	(1.41)				
Net_3		0.012			
		(1.10)			
Net_6			0.015		
			(1.38)		
Net_12				0.017	
				(1.43)	
Net_18					0.008
					(0.68)
Observations	552,569	551,760	539,618	507,103	474,410

Table 6: (Continued)

Panel B: Different Anomaly Types

	(1) Event	(2) Fundamental	(3) Market	(4) Valuation
Anomaly Var.	0.052	-0.057	0.072	-0.164
	(3.08)***	(3.83)***	(2.43)**	(6.40)***
Mean Rec.	-9.385	-9.395	-9.393	-9.434
	(21.98)***	(22.01)***	(21.99)***	(22.21)***
Number of Recs.	-0.052	-0.052	-0.044	-0.060
	(7.53)***	(7.62)***	(4.97)***	(8.12)***
Single Rec.	0.432	0.452	0.426	0.493
	(0.67)	(0.70)	(0.65)	(0.76)
Std. Dev. Rec.	0.090	0.078	0.096	0.074
	(0.70)	(0.61)	(0.74)	(0.57)
Observations	953,736	953,736	953,736	953,736

Table 7: Analysts and Anomalies over Time

This table reports the results from a regression of target-based Forecasted returns (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 types. These are based on the 4 groups created in McLean and Pontiff (2016): (i) Event; (ii) Market; (iii) Valuation; and (iv) Fundamentals. 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. The sample period is 1994-2014.

Panel A: Target-Based Forecasted Returns

	(1) Net	(2) Event	(3) Fundamental	(4) Market	(5) Valuation
Anomaly Variable	-1.474	-2.040	-4.556	2.115	-4.176
	(8.89)***	(6.46)***	(9.17)***	(7.42)***	(8.24)***
*Time * Anomaly Var.*	0.804	1.151	2.601	-1.698	3.118
	(6.56)***	(4.90)***	(7.44)***	(7.79)***	(8.57)***
Number of Targets	-0.821	-0.703	-0.686	-0.650	-0.760
	(7.22)***	(6.25)***	(6.11)***	(5.71)***	(6.70)***
Single Target	12.536	12.256	11.651	11.388	12.275
	(9.27)***	(9.15)***	(8.73)***	(8.50)***	(9.10)***
Std. Dev. Targets	75.171	80.289	75.068	81.589	77.372
	(17.09)***	(17.93)***	(17.28)***	(18.20)***	(17.61)***
Observations	561,287	561,287	561,287	561,287	561,287

Panel B: Recommendations

	(1) Net	(2) Event	(3) Fundamental	(4) Market	(5) Valuation
Anomaly Variable	-0.019	-0.007	-0.006	0.001	-0.067
	(15.91)***	(2.77)***	(1.84)*	(0.33)	(22.68)***
*Time * Anomaly Var.*	0.008	0.000	-0.003	0.002	0.031
	(10.78)***	(0.16)	(1.47)	(1.66)	(15.03)***
Number of Recs.	-0.008	-0.006	-0.006	-0.006	-0.007
	(13.84)***	(11.71)***	(11.50)***	(10.37)***	(13.45)***
Single Rec.	-0.154	-0.152	-0.153	-0.152	-0.153
	(15.97)***	(15.69)***	(15.88)***	(15.62)***	(15.91)***
Std. Dev. Recs.	-0.094	-0.105	-0.107	-0.108	-0.095
	(4.77)***	(5.38)***	(5.47)***	(5.48)***	(4.84)***
Observations	953,736	953,736	953,736	953,736	953,736

Table 8: Analysts, Anomalies, and Cross-Sectional Stock Returns

This table reports the results from regressions of monthly stock returns on lagged values of target-based forecasted returns, recommendations, and anomaly variables. The variables are defined in Table 1. *Lag Forecasted Ret.* is the target-based Forecasted return lagged one-year (instead of 1 month). We also include the lagged change in median price target, the lagged change in mean recommendation, the dummy variable "Buy" equal to 1 f 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. The sample period is 1994-2014.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Forecasted Ret.	-1.273		-1.252		
	(7.34)***		(7.36)***		
Lag Forecasted Ret.				-1.016	-1.035
				(9.67)***	(9.76)***
Target Chg.	0.956		0.787	0.199	0.013
	(1.57)		(1.31)	(0.47)	(0.03)
Rec. Chg.	0.379		0.360	0.335	0.314
	(3.17)***		(3.06)***	(3.11)***	(2.96)***
Buy	0.050		0.076	-0.091	-0.060
	(0.34)		(0.54)	(0.74)	(0.50)
Sell	-0.424		-0.430	-0.330	-0.340
	(3.56)***		(3.62)***	(2.77)***	(2.86)***
Number of Targets	-0.023		-0.012	-0.029	-0.019
	(2.10)*		(1.24)	(2.69)**	(1.95)*
Single Target	-0.369		-0.389	-0.428	-0.443
	(1.89)*		(1.97)*	(2.29)**	(2.35)**
Std. Dev. Targets	-2.580		-2.197	-3.254	-2.822
	(1.67)*		(1.47)	(2.18)**	(1.97)*
Std. Dev. Recs.	0.003		0.026	0.093	0.113
	(0.03)		(0.28)	(1.28)	(1.53)
Net		0.070	0.054		0.054
		(4.26)***	(4.17)***		(4.21)***
Observations	539,452	558,405	539,452	470,787	470,787