Analysts and Anomalies[Ψ]

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Abstract

Analysts' price targets and recommendations contradict stock return anomaly variables. Using an index based on 125 anomalies, we find that analysts' annual stock return forecasts are 11% higher for anomaly-shorts than for anomaly-longs. Anomaly-shorts' return forecasts are excessively optimistic, exceeding realized returns by 34%. Recommendations also tend to be more favorable for anomaly-shorts, although this result varies across anomaly types. Consistent with analysts' slowly incorporating anomaly information, anomalies forecast revisions in both price targets and recommendations. Our findings imply that investors who follow analysts' actionable 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, buy and sell recommendations, and future stock price targets. Revenue and earnings forecasts communicate a firm's financial prospects, and the brunt of academic research on analysts focuses on such financial forecasts (see for example, Bradshaw, 2011, and Kothari, So, and Verdi, 2016). Unlike financial forecasts, recommendations and price targets provide direct, actionable information to 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 current market prices provide investors with an estimate of analysts' return forecasts.

At the same time, 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.

In this paper, we ask whether price targets and recommendations reflect the information in anomaly variables. McLean and Pontiff (2016) and Engelberg, McLean, and Pontiff (2018) provide evidence that anomaly return predictability reflects mispricing. Analysts' recommendations and price targets are also purported

[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.

to convey information about mispricing. Analysts could uncover mispricing either by conducting firm-level security analysis or by conditioning on anomaly variables. In both cases, we would expect analysts' actionables to predict returns in the same direction as anomaly variables.

Our investigation builds on Jegadeesh, Kim, Krische, and Lee (2004)–JKKL hereafter–who study 12 anomalies, and find that recommendations reflect momentum-like anomalies, but contradict contrarian-like anomalies. We expand the list of anomalies to 125, documented in accounting, economics, and finance journals over the past 46 years, and consider both analysts' return forecasts and recommendations.

Earlier studies find that price targets and recommendations are distinct from one another. Bradshaw, Brown, and Huang (2014) conclude that price targets are more informative to investors than both earnings forecasts and recommendations. Brav and Lehavy (2003) find that changes in price targets are informative even after controlling for changes in recommendations and earnings forecasts. Hence, an investigation of price targets in addition to recommendations is warranted. We also consider whether anomaly variables predict changes in price targets and recommendations, which has not been examined.

Our findings can be summarized as follows. Anomaly variables predict returns across stocks covered by analysts, however analysts' actionables tend to conflict with anomaly variables. Return forecasts based on the median 12-month price target predict returns in the *opposite direction* as forecasted by anomaly variables. Stocks in the bottom quintile of our comprehensive anomaly index (anomaly-sells) have a mean one-year return forecast of 45%, while stocks in the top quintile (anomaly-buys) have a mean one-year return forecast of 33%. The return forecast error, which is equal to the return forecast minus the realized stock return, averages 34% for the anomaly-shorts and decreases monotonically across the anomaly portfolios, down to 18% for the anomaly-longs. Like earlier studies, we therefore find that return forecasts based on 12-month price targets are biased upwards. We further show that this bias increases monotonically with anomalies and is more than twice as large for anomaly-shorts as compared to anomaly-longs. These findings persist when we focus on *Institutional Investor* "All-Star" analysts, firms with large increases in analyst coverage, and firms that did not embark on investment banking activity in the previous or subsequent year. We also find this effect among firms with recent changes in median price targets, although the relation is about half as large, suggesting that changes in price targets bring prices more in line with anomaly variables.

We then turn to recommendations, which is the focus of JKKL. In our sample of 125 anomalies, we find that stocks for which anomaly signals predict higher returns have less favorable recommendations as compared to stocks for which anomaly signals forecast lower returns. However, the effect is economically small and is observed in regressions, but not in simple portfolio sorts. The mean recommendation in our sample is 3.77, while the standard deviation is 0.67, so the variation in recommendations is small.

We then test whether our findings vary across different anomaly types. We follow JKKL, and assign stocks to either *Momentum* or *Contrarian* groups based on

JKKL's classification criteria. JKKL argue that analysts have "significant economic incentives to publicly endorse high growth stocks with glamour characteristics" (pg. 1085). These growing firms are more likely to be investment-banking customers. JKKL find that analysts are more likely to recommend momentum-like stocks than contrarian or value-like stocks, even though both groups have higher expected returns.

We assign 33 of our 125 anomalies to *Contrarian* and *Momentum* categories. Like JKKL, we find that recommendations reflect *Momentum* anomalies, but contradict *Contrarian* anomalies. With respect to return forecasts, we find that for both *Contrarian* and *Momentum* anomalies, return forecasts are higher for anomaly-shorts than for anomaly-longs. The differences are large. For *Momentum* anomalies, the return forecast error is 45% for the shorts and 12% for the longs. For *Contrarian* anomalies, the forecast error is 35% for the shorts and 15% for the longs.

When it comes to changes in targets and recommendations, analysts do a better job, but with some delay. We find that anomalies forecast the forecasters: our anomaly index predicts changes in both analysts' price targets and recommendations. Stocks for which the anomaly-index forecasts higher (lower) returns subsequently have increases (decreases) in price targets and recommendations. This effect persists for up to 12 months; i.e., the anomaly index today can predict increases in price targets over the next month and continuing on for the next 12 months. These results are robust across all anomaly groups. Earlier studies show that analysts' revisions for both actionables and earnings are informative, with immediate stock price reactions that are consistent with the revision followed by a post-revision drift (e.g., Brav and Lehavy, 2003; Gleason and Lee, 2003; and Jegadeesh et al., 2004). Our findings suggest that some of this effect may be analysts incorporating more anomaly-information. However, our results also show that even after these updates, the levels in targets and recommendations still contradict anomaly variables. Therefore, a good part of the stock price reactions documented in these other studies is likely due to information not reflected in anomalies.

Over time, many anomaly variables have become widely known and we find that analysts have incorporated more of this information into their price targets, but not their recommendations. However, even during the later years of our sample, we still find a negative relation between the anomaly index and return forecasts. Thus, analysts today are still overlooking a good deal of valuable, anomaly-related information.

To summarize, our paper makes at least three broad contributions to the literature. First, when issuing actionables, analysts fail to incorporate some of the key findings from the anomalies literature, and, in fact, issue actionables that contradict the findings from this literature. This is especially true with stocks that contrarian signals imply should be shorted. Second, the tendency for analysts to contradict anomaly signals is more salient with price targets than recommendations. Third, analysts seem to improve with respect to anomaly signals over time. However, even at the end of our sample period, they still issue actionables that contradict anomalies, albeit not as strongly as before.

Our paper is related to a literature that studies how sophisticated investors use anomaly strategies. Drake, Rees, and Swanson (2011) study the same anomalies as JKKL. Drake et al. find that short-sellers agree with analyst recommendations and short momentum-sells, but ignore analysts and profit by shorting glamour (contrarian) stocks, despite the fact that these stocks have favorable analyst recommendations. McLean and Pontiff (2016) use a sample of 97 anomalies and find that short sellers tend to target stocks in anomaly-short portfolios, and further show that this effect increases after an anomaly has been highlighted in an academic publication. Lewellen (2011) finds that institutional investors fail to take advantage of anomalies when forming their portfolios. Edelen, Ince, and Kadlec (2016) suggest that institutions contribute to anomalies. 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, follow anomaly strategies, but only after an anomaly is highlighted in an academic publication.

Our paper is also related to a literature that asks whether analyst information is useful in predicting stock returns. Papers linking analyst-actionable 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 generally finds that *changes* in analyst actionables, but not levels, are informative because they predict returns in the direction intended by the analyst.

Our paper shows that changes in actionables are forecasted by anomaly variables and thus reflect the information embedded in anomaly variables.

1. Sample, Data, and Descriptive Statistics

1.1 Sample

Our analyst data are obtained from IBES. Our anomaly variables use data from CRSP, Compustat, and the Insiders and 13F databases from Thompson Reuters. We exclude stocks with prices less than $1 and stocks that do not have CRSP stock price data.[2] The IBES price target data begin in 1999 and end in 2017, while recommendations data begin in 1994 and end in 2017. Our return forecast sample consists of 670,177 firm-month observations, while the recommendation sample consists of 929,862 observations.

1.2. Analyst Variables

We estimate the median 12-month price target using the IBES Details database. For each firm-month observation, we build a price target sample that includes the most recent 12-month price target issued by each analyst during the last 12-months. The median value from this sample is our 12-month price target estimate. We exclude 9 observations with a median price target of zero. This procedure produces median price targets that closely match the medians provided in the IBES Summary database.

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

With respect to measuring the median price target, it is unclear whether a long or short look-back horizon is optimal. On the one hand, analysts may not update their price targets because they believe the current target price is meaningful. On the other hand, inertia may cause stale price targets to be less accurate. According to Brav and Lehavy (2003), the median time to update a price target is 59 days, so inertia is typically not an issue, and it seems to us that updating is relatively easy if the situation warrants. For robustness, we estimate median price targets using targets issued either over the last quarter or the last month. We obtain similar results with these shorter horizons, so we only report results with the 12-month horizon, which offers a larger sample of targets. Moreover, the magnitude of our findings is too large to be explained by stale prices over horizons of a month or two.

We estimate the 12-month return forecast by scaling the median 12-month price target by the current stock price and subtracting 1 from this ratio. We drop return forecasts that are more than 5 standard deviations above the mean, and then winsorize at the 1st and 99th percentiles. Our mean return forecast is 37%, while the standard deviation is 0.58. Similarly, Bradshaw (2002) reports a mean return forecast of 38%, while Brav and Lehavy (2003) report a mean return forecast of 33%. Table 1 further shows that, among firms that have price targets, the average number of targets issued is 7.13. Fifteen percent of firms with price targets have only a single analyst issuing a target.

Like Jegadeesh et al. (2004), we estimate the mean recommendation by including the most recent recommendation from each analyst within the last 12 months. Recommendations can take on one of five values: strong sell, sell, hold, buy, and strong buy. We assign numerical values ranging from 1 (strong sell) to 5 (strong buy).

Table 1 shows that the mean recommendation value is 3.77, while the standard deviation is 0.67. It is well known that analyst recommendations are biased towards buy and strong buy. Similar to us, JKKL report a mean recommendation of 3.67. The average firm with a recommendation has 5.25 analysts issuing recommendations, and 20% of firms with recommendations have only a single analyst issuing a recommendation.

1.3. Anomaly Variables

Our sample of anomalies contains 125 different variables that have been shown to predict the cross-section of stock returns. The anomalies are drawn from studies published in peer-reviewed finance, accounting, and economics journals. We do not include anomalies that are based on analysts. The 125 anomalies include 91 of the 97 anomalies that are studied in McLean and Pontiff (2016) and Engelberg, McLean, and Pontiff (2018). We exclude 6 of the anomalies that are related to analyst information. The 125 anomalies used in this study are described in the paper's online appendix.[3]

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

[3] The six excluded variables are: Analyst Value (Frankel and Lee, 1988); Change in Recommendation (Jegadeesh et al, 2004); Forecast Dispersion (Diether, Malloy, and Scherbina, 2002); Increase in Forecast (Barber et al, 2001); Decrease in Forecast (Barber et al., 2001); Change in Recommendation + Accrual (Barth and Hutton, 2004).

as the extreme quintiles produced by the sorts. Some of our anomalies are indicator variables (e.g., credit rating downgrades). For these anomalies, 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.

Like Engelberg, McLean, and Pontiff (2018), we create an anomaly index *Net*; it is the difference between the number of long and short anomaly portfolios that a stock belongs to in a 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*. Table 1 shows that, among stocks with analyst recommendations, *Net* has a mean value of -2.13, and minimum and maximum values of -51 and 39 respectively.

We construct two groups that are similar in spirit to the groupings of Jegadeesh et al. (2004): *Momentum* and *Contrarian*. Jegadeesh et al. place 11 of their 12 anomalies into these two groups. Closely following their criteria, we place 33 of our 125 anomalies into the two groups. We have 10 *Momentum* anomalies and 23 *Contrarian* anomalies. *Momentum* anomalies are variables that predict returns in a direction that is consistent with the market underestimating the continuation of the trend. *Momentum* anomalies include past 6-month returns, past returns from month t-7 to t-12, industry momentum, and momentum conditional on trading volume. *Contrarian* anomalies include ratios of fundamentals to market prices, and variables that assume investors will naively extrapolate a trend. *Contrarian* anomalies include price-to-book, price-to-earnings, accruals, and long-term reversal. We provide a complete list of both anomaly groups in the paper's online appendix.

2. Univariate Tests

2.1. Do Analysts' Actionables Agree with Anomaly Variables? Evidence from Portfolio Sorts

In this section of the paper, we present our main findings. Table 2 presents results based on monthly sorts of the anomaly variable *Net*, and anomaly variables based on *Momentum* and *Contrarian* anomalies. With respect to *Net*, Table 2 shows that *Net* longs have annual returns of 16% and shorts have returns of 9%. The returns increase monotonically from shorts to longs. Most of the anomaly literature documents monthly return-predictability, but we see here that anomalies are also relevant for the annual horizon, which is the period that price targets and recommendations forecast.

Table 2 shows that return forecasts contradict *Net*. Return forecasts are 45% for the shorts and 33% for the longs. Moreover, the forecasts decline monotonically from the short to long quintiles, so the return forecast pattern across the *Net* quintiles is the mirror *opposite* of the realized return pattern of the anomaly portfolios. The forecast error, which is the return forecast minus the realized return, is 34% for the shorts and 18% for the longs. Hence, like earlier studies, we find that return forecasts are too high. We further show that this effect increases monotonically with anomaly variables. These results are also displayed in Figure 1.

Recommendations are uncorrelated with *Net*. In the subsequent tables that present regressions with controls, we report a negative, statistically significant relation. In Table 2, however, the average recommendation for the longs is 3.75, and for the shorts it is 3.74, and the difference, 0.01, is neither statistically significant nor economically meaningful. As we mention above, longs have higher realized returns than shorts, so analysts are making a mistake by giving the two groups similar recommendations. This effect is also displayed in Figure 2.

The next two panels report results for the *Momentum* and *Contrarian* anomaly groups. With respect to the *Momentum* anomalies, both the return forecasts and forecast errors are largest for the shorts, smallest for the longs, and decline monotonically from the short to long quintiles. The return forecast for the shorts is an incredible 63%, while the forecast for the longs is 21%. The difference is statistically significant. Similarly, the forecast error is 45% for the shorts and 12% for the longs. As with *Net*, we see that analysts are overly optimistic with virtually all stocks, and that this optimism is greatest with the shorts.

Like Jegadeesh et al. (2004), we find that recommendations are consistent with momentum anomalies. The average recommendation is 3.89 for the longs, whereas for the shorts it is 3.59. The difference, 0.30, is statistically significant and economically meaningful. The difference shows that recommendations are on average 8.4% higher for the longs as compared to the shorts. It is puzzling that recommendations are positively correlated with anomaly forecasts, whereas price targets are negatively correlated. It seems as if analysts fail to be internally consistent with their advice.

In the final Panel, we see that *Contrarian* anomalies contradict anomaly variables with both return forecasts and recommendations. Return forecast averages 46% for the shorts and 31% for the longs. The return forecast error averages 35% for the shorts and 15% for the longs. Both the forecast and the forecast error decrease monotonically across the anomaly quintiles from the shorts to the longs.

Our recommendation results are consistent with Jegadeesh et al. (2004), who also find that recommendations conflict with contrarian anomalies. Recommendations average 3.80 for the shorts, 3.67 for the longs, and decrease monotonically from shorts to longs. The difference, -0.13, is statistically significant. Analysts therefore get both price targets and recommendations wrong with respect to *Contrarian* anomalies, just as they do for anomalies overall.

3. Regression Evidence

Table 3 reports regression evidence of whether analyst return forecasts and recommendations incorporate the information in anomaly variables. We report results using *Net*, *the Momentum* and *Contrarian* anomalies, and 4 different subsamples, which we describe below.

3.1 Subsamples

Changes in Median Price Target or Mean Recommendation. Our return forecast is based on the median price target, which is computed using the most recent price target issued by each analyst over the last 12 months. As we mentioned earlier, analysts, on average, update their price targets every two months, and we have experimented with return forecasts that only use targets issued over the last month or quarter and obtained similar findings. For robustness, we report results where we only use firms that had a change in the median price target over the last month. This excludes 59% of the sample. The remaining sample reflects firms with a good deal of recent analyst price target activity. We conduct the same exercise for recommendations, excluding firms that did not have a change in mean recommendation over the past month. This eliminates 60% of the sample.

Coverage Increases. Lee and So (2017) argue that analysts are constrained and so the decision to initiate coverage on a stock is associated with an increase in resources devoted to analyzing the firm. We therefore might expect analysts' actionable to be more informative if there is a large increase in coverage. We thus report results for subsamples consisting only of firms that are at or above the 90th percentile for the percentage change in the number of analysts issuing price targets (Panel A) or recommendations (Panel B).

All-Star Analysts. Perhaps highly acclaimed analysts do a better job utilizing information from anomaly variables. Clarke, Khorana, Patel, and Rau (2007) argue that analysts determined by *Institutional Investor* magazine to be "All-Stars" might be more adept than typical analysts. In regression 4, 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 in any prior November issue of the magazine.

Investment Banking Activity. It could be the case that analysts have worse incentives to provide accurate actionables when faced with potential investment banking business. Lin and McNichols (1998) find that analysts that are affiliated with the firm's investment bank make more positive recommendations. We therefore create a limited sample of firms which, in both the previous and the subsequent year, did not do any of the following: (i) make it into the top quintile for use of external finance, according to the measure of Bradshaw, Richardson, and Sloan (2006); (ii) acquire another firm; or (iii) spin off a firm.

3.2. Regression Results for Return Forecasts and Recommendations

In this section we report regression results for return forecasts and recommendations. Panel A of Table 3 reports the return forecast results. 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 median price target. Standard errors are clustered on both firm and time. The results in Panel A of Table 3 mirror the univariate findings in Table 2.

In the first column, the *Net* coefficient is -0.008 and statistically significant, so a stock with a *Net* value of -10 has an estimated return forecast 16% higher than a stock with a *Net* value of 10, which is a sizeable difference. If price targets reflected the information in anomaly variables, then the *Net* coefficient would be positive.

Looking across the columns in Panel A, we see that analysts' return forecasts are in the wrong direction for all four of the subcategories that we describe above, as well as for *Momentum* and *Contrarian* anomalies. The subcategories are not mutually exclusive, i.e., a firm can be in more than one subcategory at a point in time. For all cases, the coefficient for the anomaly variables is negative and statistically significant. This shows that analysts' return forecasts contradict anomalies even when there is a recent change in the median price target, a large increase in the number of analysts covering the firm, weaker potential banking conflicts, and when All-Star analysts' make the return forecasts. The negative relation between return forecasts and anomaly variables is completely robust.

With respect to the control variables, return forecasts are lower for stocks with fewer analysts issuing 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.

Panel B reports the results for mean recommendations. Similar to Panel A, the regressions include time fixed effects, the number of analysts issuing recommendations, whether there is only a single recommendation, and the standard deviation of the recommendations. Standard errors are clustered on both firm and time. In the first column, the *Net* coefficient is -0.001 and statistically significant. Thus, a stock with a *Net* value of -10 has a mean recommendation that is higher by 0.020 than a stock with a *Net* value of 10. The mean recommendation is 3.77, so, like in Table 2, this difference is not large economically, however here it is in the wrong direction and statistically significant. This further confirms the idea that analysts do not incorporate the information reflected in anomalies when issuing actionables.

The recommendations are in the wrong direction across all of the groups, with the exception of *Momentum* anomalies, which is consistent with what we report in Table 2 and JKKL. Hence, regardless if there is large change in the number of analysts issuing recommendations, a change in the mean recommendation, all-star analysts, or weaker banking incentives, it is still the case that recommendations conflict with anomaly variables.

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 (except for number of recommendations in the All-Star regression). Hence, firms with more analyst coverage, more dispersion in recommendations, and those that only have a single analyst offering a recommendation tend to have less favorable recommendations.

For both panels of Table 3, previous versions of this paper included analyst-forecasted-earnings-to-price ratio, i.e., the forecasted earnings over the subsequent year scaled by current price, as a control variable. It is known that anomalies are related to biases in earnings forecasts (see Engelberg, McLean, Pontiff, 2018). These specifications generated similar slope coefficients on *Net* as Table 3. Thus, the errors in analysts' earnings forecasts do not drive our results.

3.3. Return Forecast Error

In Table 4, we estimate regressions using the same seven specifications as in Panel A of Table 3, only here we use the return forecast error as the dependent variable. Like in Table 3 the regressions in Table 4 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. In addition, we also include the mean recommendation and change in recommendation as control variables. Recall that the forecast error is equal to the 12-month return forecast minus the realized yearly return:

Forecast Error = Return Forecast – Return Realized

The portfolio sorts reported in Table 2 show that return forecast errors are significantly higher for shorts than longs, and decrease monotonically across anomaly quintiles from shorts to longs. The results in Table 4 confirm this, and further show that *Net* has a negative relation with return forecasts in all seven specifications.

In regression 1, the *Net* slope coefficient is -0.008 (*t*-statistic = 12.06). This result is economically meaningful. For example, a firm with a *Net* value of 10 has a forecast error that is 16% lower than a firm with a *Net* value of -10. Like Table 3, we see here that analysts issue extremely high price targets for anomaly shorts.

The results reported across the next six columns are largely the same. Anomaly-shorts and, indeed, all stocks with negative values of *Net*, have significantly higher return forecast errors. The smallest (in absolute value) *Net* coefficient is -0.007 in regression 2, which is for the sample of firms that recently had changes in the median price target. Yet even here, the difference in return forecast between firms with *Net* values of 10 and -10 is 14%. The final two columns show that the forecast error result is robust with both the *Momentum* and *Contrarian* anomalies, confirming the results in Table 2.

The results also show that return forecast errors are higher for stocks with higher mean recommendations and for stocks with increases in mean recommendations over the last year. This means that price targets are typically 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 forecast errors as well, so price targets are too high for firms with only one analyst issuing a target and for firms that have more disagreement among the analysts that follow it. The number of analysts issuing price targets is associated with lower forecast errors, i.e., a larger number of analysts leads to a more reasonable (or less unreasonable) forecast.

3.4. 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 is 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 predict changes in analyst price targets and recommendations. If anomaly variables 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 recommendations in Table 6. In both cases, we use the percentage change and multiply this number by 100 for readability. Summary statistics for these variables are reported in Table 1. We include the same control variables as were used in

Tables 3 and 4, along with the median price target (Table 5) and mean recommendation (Table 6). *Net* is 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 time and we include time fixed effects. We also experimented with including lagged values of changes in targets and recommendations, and our results do not change.

The dependent variable in Panel A of Table 5 is the change in price target (price target $target_{t+1}$/price $target_{t-1}$) multiplied by 100. In the first regression, *Net* is lagged one month. The coefficient for *Net* is 0.062 and is statistically significant. This means that if a firm has a *Net* value of 10, then its median price target increases by about 0.62% in the next month. Regressions 2-5 repeat these tests using *Net* lagged from 3, 6, 12, and 18 months. The coefficients are all positive and statistically significant up to 12 months. Hence, even after 12 months, analysts are still incorporating the public information that is reflected in anomaly variables. The coefficient for *Net* lagged 12 months is 0.012. This means if at *t-12* a firm had a *Net* value of 10, then its median price target is expected to increase by 0.12% in month *t+1*. The coefficients are also monotonically decreasing as the number of lags increase, which suggests that analysts are slowly incorporating the public information reflected in the anomalies. 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 across the various subsamples. In all specifications, the anomaly variable is lagged by one month, and in all specifications the anomaly variable predicts increases in the price target. The coefficient is smallest for the All-Star analysts, and largest for the *Momentum* anomalies, although Table 1 shows that the *Momentum* variable also has the lowest standard deviation. The coefficient is 0.503, so a one standard deviation increase in the *Momentum* anomaly index yields an increase in the price target of 1.09%.

Table 6 reports the results for monthly changes in mean recommendations ($\text{recommendation}_{t+1}/\text{recommendation}_{t}$ - 1) multiplied by 100. 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 all specifications, except for the 18-month lag, where *Net* is positive and insignificant. In regression 1, the *Net* coefficient is 0.012. *Net* has a standard deviation of 8.90 so a one standard deviation increase in *Net* leads to a 1.07% increase in recommendation. The net coefficient decays as the lags increase, but is significant for up to one year.

In Panel B, we explore the effects across the six groups, using the *Net* variables lagged one month. The effects are positive and significant across all groups, with the exception of *Contrarian* anomalies, which have a negative and insignificant coefficient. As with price targets, the largest coefficient is for the *Momentum* anomalies. A one standard deviation increase in the *Momentum* anomaly index yields a change in recommendation of 0.29%. Tables 2 and 3 show that recommendations reflect *Momentum* anomalies, i.e., they are higher for the longs than the shorts. Analysts still update in the direction of *Momentum* anomalies, and therefore overlook some of the information reflected in these variables.

3.5. 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 these effects via the same regression framework 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, and increases by 1/100 each month. The regressions include month-fixed effects, so we do not include *Time* in the regressions.

In Table 7, regressions 1 through 3 report the results for return forecasts, while regressions 4-6 report results for recommendations. We report results for the total sample of anomalies and the *Momentum* and *Contrarian* anomaly groups.

In regression 1, 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 -0.012 and the interaction coefficient is 0.002. *Time* ranges from 0.62 to 2.88 in this specification (our recommendation sample starts several years earlier), so, during the first month of our sample, the overall *Net* coefficient (*Net* + *Net* * *Time*) is about -0.012 during the first month and -0.006 during the final month, which is closer to neutral, but still negative.

Regressions 2 and 3 show that there are positive time trends for the both the *Momentum* and *Contrarian* anomalies. The coefficients show that the overall *Momentum* index coefficient was -0.119 during the first month and -0.015 during the last month. The *Contrarian* index coefficient is -0.025 during the first month and

-0.011 during the last month. So, the improvement over time is ubiquitous with respect to different types of anomalies.

The recommendation results reported in columns 4 to 6 show that in the full sample, recommendations have not become more in line with *Net* over time. In regression 1, the *Net x Time* interaction is positive but insignificant, showing that analysts have not overall improved over time with respect to having recommendations reflect *Net*.

The *Momentum* and *Contrarian* anomalies tell different stories. Analysts have improved over time with *Contrarian* anomalies, but have gotten worse over time with *Momentum* anomalies. The *Momentum* results are different than those reported for price targets, where analysts improve over time.

We can say that overall, analysts significantly improve over time with price targets but not recommendations, although they do improve with *Contrarian* anomalies and recommendations.

3. Conclusion

In this paper, we study several relations between analyst price targets, recommendations, and stock return anomalies. We find that anomaly-shorts have, on average, higher return forecasts, and higher return forecast errors than anomaly-longs. Anomaly-shorts also have more favorable recommendations than anomaly-longs, although there is some variation in the recommendation results across anomaly types. These findings continue to hold when we focus on *Institutional Investor* "All-Star" analysts, firms with large increases in analyst coverage, firms with recent changes in median price targets and mean recommendations, and firms that do not embark on investment banking activity in the previous or subsequent year.

Consistent with the idea that analysts overlook the public information captured by anomalies, 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 for lags up to 12 months. We find the same effect with recommendations for lags up to 12 months. Yet even with this updating, it is still the case that stocks with recent changes in median targets and mean recommendations have return forecasts and recommendations that contradict anomaly variables.

If investors who pay attention to analysts exert price impacts, then our results imply a link between analyst actions and market efficiency. Specifically, analyst return forecasts may contribute to anomaly mispricing and market inefficiency. Analyst recommendations may also contribute to anomaly mispricing, although they could reduce mispricing in *Momentum* anomalies. That said, we cannot measure the extent to which analysts may impact anomalies, so we do not know whether and to what extent the anomalies would persist, even if analysts "got it right."

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Figure 1: Stock Returns, Return Forecasts, and Return Forecast Errors Across Anomaly Quintiles

In this figure, we report the results from monthly portfolio sorts based on the comprehensive anomaly variable, *Net*. We report average values, within each *Net* quintile of the 1-year return forecast, the annual stock return, and the return forecast error, which is equal to the return forecast minus the annual stock return. The 1-year return forecast is based on the median 12-month price target.

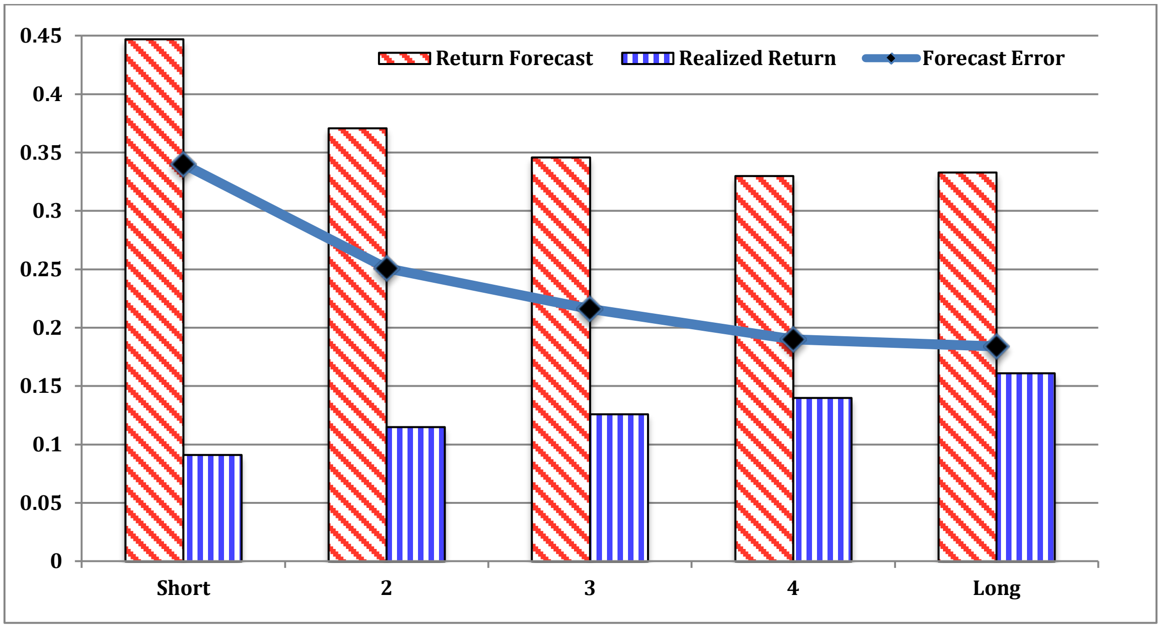

Figure 2: Stock Returns and Recommendations Across Anomaly Quintiles

In this figure, we report the results from monthly portfolio sorts based on the comprehensive anomaly variable, *Net*. We report average values, within each *Net* quintile, for the buy/sell recommendation (left vertical axis) and the annual stock return (right vertical axis). Our recommendation and anomaly data begin in 1994, while our price target data begin in 1999. Both datasets end in 2017.

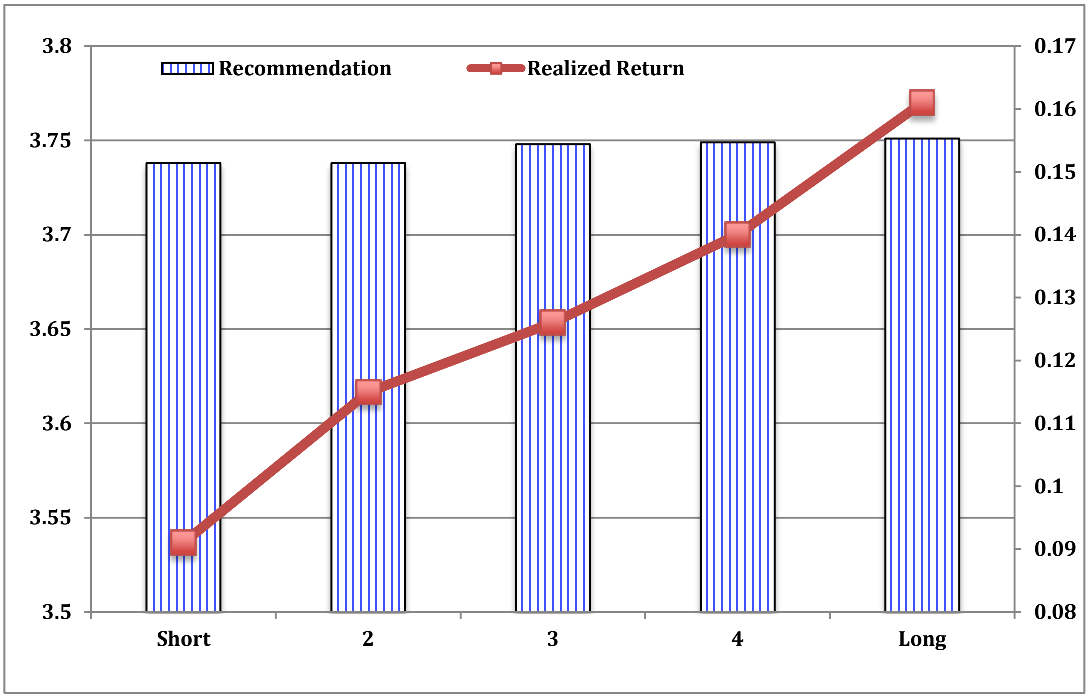

Table 1: Summary Statistics

This table reports summary statistics for the main variables used in this study. Forecasted Return 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 12 months, using only the most recent forecast for each analyst. Number of Targets is the number of analysts providing a price target. Std. Dev. Target is the standard deviation of the price targets scaled by the median 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 issuing a target, and 0 if there are multiple analysts issuing targets. Target Change is the monthly percentage change in price target, multiplied by 100. Mean Rec. is the mean analyst recommendation. We construct the Mean Recommendation variable such that 5 reflects a strong buy and 1 reflects a strong sell. Rec. Change is the monthly percentage change in the mean recommendation, multiplied by 100. Num. Recommendations is the number of analysts offering recommendations. Std. Dev. Recs. is the standard deviation of the analysts' recommendations. Std. Dev. Recs. is equal to 0 for firms with only 1 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 125 anomalies, which builds on the 97 anomaly-sample in McLean and Pontiff (2016). We classify 33 of our anomalies as either *Momentum* (10 anomalies) or *Contrarian* (23 anomalies). These categories are based on those defined in Jegadeesh et al. (2004). Our recommendation data begin in 1994 and our price target data begin in 1999. Both datasets end in 2017.

Table 1: (Continued)

Variable	Observations	Mean	Std. Dev.	Min	Max
Forecasted Return	670,168	0.37	0.58	-0.59	5.71
Number of Targets	673,219	7.13	6.61	1.00	59.00
Std. Dev. Target	673,210	0.16	0.18	0.00	2.19
Single Target	673,219	0.15	0.36	0.00	1.00
Target Change (%)	663,499	0.11	8.62	-60.00	89.29
Mean Recommendation	929,862	3.77	0.67	1	5
Num. Recommendations	929,862	5.25	4.75	1	54
Std. Dev. Rec.	929,862	0.59	0.45	0	2.83
Single Rec.	929,862	0.20	0.40	0	1
Rec. Change (%)	913,778	-0.05	5.92	-31.25	50
Net	971,242	-2.13	8.90	-51	39
Momentum	971,242	0.10	2.17	-9	9
Contrarian	971,242	-1.00	4.08	-20	16

Table 2: Return Forecasts and Recommendations Across Anomaly Quintiles

In this table, we sort firms on our anomaly variables into quintiles each month. We then report averages for each quintile of the following variables: annual returns, 12-month return forecasts, the return forecast error, which is the return forecast minus the annual realized return, and the recommendations. The 12-month return forecast is based on the median 12-month price target. The anomaly variable *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. We classify 33 of our anomalies as either *Momentum* (10 anomalies) or *Contrarian* (23 anomalies). These definitions build on the groups in Jegadeesh et al. (2004). The standard errors are computed using the method of Newey and West (1987) with 12 lags. Our recommendation and anomaly data begin in 1994, while our price target data begin in 1999.

	All Anomalies (Net)				**Momentum Anomalies**			**Contrarian Anomalies**		
Anomaly Quintile	**Annual Return**	**Return Forecast**	**Return Forecast Error**	**Rec.**	**Return Forecast**	**Return Forecast Error**	**Rec.**	**Return Forecast**	**Return Forecast Error**	**Rec.**
1 (Short)	0.091	0.447	0.340	3.738	0.627	0.450	3.587	0.457	0.353	3.798
2	0.115	0.371	0.251	3.738	0.350	0.232	3.759	0.393	0.269	3.775
3	0.126	0.346	0.216	3.748	0.279	0.165	3.799	0.341	0.211	3.757
4	0.140	0.330	0.190	3.749	0.247	0.143	3.829	0.305	0.172	3.694
5 (Long)	0.161	0.333	0.184	3.751	0.211	0.120	3.885	0.309	0.152	3.669
L-S	0.070	-0.114	-0.156	-0.013	-0.416	-0.330	0.298	-0.149	-0.197	-0.129
t-stat.	(3.40)	(3.01)	(2.76)	(0.76)	(5.40)	(4.51)	(12.39)	(4.21)	(3.62)	(7.58)

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

This table reports the results from a regression of return forecasts (Panel A) and recommendations (Panel B) on 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 to create *Net*. 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 the standard errors are clustered on firm and time. *, **, and *** stars denote statistical significance at the 10%, 5%, and 1% level. The regressions are estimated in different samples. Regression 1 includes the full sample. Regression 2 includes observations that had a change in the median target (Panel A) or mean recommendation (Panel B). Regression 3 includes 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 4, we limit the sample to forecasts and recommendations issued by All-Star analysts. In regression 5, we limit the sample to observations that, during the previous year and over the subsequent year, did *not* do any of the following: (i) end up in the top quintile for net external finance; (ii) acquire another firm; (iii) spin off a firm; i.e. these are firms that did *not* engage in banking business in the previous or subsequent year. Regressions 6 and 7 use *Net* variables created with *Momentum* and *Contrarian* anomalies only.

Table 3: (Continued)

Panel A: Return Forecasts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full Sample	Median Target Change	Coverage Increase	All-Star Analysts	No Investment Banking	Momentum Anomalies Only	Contrarian Anomalies Only
Net	-0.008	-0.006	-0.010	-0.007	-0.009	-0.057	-0.017
	(14.05)***	(12.35)***	(11.66)***	(9.64)***	(13.79)***	(16.89)***	(16.74)***
Number of Targets	-0.015	-0.010	-0.023	-0.005	-0.018	-0.011	-0.014
	(21.27)***	(19.53)***	(15.51)***	(5.12)***	(20.85)***	(21.33)***	(21.96)***
Single Target	0.278	0.228		0.360	0.283	0.216	0.278
	(22.18)***	(17.78)***		(7.84)***	(20.99)***	(20.82)***	(22.37)***
Std. Dev. Target	0.778	0.684	0.995	0.989	0.820	0.615	0.775
	(21.45)***	(16.97)***	(17.23)***	(10.92)***	(22.44)***	(19.22)***	(21.03)***
Observations	670,168	274,932	65,658	195,452	462,882	670,168	670,168

Table 3: (Continued)

Panel B: Recommendations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full Sample	Mean Rec. Changes	Coverage Increase	All-Star Analysts	No Investment Banking	Momentum Anomalies Only	Contrarian Anomalies Only
Net	-0.001	-0.002	-0.001	-0.003	-0.001	0.054	-0.015
	(3.88)***	(4.92)***	(2.73)***	(5.42)***	(2.43)**	(37.35)***	(21.20)***
Number of Recs	-0.011	-0.008	-0.010	0.004	-0.011	-0.011	-0.013
	(15.31)***	(12.54)***	(7.50)***	(3.13)***	(13.18)***	(14.66)***	(17.99)***
Single Rec	-0.056	-0.115		-0.185	-0.098	-0.052	-0.042
	(4.03)***	(7.14)***		(5.99)***	(6.67)***	(3.82)***	(3.06)***
Std. Dev. Rec	-0.090	-0.121	-0.131	-0.183	-0.111	-0.090	-0.091
	(7.75)***	(10.70)***	(8.12)***	(9.94)***	(8.64)***	(7.90)***	(7.89)***
Observations	929,862	368,693	124,056	271,319	651,011	929,862	929,862

Table 4: Return Forecast Error and Stock Return Anomalies

The dependent variable in these regressions is the analysts' return forecast error, which is the return forecast minus the annual realized return. The forecast error 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 include the number of analysts issuing price targets, whether the firm only has a single analyst issuing a target, the standard deviation of the price targets, the mean recommendation, and the change in mean recommendation as control variables. The regressions have time-fixed effects and standard errors are clustered on the time and firm. *, **, and *** stars denote statistical significance at the 10%, 5%, and 1% level. The regressions are estimated in different samples. Regression 1 includes the full sample. Regression 2 includes observations that had a change in the median target. Regression 3 includes observations which are in the top decile for percentage increase in the number of analysts issuing price targets. In regression 4, we limit the sample to forecasts and recommendations issued by All-Star analysts. In regression 5, we limit the sample to observations that, during the previous year and over the subsequent year, did *not* do any of the following: (i) end up in the top quintile for net external finance; (ii) acquire another firm; (iii) spin off a firm; i.e. these are firms that did *not* engage in banking business in the previous or subsequent year. Regressions 6 and 7 use *Net* variables created with *Momentum* and *Contrarian* anomalies only.

Table 4 (Continued)

	(1) Full Sample	(2) Median Target Change	(3) Coverage Increase	(4) All-Star Analysts	(5) No Investment Banking	(6) Momentum Anomalies Only	(7) Contrarian Anomalies Only
Net	-0.008	-0.007	-0.013	-0.008	-0.009	-0.051	-0.017
	(12.06)***	(10.72)***	(10.98)***	(9.12)***	(11.66)***	(15.86)***	(12.02)***
Mean Rec.	0.180	0.189	0.193	0.179	0.192	0.207	0.171
	(24.73)***	(24.20)***	(14.78)***	(10.69)***	(23.06)***	(26.00)***	(24.26)***
Change in Rec.	0.004	0.006	0.005	0.004	0.005	0.005	0.004
	(17.47)***	(20.55)***	(7.90)***	(8.41)***	(15.95)***	(19.42)***	(16.39)***
Number of Targets	-0.011	-0.007	-0.015	-0.002	-0.013	-0.007	-0.010
	(16.29)***	(12.22)***	(7.81)***	(2.19)*	(16.65)***	(13.46)***	(15.48)***
Single Target	0.216	0.171		0.261	0.225	0.165	0.213
	(11.62)***	(7.96)***		(4.30)***	(11.34)***	(9.77)***	(11.64)***
Std. Dev. Target	0.729	0.632	1.099	0.823	0.787	0.609	0.723
	(10.02)***	(7.47)***	(14.46)***	(6.07)***	(11.31)***	(8.66)***	(9.93)***
Observations	541,320	233,021	57,426	181,609	394,603	541,320	541,320

Table 5: Can Anomalies Predict Changes in Analysts' Price Targets?

In this table, the dependent variable is the monthly change in price target (price $target_{t+1}$/price $target_t$) multiplied by 100. It is regressed on lagged values of *Net*. We use lags of 1, 3, 6, 12, and 18 months. *Net_t* is the difference between the number of long and short anomaly portfolios that a stock is in *t* month*s* ago. We use 125 different anomalies. 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 time. *, **, and *** stars denote statistical significance at the 10%, 5%, and 1% level. In Panel B, regression 1 includes the full sample. Regression 2 includes observations that had a change in the median target. Regression 3 includes observations which are in the top decile for percentage increase in the number of analysts issuing price targets. In regression 4, we limit the sample to forecasts and recommendations issued by All-Star analysts. In regression 5, we limit the sample to observations that, during the previous year and over the subsequent year, did *not* do any of the following: (i) end up in the top quintile for net external finance; (ii) acquire another firm; (iii) spin off a firm; i.e. these are firms that did *not* engage in banking business in the previous or subsequent year. Regressions 6 and 7 use *Net* variables created with *Momentum* and *Contrarian* anomalies only.

Panel A: *Net* at various Lags

	(1)	(2)	(3)	(4)	(5)
Median Target	0.000	0.000	0.000	0.000	0.000
	(25.30)***	(19.92)***	(16.87)***	(6.45)***	(2.90)***
Number of Targets	0.005	0.001	-0.004	-0.013	-0.018
	(1.02)	(0.28)	(0.85)	(2.76)***	(3.68)***
Single Target	-0.418	-0.394	-0.372	-0.322	-0.290
	(6.07)***	(5.70)***	(5.36)***	(4.55)***	(4.01)***
Std. Dev. Target	-2.799	-2.893	-3.049	-3.151	-2.987
	(6.83)***	(6.99)***	(7.31)***	(7.40)***	(6.88)***
Net_1	0.062				
	(16.97)***				
Net_3		0.051			
		(14.67)***			
Net_6			0.035		
			(11.14)***		
Net_12				0.012	
				(4.35)***	
Net_18					0.004
					(1.33)
Observations	660,817	655,572	646,659	628,335	610,382

Table 5: (Continued)

Panel B: Predicting Price Target Changes with Different Specifications

	(1) Full Sample	(2) Median Target Change	(3) Coverage Increase	(4) All-Star Analysts	(5) No Investment Banking	(6) Momentum Anomalies Only	(7) Contrarian Anomalies Only
Net_1	0.062	0.116	0.086	0.051	0.066	0.503	0.065
	(16.97)***	(17.39)***	(12.13)***	(11.20)***	(16.34)***	(24.69)***	(8.36)***
Median Target	0.000	-0.000	0.000	0.000	0.000	-0.000	0.000
	(25.30)***	(4.23)***	(3.84)***	(12.93)***	(23.87)***	(1.14)	(5.62)***
Number of Targets	0.005	-0.137	-0.022	-0.009	0.008	-0.021	-0.010
	(1.02)	(17.61)***	(1.32)	(1.64)	(1.54)	(4.55)***	(2.13)*
Single Target	-0.418	4.427		-0.922	-0.428	0.107	-0.364
	(6.07)***	(14.59)***		(4.77)***	(6.00)***	(1.61)	(5.22)***
Std. Dev. Targets	-2.799	-0.156	-3.166	-2.558	-2.936	-1.355	-3.010
	(6.83)***	(0.22)	(7.40)***	(4.77)***	(7.53)***	(3.31)***	(7.31)***
Observations	660,817	253,223	65,172	190,619	493,481	660,817	660,817

Table 6: Can Anomalies Predict Changes in Recommendations?

In this table, the dependent variable is the monthly change in mean recommendation (recommendation$_{t+1}$/recommendation$_t$) multiplied by 100. 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. 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. Regression 1 includes the full sample. Regression 2 includes observations that had a change in the mean recommendation (Panel B). Regression 3 includes observations which are in the top decile for percentage increase in the number of analysts issuing recommendations. In regression 4, we limit the sample to forecasts and recommendations issued by All-Star analysts. In regression 5, we limit the sample to observations that, during the previous year and over the subsequent year, did *not* do any of the following: (i) end up in the top quintile for net external finance; (ii) acquire another firm; (iii) spin off a firm; i.e. these are firms that did *not* engage in banking business in the previous or subsequent year. Regressions 6 and 7 use *Net* variables created with *Momentum* and *Contrarian* anomalies only.

Table 6: (Continued)

Panel A: *Net* at various lags

	(1)	(2)	(3)	(4)	(5)
Mean Rec.	-1.698	-1.700	-1.711	-1.732	-1.732
	(54.75)***	(54.64)***	(54.50)***	(54.21)***	(53.51)***
Number of Recs.	-0.019	-0.019	-0.020	-0.022	-0.024
	(8.30)***	(8.23)***	(8.66)***	(9.23)***	(10.14)***
Single Rec.	0.116	0.125	0.148	0.172	0.183
	(3.90)***	(4.18)***	(4.87)***	(5.46)***	(5.68)***
Std. Dev. Rec.	-0.217	-0.210	-0.205	-0.193	-0.164
	(7.26)***	(6.97)***	(6.74)***	(6.19)***	(5.18)***
Net_1	0.012				
	(11.67)***				
Net_3		0.010			
		(10.81)***			
Net_6			0.006		
			(7.15)***		
Net_12				0.002	
				(2.26)*	
Net_18					0.000
					(0.40)
Observations	913,778	904,662	888,524	854,014	820,826

Table 6: (Continued)

Panel B: Predicting Recommendation Changes with Different Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full Sample	Mean Rec. Changes	Coverage Increase	All-Star Analysts	No Investment Banking	Momentum Anomalies Only	Contrarian Anomalies Only
Net_1	0.012	0.013	0.013	0.007	0.012	0.136	-0.003
	(11.67)***	(10.00)***	(5.97)***	(3.66)***	(10.62)***	(25.87)***	(1.34)
Mean Rec.	-1.698	-1.730	-1.364	-0.943	-1.665	-1.782	-1.702
	(54.75)***	(49.02)***	(31.55)***	(23.35)***	(53.91)***	(56.21)***	(54.78)***
Number of Recs.	-0.019	-0.016	-0.025	0.002	-0.018	-0.025	-0.024
	(8.30)***	(7.11)***	(4.89)***	(0.64)	(7.25)***	(10.86)***	(10.53)***
Single Rec.	0.116	0.159		-0.107	0.076	0.155	0.148
	(3.90)***	(2.30)**		(1.30)	(2.46)*	(5.12)***	(4.89)***
Std. Dev. Rec.	-0.217	-0.182	-0.238	0.238	-0.221	-0.228	-0.220
	(7.26)***	(3.87)***	(4.43)***	(4.34)***	(6.90)***	(7.70)***	(7.37)***
Observations	913,778	365,619	122,801	260,100	690,858	913,778	913,778

Table 7: Analysts and Anomalies over Time

This table reports the results from a regression of target-based return forecasts (regressions 1-3) and mean recommendations (regressions 4-6) on *Net*, *Net* interacted with time, and controls. *Net* is the difference between the number of long and short anomaly portfolios that a stock is in for month *t*. We interact *Net* with *Time*, which is equal to 1/100 during the first month of our sample and increases by 1/100 each month. In regressions 1-3, 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 firm and time. *, **, and *** stars denote statistical significance at the 10%, 5%, and 1% level.

	Return Forecasts			**Recommendations**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Net	**Momentum**	**Contrarian**	**Net**	**Momentum**	**Contrarian**
Net	-0.012	-0.119	-0.025	-0.002	0.078	-0.020
	(6.82)***	(9.63)***	(7.15)***	(3.32)***	(36.68)***	(15.99)***
*Time * Net*	0.002	0.036	0.005	0.001	-0.018	0.003
	(3.02)***	(6.11)***	(2.75)***	(1.29)	(14.38)***	(4.19)***
Num. of Targets or Recs.	-0.014	-0.012	-0.014	-0.011	-0.011	-0.013
	(21.61)***	(21.41)***	(22.08)***	(15.31)***	(14.75)***	(18.05)***
Single Target or Rec.	0.279	0.212	0.278	-0.055	-0.052	-0.041
	(21.96)***	(21.58)***	(22.26)***	(4.02)***	(3.81)***	(3.02)***
Std. Dev. Targets or Rec.	0.773	0.604	0.772	-0.090	-0.089	-0.091
	(22.07)***	(20.55)***	(21.50)***	(7.75)***	(7.78)***	(7.88)***
Observations	670,168	670,168	670,168	929,862	929,862	929,862