Analysts Are Good at Ranking Stocks

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Abstract

Sell-side analysts' forecasts of future stock returns are highly biased and the aggregated consensus forecast is a poor predictor of future returns. In sharp contrast, we show that the information revealed through the implicit ranking of return forecasts conducted individually by each analyst is highly informative of subsequent returns. Long-short portfolios sorted on these rankings result in large and highly significant excess returns that cannot be explained by previous anomaly characteristics or information extracted from consensus forecasts. The strong performance of the relative ranking forecasts is most easily understood by noting their similarity with within-analyst demeaned forecasts. The latter are equivalent to removing each analyst's fixed effect and thus controlling in a general manner for unobservable analyst-specific biases, an effect which cannot be achieved when starting with the aggregated consensus forecast. We also show that analysts' rankings of earnings forecasts exhibit greater predictive power for subsequent stock returns compared to consensus forecasts.

Keywords: Sell-side analysts; Cross-section of stock returns; Relative valuation; Target price; Earnings forecasts
JEL Classification: G12, G14, G24

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1 Introduction

The consensus target return for an individual stock—calculated from sell-side analysts' price targets as the mean or median of the implied monthly return across all analysts—tends to be much higher than the subsequent realized return. Over the period 1999 to 2021, the average monthly consensus target return across all stocks was 2.20% whereas the actual average realized return was only 1.15%. Moreover, consensus target returns are not only biased but they also have weak cross-sectional predictive power for future returns: investment strategies that go long stocks with high consensus returns and short those with low consensus returns do not results in significant excess returns. We are by no means the first to point to this poor performance (see, among others, Brav and Lehavy, 2003; Da and Schaumburg, 2011; Bradshaw et al., 2013) and some recent work try to correct the forecasts in order to produce better investment signals (see, e.g., Dechow and You, 2020; Loudis, 2022). In common for all these studies is the focus on the consensus forecast; i.e., the average (or median) target return across analysts.

In this paper, we turn away from the prevailing custom of focusing on consensus target returns and instead look at the information contained within each analyst's set of target returns. That is, in a given month, an analyst may issue target returns for a number of different stocks. We show that whereas the absolute level of these target returns (as reflected in the consensus forecast) are severely biased and weak predictors of future returns, the implicit ranking reflected in the target returns is in fact very informative of future returns. In other words, analysts are actually very good at ranking the *relative* performance of stocks in their portfolios, despite not being able to pin down the *absolute* performance. Our study thus offers a novel and positive view on the value added by sell-side analysts.

The main innovation of our analysis is the use of *within-analyst* information. Rather than averaging target returns across analysts for a given stock, we average the relative ranks of a given stock's target returns across the analysts covering that stock—with the relative ranks calculated within each analyst's set of covered stocks. Using portfolio sorts, we show that stocks with higher average ranks outperform those with lower average ranks. A long-short equal-weighted portfolio that buys (sells) stocks with the highest (lowest) ranks brings an average monthly return of 0.89% with a t-statistic of 5.31. A value-weighted strategy delivers an average monthly return of 0.47% with a t-statistic of 2.69. In a comparison with 140 different anomaly strategies from Chen and Zimmermann (2021), we find that the relative rank strategy results in a Sharpe ratio that is second only to one other strategy among these 140 in the equal-weighted case, and third among the value-weighted strategies.

Our second implementation of the relative forecast strategy uses not only the relative ranking but the actual relative returns within each analyst's set of stocks. Specifically, rather than using the ranking of the target returns, we form within-analyst *demeaned* target returns. For each analyst who covers a given stock, we subtract from her target return for this stock the average of her target returns across all the stocks she covers. We average the resultant demeaned returns across all analysts to obtain a measure of analyst-level relative valuation for this stock. Similar to the ranking based approach, these "demeaned" returns provide a relative valuation as well. The ranking- and demeaning-based approaches of extracting the implicit relative valuation of each analyst deliver very similar results in terms of predicting the cross-section of future returns. The advantage of the implementation using within-analyst demeaning is not any gains in performance, but rather the clear analytical framework it provides when comparing the relative forecast with the consensus forecast. We elaborate on this in more detail below. Since both the ranking- and demeaning-based implementations use the information in analysts' relative valuation, we refer to ranking and relative valuation interchangeably below, and only specify the exact approach when we want to make a certain point.

The returns to the long-short strategies are virtually unaffected after adjusting for well-known risk factors. The information contained in analysts' rankings of their stocks is therefore not spanned by the characteristics used to explain variations in the cross-section of stock returns. Rather, the rankings appear mostly unrelated to these characteristics. Previous findings show that consensus target returns typically contradict the forecast direction implied by the characteristics (see e.g., Engelberg et al., 2020). Our results here suggest that analysts bring relevant information—contained in their relative forecasts—to the market and that such information is not related to publicly available information captured by common stock characteristics.

It is important to understand the difference between long-short portfolio strategies based on consensus forecasts versus relative forecasts. In the former case, the signal is the average forecast across all analysts, whereas in the latter, the signal is the average of all within-analyst demeaned forecasts. This demeaning controls for individual analyst-specific biases (e.g., consistent over-optimism or a faiblesse for growth stocks). When using the consensus forecast as the signal, such biases are only controlled for in the long-short strategy *when they are identical across analysts.* To use the language of regression analysis, within-analyst demeaning can identically be thought of as controlling for analyst fixed effects. It is well known from decades of microeconometric studies that fixed effects are an extremely useful and robust method to control for individual heterogeneity that might otherwise bias the main effect. Our use of relative forecasts play an analogous role in the context of extracting information from analysts' forecasts.

To the best of our knowledge, our study is the first to emphasize the strong information content in analysts' relative ranking of stock returns.[1] As pointed out above, previous literature primarily focuses on analysts' consensus forecasts, which does not capture the information in individual analysts' relative rankings; see, among others, Brav and Lehavy (2003); Dechow and You (2020); Loudis (2022), as well as Bradshaw (2011); Kothari et al. (2016) for reviews. Bradshaw et al. (2013) do consider the rank correlation between implied target returns and realized returns for individual analysts. They conclude that the information contained in the within-analyst rankings appears mostly uncorrelated with other measures inferred from the analysts' price targets, which

[1] Analysts themselves often appear to use relative valuation when forming their return forecasts (see, e.g., Asquith et al., 2005), which could perhaps be a contributing factor to the strong performance of our relative valuation measures based on these forecasts.

is also in line with our findings. However, the focus of their study is on differential forecasting abilities across analysts and they do not uncover the strong information content of the average within-analyst rankings; their overall conclusion is that analysts' forecasting abilities are, at best, limited. In the context of earnings forecasts, Harford et al. (2019) rank stocks in sell-side analysts' portfolios based on their significance for the analysts' careers and discover that earnings forecasts are more accurate for higher-ranked stocks.

Da and Schaumburg (2011) study industry-level relative valuation. This bears some conceptual resemblance to our analysis, but does not touch upon the within-analyst information that is key to our study, since the starting point of their signal construction is the consensus return forecast. Their adjusted target return can be viewed as an industry-corrected forecast, whereas ours can be viewed as an analyst-corrected forecast. We show that controlling for the modified target return measure proposed by Da and Schaumburg (2011) barely affects the excess returns of the portfolio strategy based on the relative valuation measure proposed here. This result likely reflects that while analysts may be industry specialists, they still follow stocks in multiple industries, and it is only part of their task to rank stocks within an industry.[2] Even when an analyst only covers one sector, analyst-level relative valuations will still generally differ from the industry-level relative valuations because the analyst only covers a limited set of stocks in a sector.[3]

We provide some evidence on the nature of the predictive information contained in the analysts' relative rankings. As mentioned previously, the forecasting power cannot be explained by common stock characteristics. Likewise, we show that there is no relationship between the predictability in the rankings and the presence of firm-level earnings announcements. We further separate an-

[2] In our sample, each analyst on average covers 2.5 sectors and 3.3 industries (using 2- and 3-digit GICS codes). Kaustia and Rantala (2021) find that analysts' coverage choices reflect many aspects of firm similarity, such as the linkage in terms of industry, supply chain, and geographical distance. Kadan et al. (2012) uncover that analysts possess across-industry expertise.

[3] Consider an analyst's portfolio comprising glamour stocks from the same sector. These stocks usually receive favorable analyst target returns (Jegadeesh et al., 2004; Engelberg et al., 2020), which could be much higher than the sector-level forecasts. The industry-level relative valuation in Da and Schaumburg (2011) would imply buying all stocks in this analyst's portfolio since they outperform the industry average.

alyst target returns into "bold" and "herding" forecasts, following Clement and Tse (2005). The results show that the predictive power comes from the bold forecasts, which prior studies argue are more likely to reflect private information (see, e.g., Hong and Kubik, 2003; Clement and Tse, 2005; Chen and Jiang, 2006). Finally, we also distinguish between low- and high-information environments, as measured by analyst coverage, and show that predictability tends to be stronger in low-information environments. Overall, the evidence suggests that analysts possess some form of "private" information when ranking the returns of stocks.

Finally, we also examine the link between the relative forecasts explored in this paper, and the consensus forecasts focused on in previous works. As discussed at length above, the relative forecasts are highly informative whereas the consensus forecasts mostly lack predictive power. Understanding the link between the two forecasts offers hope of understanding the sources of the poor performance of the consensus forecast. As pointed out previously, using the within-analyst demeaned forecasts, we can show that the difference between the investment signal generated by relative valuations and consensus forecasts is captured by the analyst fixed effects.

We show that these fixed effects can most successfully be explained by the prior forecasts of other analysts' covering the same stocks as well as the average of the analyst's own history of forecasts.[4] This suggests that the biases in consensus forecasts are to a large extent either inherent to the analyst (consistently optimistic or pessimistic) or a result of "learning" from analyst peers; the "learning" here is negative in the sense that the wrong lesson is acquired from one's peers.[5] Based on these insights, and the fact that consensus forecasts tend to be severely *upward* biased,

[4]The analyst's own history of forecasts refers not just to the prior average forecast of the given stock, but to the average prior forecasts of *all* stocks considered by this analyst. Likewise, the average forecasts of other analysts refer to the prior forecasts for all the stocks that are covered by the current analyst. These definitions follow naturally from the focus on analyst fixed effects and results in different measures from those based only on histories and other forecasts of a given stock.

[5]This also suggests that analysts' expertise in relative valuation is not due to learning from other analysts, unlike the channel uncovered in previous studies. For example, when studying analysts' forecast for earnings, Clement et al. (2011) and Kumar et al. (2022) show that extracting information from peers is an important source of analyst expertise.

we propose a very simple bias correction to the consensus forecast. If one removes the historically most upward-biased ("optimistic") analysts prior to forming the consensus forecast for a given stock (e.g., remove the analysts with the 10 percent highest average *historical* forecasts), the bias in the consensus forecast is to a great extent corrected.

The main part of our analysis shows that the within-analyst demeaning (i.e., a fixed-effects transformation) of the analysts' forecasts results in a substantial improvement in predictive ability. The analysis described in the previous paragraph aims to explain this improvement in terms of observable variables. We go some way towards such an explanation (the R^2s are around 45%) and this allows for an improvement of the consensus forecast via observable variables. However, such a correction only captures part of the gains obtained via the fixed-effects transformation implicit in the relative forecasts. That is, the relative forecasts provide a very general and comprehensive way of controlling for the optimistic bias of analysts and the negative "learning" effect from other analysts' forecasts, but also for other *unobservable* effects that may be detrimental to analysts' ability to provide accurate forecasts.[6] It is this "catch-all" nature that makes fixed effects estimation so useful and which we implicitly rely on in our measures based on the relative valuations.

Finally, we extend our analysis to encompass two additional important forecasts provided by sell-side analysts: earnings and recommendations. Consistent with our results from target price forecasts, we observe outperformance of stocks that are ranked higher within analysts' portfolios according to their forecasted earnings-price ratios and recommendations, when compared to their peers with lower rankings. The long-minus-short return spreads are sizable and significant under both equal- and value-weighted schemes. Furthermore, these results remain robust after controlling for common risk factors, unlike the results based on consensus earnings forecasts or rec-

[6]For instance, some analysts (or the firms they work for) might have an incentive to issue highly positive return forecasts for certain stocks, because the underlying company might have other business relationships with the firm issuing the forecast. An analyst might therefore issue an unduly positive forecast for such a stock, but his ranking of stocks might still reflect a truthful opinion by giving other stocks similarly upward biased, but correctly ranked, forecasts. Focusing on the relative forecasts might therefore alleviate some of these incentive concerns as well.

ommendations. Overall, our exploration of the three most common forecasts from sell-side analysts consistently highlights their skill in ranking stocks.

2 Predictive performance of relative valuations

2.1 Data and main variables

We obtain individual analyst price targets from the Institutional Brokers' Estimate System (IBES) Unadjusted Detail file. Since we focus on the within-analyst relative valuation, we need to identify the issuing analyst for each individual price target. Therefore, observations with missing analyst names are removed from the sample. Only price targets with the 12-month forecasting horizon are used, which constitutes the vast majority of the available observations. The data are available from March 1999 to December 2021. The firm-level characteristics and stock returns data are obtained from CRSP and Compustat. We consider all common stocks (share codes 10 or 11) traded on the AMEX, NYSE, or NASDAQ. The IBES data set is merged with CRSP, and share splits are accounted for by the split factor in CRSP.

Let TP_{jkt} denote the price target issued by analyst k for stock j during month t. If the analyst issued multiple price targets for the same stock during the month, only the most recent one is considered. The *target return* corresponding to a specific price target announcement is then calculated as

$$TR_{jkt} = \left(\frac{TP_{jkt}}{P^{-}_{jkt}} - 1 \right) /12 \ , \tag{1}$$

where P^{-}_{jkt} the split-adjusted closing price of stock j on the day before TP_{jkt} was announced. We divide by 12 so that the target returns are expressed in monthly values. The definitions of all the variables used throughout the paper are collected in Appendix A.

The typical approach in prior literature is to study the "consensus" return forecasts, which aggregate individual target returns across the analysts who cover the firm in question (e.g., Brav and Lehavy, 2003; Da and Schaumburg, 2011; Dechow and You, 2020; Engelberg et al., 2020; Loudis, 2022). Accordingly, let CTR_{jt} denote the *Consensus Target Return* for stock j in month t, calculated as the average target return for stock j across the analysts who cover the stock in month t; see equation (A1) in Appendix A.[7]

While the consensus forecast uses analysts' *absolute* return expectations, we aim to focus on their *relative* return forecasts instead. More specifically, we propose to evaluate the return forecast for stock j of analyst k relative to all the other forecasts issued by analyst k. We consider two alternative definitions of these relative forecasts. First, we use the *within-analyst demeaned* forecast, which removes each analyst's own average from their forecasts. Second, we use the *within-analyst ranking* of the return forecasts.

Start with formally defining the within-analyst demeaned forecast. Let $\overline{TR}_{kt}$ denote the average target return of analyst k across the stocks that she announced a target price for during month t; see equation (A3). Our first stock-level measure of relative valuation aggregates analysts' relative forecasts, obtained via de-meaning by the within-analyst average forecast. In particular, we first subtract from each individual target return the issuing analyst's average target return, i.e., create $TR_{jkt} - \overline{TR}_{kt}$, and then aggregate these demeaned target returns across the analysts covering stock j in month t. We refer to the resulting stock-level measure as *Consensus Demeaned Target Return*, or $CDTR_{jt}$; see equation (A2). An analyst has to cover a few stocks for the idea of relative valuation to make sense. Therefore, only analysts who issued a target price for at least three different firms during month t are included when we construct the $CDTR_{jt}$ variable.[8]

Next, we consider the rank of the within-analyst target returns, mapped into the $[0, 1]$ interval, such that the lowest forecast receives the value of zero, while the highest forecast is assigned the

[7] Consensus returns are often defined as the *median*, rather than mean, forecast across analysts. As shown in the Online Appendix, our results are robust to using the median instad of the mean. We use the mean specification here since it provides a clear analytical link with the relative forecast, as discussed further below.

[8] We show in Section 2.5.2 that the main empirical results remain qualitatively unchanged if the required minimum number of stocks per analyst is lowered to two or no minimum requirement is used at all.

value of one.[9] These (scaled) rank values are averaged across the analysts that cover a given stock to arrive at our second definition of a stock-level measure of analysts' relative return forecasts. We label this measure as *Consensus Ranked Target Returns* or $CRTR$; see equation (A4) in Appendix A.

The key feature of both definitions is that they eliminate all level effects in the analyst's forecasts. The first definition ($CDTR$) retains some of the information embedded in the actual values of the return forecasts, while the second definition ($CRTR$) focuses exclusively on their ordinal ranking. If there is, for instance, a large dispersion in an analyst's target returns, this will be reflected in the first definition but not in the second. To that extent, one might view $CRTR$ as the most intuitive way of utilizing the relative information in an analyst's forecasts, since it is more robust in terms of controlling for biases in the absolute level of forecasts. However, $CDTR$ might be more efficient in case it is only the overall mean forecast that is biased.

As seen from the results presented in the main text below and in the Online Appendix, the two measures lead to qualitatively identical results. This suggests that the key step for extracting the information in analysts' return forecasts is to eliminate the analyst-specific level effects; which is achieved by both definitions. We present the key results for both measures in the following sub-section, but then, in order to keep the main text easy to follow, we focus on results using the demeaned forecasts. The main reason for focusing on the demeaning approach is the clean analytical link between $CDTR$ and the consensus target return (CTR) that allows for their comparative analysis in Section 4. A complete set of results for the ranking-based measure, $CRTR$, is found in the Online Appendix.

[9] For example, if analyst k issues three target returns in month t, the values of $\{0, 0.5, 1\}$ are assigned in order from the lowest to the highest target return. The values of $\{0, 0.33, 0.66, 1\}$ are assigned in the case of four target returns, the values of $\{0, 0.25, 0.5, 0.75, 1\}$ in the case of five target returns, and so forth.

2.2 Portfolios sorted on relative valuation

We test the usefulness of the two above measures of analyst-level relative valuations by relating them to future returns. At the end of each month, we sort all stocks with available $CDTR$ into quintile portfolios and form a long-short portfolio that buys the stocks with the highest $CDTR$ and sells those with the lowest $CDTR$. We perform analogous portfolio sorts with the rank-based $CRTR$.

Table 1 reports the average equal- and value-weighted portfolio excess returns in the month following portfolio formation. The left-hand side of the table shows results for $CDTR$ and the right-hand side shows results for $CRTR$. In the case of equal-weighted portfolios (Panel A), stocks with high within-analyst demeaned returns (high $CDTR$) earn an average excess return of 1.44% per month, while those with low demeaned returns earn 0.48% per month. The long-short portfolio earns an average return of 0.96%, which is highly statistically significant with a t-statistic of 5.27. Similarly, stocks that are ranked relatively high by analysts (high $CRTR$) earn an average excess return of 1.44% per month while those that are ranked relatively low earn 0.54% per month. The long-short portfolio earns an average return of 0.89% with a t-statistic of 5.31.

Results for value-weighted portfolios (Panel B) are in line with those for the equal-weighted portfolios. Specifically, the value-weighted returns are somewhat lower but still highly statistically significant: the long-short portfolios sorted on $CDTR$ and $CRTR$ earn average returns of 0.57% and 0.47% per month, respectively, with t-statistics of 2.78 and 2.69.

[Table 1 about here]

In addition to raw returns, Table 1 also reports risk-adjusted returns to evaluate whether the return spreads are driven by exposures to commonly used risk factors. We consider the five-factor model of Fama and French (2015), its six-factor extension by adding the momentum factor, the q-factor model of Hou et al. (2015), and the behavioral factor model of Daniel et al. (2020). The abnormal returns for the long-short portfolios are sizable and statistically significant under all factor models. In case of the equal-weighted portfolios using sorts on $CDTR$, the lowest long-short α is produced by the five-factor Fama-French model: 0.83% per month with a t-statistics of 5.88. For the value-weighted portfolios, the lowest long-short α is associated with the q-factor model: 0.42% per month with a t-statistics of 2.08. The results are very similar if one instead sorts on $CRTR$. Controlling for common risk factors thus has a very limited effect.

Figure 1 shows the cumulative returns of the $CDTR$-sorted and $CRTR$-sorted long-short quintile strategies. For reference, the figure also shows the performance of similarly constructed long-short quintile strategies based on commonly used firm characteristics. The $CDTR$-sorted strategy has the highest total return over the sample period, followed by the $CRTR$-based strategy, both in the case of equal- and value-weighted portfolios.

[Figure 1 about here]

Table 2 reports the average *characteristic* rank of the stocks in each quintile portfolio. We cross-sectionally transform the values of the characteristics month-by-month before calculating portfolio averages. In particular, in each month, for a given characteristic, we use all available CRSP stocks and divide the ranks by the number of non-missing observations. This maps characteristics into the $[0, 1]$ interval (from low to high) and focuses on their ordering as opposed to their magnitude. In general, there are no major differences between the low- and high-$CDTR$ (or low- and high-$CRTR$) portfolios in terms of the average characteristics of their constituents, consistent with the small effects of controlling for common risk factors seen in Table 1. There are two observations, however, that are worth noting. First, stocks in the high-$CDTR$ ($CRTR$) portfolio tend to have somewhat poorer performance in the past year (lower momentum) but experience slightly more favorable returns in the current month (higher short-term reversal) compared to stocks in the low-$CDTR$ ($CRTR$) portfolio. The pattern suggests that analysts' relative forecasts may be influenced by the stocks' return histories.[10] Second, stocks in the two extreme portfolios tend to be somewhat

[10] Greenwood and Shleifer (2014) and Jin and Sui (2022) show that investors extrapolate from past returns,

smaller and less liquid compared to the stocks in the three middle portfolios. Nevertheless, these are still relatively large and liquid firms compared to the general population of stocks, since analysts typically cover larger and more liquid stocks.

[Table 2 about here]

In the remainder of the main text, we only present and discuss results for $CDTR$, since all the results for $CRTR$ are very similar and there is little gain from presenting both sets of results in every table. All figures and tables from the remainder of Section 2 and from Section 3 are replicated using $CRTR$ in the Online Appendix.

2.3 Comparisons with other variables

Table 3 reports average returns to portfolios sorted on several other measures from previous literature that are related to $CDTR$ and $CRTR$. In order to facilitate easier comparison, the first row in both panels of Table 3 repeats the results obtained by sorting on $CDTR$. Panel A shows results for equal-weighted portfolios and Panel B for value-weighted portfolios.

It has been documented in previous literature that there is a positive relationship between consensus forecasts and subsequent realized returns (e.g., Brav and Lehavy, 2003; Dechow and You, 2020; Loudis, 2022). Table 3 reports average returns to portfolios based on consensus forecasts.[11] Sorting on CTR leads to a 0.46% long-short return spread in case of equal-weighted portfolios, and a 0.16% spread for value-weighted portfolios. These spreads are considerably lower than the corresponding ones documented for $CDTR$ and are both statistically insignificant.

yet Wang (2021) finds that sell-side analyst forecasts are contrarian.

[11] In order to use the same set of IBES observations as for our baseline $CDTR$ measure, we maintain the requirement that an analyst has to have at least three announcements in a month to enter our sample when constructing CTR (and also $ICTR$, introduced later in this section). We show in the Online Appendix that the conclusions regarding CTR (and $ICTR$) in this section are unchanged if we lift this requirement and use the return forecasts from all analysts. Also note that the consensus forecast is often constructed by taking the median instead of the mean of analysts' forecasts. We also show in the Online Appendix that using the median leads to almost identical results to using the mean.

[Table 3 about here]

To understand the extent to which the alternative measures in this section can explain the cross-sectional predictive ability of $CDTR$, we regress the returns from the $CDTR$-sorted long-short portfolio on the returns from long-short strategies based on those alternative measures, and look at the alpha estimates. In particular, we estimate

$$R_{CDTRt} = \alpha + \beta R_{Xt} + \epsilon_t \ , \tag{2}$$

where R_{CDTRt} is the monthly return on the long-short quintile strategy based on $CDTR$, while R_{Xt} represents the return on the long-short quintile strategy based on an alternative measure, e.g., CTR in the first case. The last column of Table 3 shows the alpha estimates. The long-short spreads on the $CDTR$-sorted portfolios remain highly significant when controlling for the CTR-sorted strategy returns.

Da and Schaumburg (2011) propose a strategy that buys (sells) stocks with high (low) *consensus* return forecasts *within each industry*. Let ITR_{jt} denote the *Industry Target Return*, calculated as the average month-t consensus target return across all the stocks that belong to the same industry as stock j; see equation (A5) in Appendix A. A stock-level measure of the within-industry relative consensus forecast can then be constructed as the consensus target return minus its industry average, which we label as *Industry adjusted Consensus Target Return*: $ICTR_{jt} = CTR_{jt} - ITR_{jt}$ (equation (A6) in Appendix A).[12] Comparing equations (A2) and (A6) from Appendix A, it is straightforward to see that $CDTR$ and $ICTR$ are related: while the former adjusts individual

[12] Da and Schaumburg (2011) consider a somewhat different implementation of the same idea by ranking the firms based on their consensus forecasts within an industry. We show in the Online Appendix that using measures that more closely follow the implementation of Da and Schaumburg (2011) lead to same conclusions as those obtained from $ICTR$. We prefer to report the results from $ICTR$ in the main text, as it is more directly comparable to our measure $CDTR$ due to the similarity of their construction. Similar to the main specification of Da and Schaumburg (2011), we use the first two GICS (Global Industry Classification Standard) digits for defining industries, but also show the results using more refined classifications in the Online Appendix.

target returns by within-analyst average target returns, the latter makes the adjustment by within-industry average consensus returns. The two approaches rely on overlapping information, since analysts tend to specialize on certain industries (Boni and Womack, 2006; Da and Schaumburg, 2011). On the other hand, analysts may cover multiple industries, cover only a limited number of stocks within an industry, and digest other information besides industry information.

Table 3 presents the results for $ICTR$-sorted portfolios. The average return for the equal-weighted long-short portfolio is 0.80% per month, with a t-statistic of 3.49, consistent with the results of Da and Schaumburg (2011). The value-weighted long-short spread is 0.33% with a t-statistic of 1.19. That is, $ICTR$ produces lower return spreads than $CDTR$ (with lower t-statistics as well). As seen from the last column of Table 3, the long-short spreads on the $CDTR$-sorted portfolios remain significant when controlling for the $ICTR$-sorted strategy returns, suggesting that the analyst-level relative forecasts contain additional information compared to industry-level relative forecasts.

Loudis (2022) develops a method that aims to remove the optimistic bias from *consensus* return forecasts (see Section 4 for more discussion on this bias) and finds that the debiased information component is more accurate for predicting future returns. The motivation behind our measures differs conceptually from his, since we focus on the analyst-level relative valuation. Nevertheless, Table 3 also shows results corresponding to the "information component" of consensus forecasts as defined by Loudis (2022). The return spread from the equal-weighted portfolios is a statistically significant 0.55% per month, but the value-weighted return spread is insignificant.[13] Both spreads are considerably lower than the ones documented for $CDTR$. The last column of Table 3 shows that the spreads on $CDTR$-sorted long-short strategies remain significant when controlling for the returns from the $Info$-based strategies in both the equal- and value-weighted cases.

Inspired by Novy-Marx and Velikov (2023) we also relate the performance of the $CDTR$-based

[13] Loudis (2022) reports significant return spread from his sample ending in 2017, but the prediction using consensus returns performs poorly afterwards.

long-short strategy to a general set of 140 strategies from the "factor zoo".[14] We estimate the same regression as in equation (2), but $R_{X,t}$ now represents the return on the long-short quintile strategy based on one of the 140 anomaly variables, considered one at a time. Figure 2 plots the histogram of the t-statistics on α from each of these 140 regressions. Panel A shows that all the t-statistics are greater than 4 when both $R_{CDTR,t}$ and $R_{X,t}$ correspond to equal-weighted portfolios. Panel B shows that all t-statistics are above 2.4 when both return series in the regression are from value-weighted portfolios. According to this evidence, $CDTR$ contains information orthogonal to a wide range of previously considered predictive variables.

[Figure 2 about here]

2.4 Fama-MacBeth regressions

Another way of testing for the predictive performance of $CDTR$ is via Fama-MacBeth regressions (Fama and MacBeth, 1973) of next month's stock returns on $CDTR$ and potential control variables. Table 4 reports the results from such regressions. The first column confirms the predictive power of $CDTR$ on next month's stock returns.

[Table 4 about here]

The next two columns consider the consensus return forecast. Unlike in the portfolio sorting exercise, CTR seems to be a significant predictor of next month's returns if considered as a single regressor in the Fama-MacBeth regression. However, when both $CDTR$ and CTR are included in

[14] The anomaly variables come from the March 2022 release of the asset pricing dataset connected to Chen and Zimmermann (2021). We require that (i) the anomaly variable is classified as "continuous", (ii) it has values for at least 10 stocks in each month throughout our sample period, and (iii) has coverage for at least 40% of the CRSP market capitalization on average over our sample period. 140 of the 207 predictors of Chen and Zimmermann (2021) satisfy these criteria. The complete list of the 140 anomaly variables can be found in the Online Appendix.

the regression, only $CDTR$ remains significant and the coefficient on CTR becomes statistically indistinguishable from zero. This suggests that the information from analyst-level relative valuations fully subsumes that from the consensus forecasts.

The fourth and fifth columns provide a comparison with the industry-level relative valuation of Da and Schaumburg (2011). $ICTR$ is a significant predictor of next month's returns if considered by itself. However, when both $CDTR$ and $ICTR$ are included, only $CDTR$ remains significant and the coefficient on $ICTR$ becomes almost zero, suggesting that the information from analyst-level relative valuations also fully subsumes that from industry-level relative valuations.

Columns 6 and 7 use the information component of Loudis (2022). $Info$ is a highly significant predictor when considered alone. The coefficients on both $CDTR$ and $Info$ are statistically significant when they are considered together (but the t-statistic on $CDTR$ is considerably higher), confirming that the measures capture somewhat different sets of information. This is not particularly surprising, given that $Info$ is formed in a very different way from $CDTR$.

The statistically significant predictive power of $CDTR$ also holds when all the variables are included in the regression, as seen in column 8, and it is worth noting that $CDTR$ is the only significant predictor in this joint regression. These results reaffirm that the predictive power of analyst-level relative valuation is not driven by related measures constructed from analyst target returns.

What happens if we control for additional stock-level characteristics? If we re-estimate all the regressions of Table 4 by adding the same firm-level characteristics that appear in Table 2, the predictive power of $CDTR$ remains highly significant in all specifications. These results are relegated to the Online Appendix.

Finally, we also test the predictive power of $CDTR$ when conditioning on each of the 140 anomaly variables that are used to construct Figure 2. We estimate the following Fama-MacBeth regression separately for each anomaly variable:

$$R_{jt+1} = \alpha + \beta_{CDTR} CDTR_{jt} + \beta_X X_{jt} + \epsilon_{jt} \ , \tag{3}$$

where X represents any one of the 140 anomaly variables. Figure 3 shows the histogram of the t-statistics on the β_{CDTR}-coefficient from the regressions above. All t-statistic are above 2.6 and the vast majority of them are greater than 4. This confirms our previous conclusion that $CDTR$ contains information orthogonal to a wide range of previously considered predictive variables.

[Figure 3 about here]

2.5 Robustness to specific implemenation choices

In this section, we consider the robustness of the $CDTR$-based strategy's performance to various changes in how the measure is constructed. Section 2.5.1 discusses how much of the CRSP stock sample is covered by the baseline definition of the $CDTR$ measure and how changes in the definition can improve the coverage. Section 2.5.2 analyzes whether the performance of the long-short strategies are sensitive to the above (and some further) changes in the definition.

2.5.1 Coverage statistics of the relative valuation measure

Panel A of Figure 4 plots the coverage statistics of our baseline $CDTR$ measure.[15] In terms of the number of stocks covered, around 15% of CRSP stocks have a $CDTR$ value at the beginning of the sample period, and the coverage steadily increases to around 45% by the end of the sample; the average coverage rate over the entire sample is 34%. The fraction of total CRSP *capitalization* covered is considerably greater: around 60% of the total CRSP capitalization is covered at the

[15] The coverage statistics for $CDTR$ and $CRTR$ are identical. If it is possible to calculate the value of $CDTR_{jt}$ for stock j in month t, then it is also possible to calculate $CRTR_{jt}$ since the two measures rely on the same set of underlying individual return forecasts.

beginning of the sample, and coverage increases to around 85% by the end. The overall mean capitalization coverage rate is 74%. It is, of course, not surprising that coverage is much better in terms of capitalization, since analysts tend to cover bigger stocks.

[Figure 4 about here]

There are two main parameters that determine the availability of $CDTR$. The first one is the minimum number of stocks that an analyst needs to issue price targets for to enter our sample; recall, that we require at least three target prices per analyst in a given month to calculate our baseline measures. However, it turns out that this requirement does not have a big effect on the coverage. Panel B of Figure 4 plots the coverage statistics when $CDTR$ is constructed without a minimum requirement on the number of announcements per analysts (i.e., when all target price announcements enter in to the sample). The average coverage over the sample period only marginally increases to 39% (from 34%) in terms of number of shares and to 82% (from 74%) in terms of capitalization, while the high variation in availability remains.

The second parameter that affects the availability of $CDTR$ is the length of the announcement collection window. Recall that we collect target prices announced during month t when calculating the values of $CDTR$ corresponding to the end of month t. Panel C of Figure 4 shows that coverage considerably improves if we instead collect announcements issued over the three-month period covering months $t-2$ to t. In terms of the number of stocks, around 35% is covered at the beginning of the sample (apart from the first few months, where the IBES data is very limited), and coverage increases to close to 70% by the end of the sample. In terms of the fraction of total CRSP capitalization, coverage starts from 90% (apart from the first few months) and increases to above 97% by the end.

The appropriate length of the announcement collection window is not obvious. A shorter window ensures that only the most up-to-date analyst information is contained in the resulting measure, because older price targets may reflect stale information. However, if analysts do not update their price targets because they still consider their outstanding target to be meaningful, a longer collection window may also be warranted.

2.5.2 Performance under various implementations

Table 5 presents the performance of $CDTR$-based long-short quintile strategies under various implementations. For each implementation, the table shows the average monthly return together with the associated t-statistic, the monthly volatilitity, the annualized Sharpe ratio, and the rank of this Sharpe ratio among the Sharpe ratios of the 140 long-short strategies that are used in Figure 2. Panel A shows the results for equal-weighted portfolios and Panel B shows the results for value-weighted portfolios.[16]

The first row in each panel in Table 5 corresponds to our baseline implementation of the $CDTR$ measure. As previously documented, the equal-weighted long-short $CDTR$ portfolio earns a 0.96% monthly average return, with a corresponding annualized Sharpe ratio of 1.20. The "SR rank" column shows that the strategy would rank second in terms of its Sharpe ratio among the 140 equal-weighted strategies from Chen and Zimmermann (2021), i.e., there is only one strategy that has a higher Sharpe ratio than that of our baseline $CDTR$ strategy. In the value-weighted case, the long-short portfolio earns a 0.57% monthly average return with an annualized Sharpe ratio of 0.58, which would rank it third among the 140 value-weighted strategies that are used for comparison.[17]

The next two rows in each panel in Table 5 show that the performance does not change much when the required minimum number of announcements per analyst in a month is lowered to two

[16] The ranked Sharpe ratios of the 140 long-short strategies used for comparison are shown in the Online Appendix both in the equal- and value-weighted cases.

[17] As seen in the Online Appendix, the $CRTR$-based strategies result in slightly lower average returns than the $CDTR$-based ones, but the volatility of the $CRTR$ strategies is also somewhat lower, resulting in near-identical Sharpe ratios. As discussed previously, one might argue that the $CRTR$ measure is more "robust" in the sense that it completely ignores any absolute levels of the forecasted returns, whereas the $CDTR$ measure might be more "efficient" if there is actually useful information in the spread of the analyst's return forecasts. The results in Table 5 lend some support to this interpretation, with somewhat higher, but also more volatile, returns for the $CDTR$ strategies.

and when no requirement on the number of announcements is used at all. The Sharpe ratios and their ranks remain similar to the baseline version both in the equal- and value-weighted cases.

Next, we consider how the length of the announcement collection window affects performance. Starting with strategies using equal-weighted portfolios, the performance deteriorates as the window gets wider: the long-short strategy's mean return, Sharpe ratio, and rank all decrease as the length of the window grows to two and then to three months from its baseline value of one month. Nevertheless, the $CDTR$-based strategy using a 3-month window would still be ranked 13th among the 140 comparison strategies in terms of its Sharpe ratio. Interestingly, the performance of the strategy improves considerably when the 2-month window is used in the value-weighted case; the resulting Sharpe ratio is higher than on any of the 140 strategies used for comparison. However, moving to the 3-month window results in a considerable decrease in the Sharpe ratio in the value-weighted case.[18]

In the final row of Table 5, we consider the effect of dropping the announcements from the last 5 calendar days of the month when constructing $CDTR$. Brav and Lehavy (2003) documents a strong short-term announcement effect of analysts' target prices. By dropping all the target returns issued in the last 5 days of the month, we ensure that the strategy's performance is not driven by this announcement effect. The $CDTR$-based strategy perform slightly worse with this filter, compared to the baseline implementation, but there is no considerable drop in performance: the strategy's Sharpe ratio would still be ranked 6th and 5th in the equal- and value-weighted cases, respectively.

Overall, the results in Table 5 show that the performance of the strategy based on analysts' relative return forecasts is quite robust to changes in the exact definition of the measure used for the portfolio sorting. This is also further reinforced by the highly similar performance of the rank-based measure, $CRTR$, as shown in the Online Appendix.

[18] The perhaps largest discrepancy between the $CDTR$ and $CRTR$ strategies is seen in the value-weighted case with a 3-month window. The $CRTR$ strategy is less affected by the longer window and outperforms the baseline implementation with a 1-month window, as seen in the Online Appendix.

3 Information sources of relative valuation

In this section, we study where the predictive ability of analysts' relative forecasts stems from. Table 6 presents the results from *individual forecast-level* Fama-MacBeth regressions, i.e., the cross-sectional dimension in month t covers all individual target price forecasts in the sample that are issued during that month. The dependent variable is next month's realized return on the stock for which the target price was issued for.

For a given stock and month, an individual analyst's relative forecast is given by the forecast (target return, TR) for that stock minus the average of all the analyst's forecasts ($\overline{TR}$) issued that month. For ease of notation, we omit the subscripts on these variables and denote the individual-level relative forecasts as simply $TR - \overline{TR}$, with exact definitions provided in Appendix A. The first column of Table 6 establishes that $TR - \overline{TR}$ is a strong predictor of future returns, as we have already seen before.[19]

[Table 6 about here]

We begin with evaluating whether the predictive power of $TR - \overline{TR}$ is spanned by firm-level public information. Our first proxy for such information is a set of the most prominent anomaly characteristics: log market value of equity ($Size$), the book-to-market ratio (BM), investment measured by asset growth (AG), profitability measured by return-on-equity (RoE), and momentum (Mom). Several papers have documented that analysts' *consensus* recommendations and return forecasts are excessively optimistic towards stocks that lie in the short-legs of anomalies (see Jegadeesh et al., 2004; Engelberg et al., 2020; Guo et al., 2020; Loudis, 2022). Here, we analyze whether the type of stocks covered by an analyst has an effect also on her *relative* forecasts. Corresponding to each individual target return, TR_{jkt}, we can find the value of characteristic X for the

[19]The sample period used in Table 6 is from September 1999 to December 2021. The identification of bold and herding return forecasts – which is needed for the specification in column 4 – relies on price targets issued during prior months. We omit the first six months of the overall sample due to the lack of sufficient prior price target observations during these months.

underlying stock j, taken from the end of month $t-1$ to ensure that it is available for the analyst when making her announcement.[20]

Column 2 of Table 6 adds these (lagged) stock characteristics to the Fama-MacBeth regressions. If the performance of $CDTR$ emerges from analysts relying on information in stock-level characteristics, the coefficient on $TR - \overline{TR}$ should decrease when controlling for these characteristics. However, as seen from column 2, the coefficient on $TR - \overline{TR}$ instead increases very slightly. This indicates that when ranking stocks in a relative sense, analysts rely on information that is unlikely to be spanned by firm-level public information (at least as captured by various characteristics).

Second, we evaluate how the performance of analysts' relative valuations relates to earnings announcements. The public release of salient firm-specific information is a useful laboratory to test the relation between the analyst's relative valuation and firm-level public information. Define $EAwindow_{jkt}$ as a dummy variable taking the value of one if the announcement date of the target return TR_{jkt} falls into an earnings announcement window of stock j, defined as the period from three days before to three days after each earnings announcement of the stock.[21] 46% of all individual forecasts fall in the above-defined windows. Column 3 of Table 6 indicates that there is no statistically significant difference in the predictive power of relative forecasts conditional on them being issued within or outside earnings announcement windows. The coefficient estimate on the interaction term is negative, suggesting that, if anything, forecasts issued within earnings announcement windows are less informative.[22] Overall, this evidence suggests that the profitability of analyst-level relative valuation is not driven by the public information from earnings

[20] All anomaly characteristics are winsorized at the 1% and 99% levels and standardized via the z-score transformation each month.

[21] The conclusions are identical if we use somewhat different announcement windows, e.g., if the window covers the period from two days before and one day after the earnings announcements as in Chan et al. (1996).

[22] For completeness, the level effect of the earnings announcements window is also controlled for in the regression, as is customary when including interaction terms. The same applies to the interactions considered in the remaining columns in Table 6. Inclusion or omission of these level effects does not affect the interaction coefficients in any meaningful way.

announcements.

Third, we follow Clement and Tse (2005) by identifying herding or bold individual forecasts. Corresponding to each target return announcement, we define the following two variables. Let PTP_{jkt} be the *Previous Target Price* announced by analyst k for stock j, i.e., her latest target price issued during the one-year period ending one day before the announcement date of TR_{jkt}. Let $OCTP_{jkt}$ be *Others' Consensus Target Price*, calculated as the average target price on stock j across the most recent announcements of all analysts *except analyst* k from the six-month period ending one day before the announcement date of TR_{jkt}. Then, TR_{jkt} is identified as a herding forecast if the underlying target price is between PTP_{jkt} and $OCTP_{jkt}$, and it is identified as a bold forecast ($Bold_{jkt} = 1$) otherwise. That is, herding (bold) forecasts are such where the analyst revises her previous forecast towards (away from) the consensus of other analysts. From the forecasts that can be identified (i.e., have non-missing PTP_{jkt} and $OCTP_{jkt}$), 70% are found to be bold forecasts. Column 4 of Table 6 shows that herding forecasts (the left-out category) do not have significant predictive power on future returns. The predictability from analysts' relative valuation thus stems from bold forecasts, which likely rely more on private information (see, e.g., Chen and Jiang, 2006; Hong and Kubik, 2003).

Finally, we investigate the performance of the relative forecasts in low- and high-information environments, where the stock-specific information environment is measured by analyst coverage. Let $Cover_{jt}$ denote the stock-level measure defined as the number of analysts that issue a target return for stock j during month t. Then, the target return TR_{jkt} is issued for a low-coverage stock ($LowCover_{jkt} = 1$) if it cross-sectionally falls in the lowest 33% of all target returns issued during month t in terms of analyst coverage of the underlying stock j. Column 5 of Table 6 shows that the predictive power of the relative forecasts is significant in both the low- and non-low-coverage environments. However, the predictive coefficient doubles for relative forecasts issued under low-coverage, and the increase in the coefficient is statistically significant. This evidence also suggests that relative forecasts contain more information when analysts have to rely more extensively on their private signals, rather than learning from other analysts.

In summary, all the evidence presented in this section suggest that analysts' relative forecasts reflect some form of private information, or at least information that is not readily available in an interpretable form and therefore not fully reflected in current prices.

4 Absolute versus relative forecasts

We end our analysis with trying to relate the strong performance of the relative forecast measure, $CDTR$, with the weak performance of the absolute consensus forecast, CTR. As discussed throughout this study, analysts' *relative* return forecasts ($CDTR$) strongly predict the cross-section of future stock returns. In contrast, analysts' *absolute* return forecasts (CTR) fail to produce a significant return spread in quintile portfolios.

Recall the definitions of the consensus forecast, CTR, and the relative forecast, $CDTR$, for a given stock. The former is simply the average forecast across all analysts covering the stock. The latter is also an average across analysts, but each analyst's forecast has been demeaned by their own average forecast (c.f., equations (A1) and (A2) in Appendix A). Phrased in regression language, we can think of the difference between CTR and $CDTR$ as the *analyst fixed effect*. Or alternatively put, the relative forecast is obtained by controlling for individual-analyst fixed effects.

Individual fixed effects play a crucial role in countless microeconometric analyses, controlling for unobserved heterogeneity that might otherwise bias the main effect. The within-analysts demeaning of their forecasts (which is identical to a fixed-effects transformation) plays the same role here: it not only corrects for biases that are common across all analysts, but also for any biases that are specific to an individual analyst and that affect all of her forecasts in a similar manner. The within-analyst demeaning is therefore a very powerful device for correcting biases, since it allows for the size of these biases to vary across analysts.

In this section, we use the relationship between the consensus forecasts and the relative forecasts to try to study what factors might bias individual analysts' forecasts (and subsequently the consensus forecast). Specifically, since the difference between the consensus and relative forecasts is made up of the analysts fixed effects, we try to relate these fixed effects to analyst-specific observable variables.

4.1 Explaining analyst fixed effects

Panel A of Table 7 presents the results from *analyst-level* Fama-MacBeth regressions. The dependent variable is $\overline{TR}$, the average forecast across stocks for a given analyst; i.e., the analyst fixed effect.[23] Our first set of candidate factors to explain the analyst fixed effects are anomaly characteristics. Similar to Section 3, we find the value of characteristic X, at the end of month $t-1$, for the underlying stock j. We then define $\overline{X}_{kt}$ as the average of these characteristic values across all the stocks that analyst k covers in month t; see equation (A7) in Appendix A. That is, $\overline{X}$ describes what type of stocks the analyst covers in the given month in terms of characteristic X. For example, low (high) values of $\overline{Size}$ indicate that the analyst covers small (big) firms, on average, during that month. We use the same anomaly characteristics as in Section 3: $Size$, book-to-market ratio (BM), investment (AG), profitability (RoE), and momentum (Mom).

In Column 1 of Panel A in Table 7, we regress each analyst's average target returns ($\overline{TR}$) on $\overline{X}$-s created from these characteristics. Analysts tend to incorporate information about firm size correctly in their forecasts: those analysts who cover smaller stocks on average issue higher return forecasts. However, all the other anomalies have the "wrong" signs: analysts issue higher target returns if the average stock they cover is (i) a growth stock, (ii) a high investment stock, (iii) a low profitability stock, or (iv) a loser stock. The average regression R^2 is 19.5% and the anomaly characteristics therefore go some way towards explaining the analyst fixed effects and consequently

[23]There are explanatory variables in Table 7 that rely on previously issued price targets (see $\overline{OCTR}$ and $PA\overline{TR}$ introduced later in this section). Therefore, similar to Table 6, the first six months of the overall sample period are omitted.

the bias in the consensus forecast. That is, analysts' incorrect collective interpretation of anomaly signals likely contributes to the bias in target returns.

Next, we focus on other, more behavioral, aspects that may bias analysts' forecasts. It has been documented that analysts display herding behavior by following other analysts' forecasts on the same firm (e.g., Trueman, 1994; Welch, 2000). Kumar et al. (2022) also show that an analyst's earnings forecast for a certain firm are not only influenced by other forecasts on the same firm, but also by forecasts on *other firms* that the analyst in question covers. We apply the findings of Kumar et al. (2022) in the context of return forecasts. Define the variable *Others' Consensus Target Return*, $OCTR_{jkt}$, as the consensus target return on stock j calculated using the most recent announcements of all analysts *except analyst* k from the *six months prior to month* t. Then $\overline{OCTR}_{kt}$ is the average $OCTR_{jkt}$ across all the stocks that analyst k covers in month t. That is, $\overline{OCTR}$ aggregates prior forecasts of others for all the stocks that are covered by the analyst.

Column 2 in Table 7 (Panel A) shows that $\overline{OCTR}$ strongly predicts the fixed effect, $\overline{TR}$; for every percentage point increase in the aggregated prior forecasts of other analysts, the target return is expected to increase by 77 basis points. The average R^2 is also quite sizable at almost 32%. Since analysts' forecasts tend to be upward biased, this "learning" effect will likely have a reinforcing effect on the (upward) bias in subsequent forecasts. That is, the spillover effects from other analysts is likely to exacerbate rather than mitigate errors in the forecasts.

Further, we also study if there are analysts who consistently have higher (or lower) return forecasts compared to other analysts, and whether this contributes to the bias in target returns. In order to do this, we construct the variable of *Past Analyst average Target Return*: $PA\overline{TR}_{kt}$ is calculated as the average $\overline{TR}$ of analyst k over all months *prior to month* t; see equation (A8) in Appendix A. A high value of $PA\overline{TR}$ thus indicates that the analyst typically issues high return forecasts, irrespective of market conditions or possible changes in the set of stocks covered.

Column 3 of Table 7 (Panel A) shows that $PA\overline{TR}$ is also a very strong predictor of $\overline{TR}$; if we compare two analysts and one of them had a one percentage point higher average forecast in the past, she is expected to issue a 82 basis points higher target. That is, analysts who had high (low) average return forecasts in the past continue to have high (low) average forecasts going forward. Like $\overline{OCTR}$, $PA\overline{TR}$ explains a considerable fraction of the variation in analyst fixed effects, with an average R^2 of 35%. Column 4 shows that when both $\overline{OCTR}$ and $PA\overline{TR}$ are included jointly in the regression, they are both highly statistically significant and with similar (large) coefficients. Since $\overline{OCTR}$ and $PA\overline{TR}$ are related (they are both calculated from past target returns), the coefficients on both of them naturally decrease when they appear jointly. The R^2 for the joint regression is 44%.

Finally, Column 5 shows the coefficient estimates when the analyst fixed effects are regressed on all analyst-specific variables considered previously; that is, the anomaly characteristics, $\overline{OCTR}$, and $PA\overline{TR}$. Adding the within-analyst average anomaly characteristics barely change the coefficients on $\overline{OCTR}$, and $PA\overline{TR}$ (compare columns 4 and 5), but the coefficients on the anomaly characteristics are only small fractions of those reported in Column 1 (where $\overline{OCTR}$ and $PA\overline{TR}$ are not included). Adding the characteristics to the regression with $\overline{OCTR}$ and $PA\overline{TR}$ alone only marginally increases the R^2, from 44% to 46%. That is, $\overline{OCTR}$ and $PA\overline{TR}$ pick up the vast majority of the variation explained by the anomaly characteristics.

The average analyst forecasts, i.e., the fixed effects $\overline{TR}$, are therefore to a fairly substantial degree (R^2 of about 45%) explained by (i) the forecasts of other analysts covering the same stocks and (ii) the average of a given analyst's own previous forecasts (across all stocks the analyst has ever covered). Both of these can be viewed as behavioral biases. The first one reflects a form of herding bias, where analysts partly base their information on the previous forecasts of other analysts. Since (these other) forecasts tend to be biased, such a "learning" mechanism is likely to have a reinforcing rather than corrective effect on the overall bias in analysts' forecasts. The second effect likely reflects some general tendency of analysts to be either consistently over-optimistic or over-pessimistic (with more of the former given the upward bias in the consensus forecasts).

4.2 A simple (partial) correction of the consensus forecasts

Consensus return forecasts from sell-side analysts tend to be positively biased (see, e.g., Brav and Lehavy, 2003; Bradshaw et al., 2013; Dechow and You, 2020; Engelberg et al., 2020). In our sample, taking the cross-sectional average of CTR month-by-month and then taking the time-series average of those values, the resulting overall mean consensus forecast is a monthly 2.20%. If we calculate the same mean for next month's realized returns (using only the stocks where CTR is available to have a comparable sample), the result is 1.15% per month. This 1.05 percentage point difference is both economically and statistically significant with a corresponding t-statistic of 2.55.

The results in the previous sub-section suggest a simple way of, at least partially, correcting for this upward bias. Specifically, we show that this difference can largely be explained by analysts who consistently issue high target returns. Recall that $PA\overline{TR}_{kt}$ is the average $\overline{TR}$ of analyst k over all months prior to month t (i.e., the analyst's historical average target returns across all stocks). In Table 8 we analyze the effects on the consensus returns if the forecasts from the historically most upward biased analysts are excluded. That is, we calculate the consensus returns, CTR, over a restricted set of analysts' forecasts, where we filter on the past forecast history of the analyst, $PA\overline{TR}_{kt}$. Specifically, on an analyst-stock-month basis, we consider excluding forecasts from analysts where $PA\overline{TR}_{kt}$ is above the 95th, 90th, or 75th percentile of $PA\overline{TR}_{kt}$. The first row of Panel A in Table 8 shows that such filtering has a surprisingly small effect on the fraction of stocks covered, as measured by market capitalization. Without applying any filtering on $PA\overline{TR}_{kt}$, a consensus forecast is, on average across all months of the sample, available for stocks representing 75% of the total market capitalization. Excluding analysts with a $PA\overline{TR}_{kt}$ above the 75th percentile in each month, this coverage rate drops to 70%.[24]

The second row in Table 8 shows the average consensus forecast (CTR) based on either all

[24]To understand why the drop in coverage is so low, despite dropping 25% of all analysts, note that stocks that matter more in terms of market capitalization (i.e., those of larger companies) are typically covered by multiple analysts. Thus, these stocks will remain in the sample even after dropping a quarter of all analysts.

analysts or the sample of anaysts filtered on $PA\overline{TR}_{kt}$. The average non-filtered CTR is equal to 2.20%, as mentioned above. Removing analysts with high historical forecasts (across all the stocks covered), quickly decreases the consensus forecast. If the analysts above the 95th percentile of $PA\overline{TR}_{kt}$ are removed, the consensus forecast drops to 1.88% and if those above the 90th and 75th and percentile are removed, the forecasts drop to 1.75% and 1.50%, respectively. The last two rows of Panel A show the average realized returns corresponding to the average consensus forecasts, as well as the difference between the forecasts and the realized values (the average realized returns differ slightly across the different filterings due to changes in the stocks covered, but this effect is small). As documented above, the unfiltered consensus forecast is 1.05 percentage points higher than the realized returns. This difference shrinks to 0.69, 0.54, and 0.30 percentage points as the analysts above the 95th, 90th, and 75th percentiles of $PA\overline{TR}_{kt}$ are removed, respectively; the corresponding t-statistics for the differences are 1.71, 1.36, and 0.77, respectively. Thus, removing the historically most optimistic, or upward biased, group of analysts, fairly quickly and substantially reduces the upward bias in the consensus forecast.

5 Ranking of earnings forecasts and recommendations

Target price forecasts stand as one of the research output from sell-side analysts. In fact, a majority of analyst reports also feature two additional important summary measures: earnings forecasts and recommendations (see, e.g., Asquith et al., 2005). If analysts consistently demonstrate skill in ranking stocks, we would expect to observe analogous results for these alternative forecasts. Specifically, within each analyst's portfolio, stocks ranked higher based on their predicted earnings-price ratios should earn greater subsequent returns, as these stocks are considered undervalued.[25] Simultaneously, stocks receiving relatively higher recommendations should also yield higher returns.

[25] Elgers et al. (2001) find that stock prices underreact to information in analysts' earnings forecasts, thereby establishing the predictive power of forecasted earnings-price ratios for future returns.

Following prior literature (see, e.g., Clement, 1999; Loh and Mian, 2006; Harford et al., 2019), for each firm we extract each analyst's earnings per share (EPS) forecast for the current fiscal year (FY1) from the IBES Unadjusted Detail file. For each analyst-firm pair, we utilize the most recent forecast issued within the current fiscal year and preceding the fiscal year-end. To mitigate the potential influence of stock price reversals on our findings, we normalize EPS forecasts using the stock prices that are available from the end of preceding year (on the same per-share basis as the unadjusted EPS forecasts). The normalization yields earnings-price ratios that are comparable across firms, and we can evaluate whether subsequent returns align with analysts' ranking of these ratios.[26]

For each stock in each month, we compute three metrics: (1) Consensus E/P (CEP), derived as the mean of predicted earnings-price ratios across analysts covering the stock within that month; (2) Consensus Demeaned E/P ($CDEP$), calculated by subtracting analyst-level mean from the consensus, akin to $CDTR$ outlined in Section 2.1; (3) Consensus Ranked E/P ($CREP$), calculated as the mean of scaled rank values for predicted earnings-price ratio, similar to $CRTR$ described in Section 2.1. We require an analyst to have at least three announcements of earnings forecasts in a month. Our sample spans from January 1983 to December 2021.

At the end of each month, we sort all stocks into quintile portfolios based on the three aforementioned metrics. We then form a long-short portfolio for each forecast by buying the stocks with the highest forecasts for earnings-price ratio and selling those with the lowest forecasts. Table 9 presents the average excess returns for each portfolio and also the long-short portfolios. Results from the left panel align with the findings in Elgers et al. (2001): stocks with the highest consensus E/P outperform those with the lowest consensus E/P by 1.09% per month ($t = 3.62$) under the equal-weighted scheme. However, the outperformance is largely driven away by $FF6$, $q5$, and the behavioral factor model. Additionally, results from value-weighted portfolios are even weaker.

[26] Our results are very similar when restricting the analysis to firms with stock prices higher than $5 or to firms with fiscal year ending in December, or when normalizing EPS forecasts by the stock prices at the end of the month preceding analysts' forecasts.

Interestingly, the long-short portfolios formed based on $CDEP$ and $CREP$ yield more significant returns ($t = 5.31$ and 5.50), and they largely survive even after adjusting for common risk factors. Furthermore, the raw and risk-adjusted returns from value-weighted portfolios are mostly significant. These results resemble those in Table 1, indicating that analysts demonstrate skill in relative valuation using earnings-price ratios. The evidence that existing risk factors fail to capture the predictive power of these relative forecasts signifies very different information compared to that embedded in the consensus forecasts.

While theoretically we could apply similar analysis on analysts' recommendations, its implementation raises doubts due to analysts assigning integers between 1 (Strong Buy) and 5 (Strong Sell) as their stock recommendations. Consequently, many stocks in an analyst's portfolio receive the same numeric value, potentially limiting the informativeness of analyst-level ranking. Nonetheless, we proceed with a similar analysis by calculating Consensus Recommendations ($CRec$), Consensus Demeaned Recommendations ($CDRec$), and Consensus Ranked Recommendations ($CRRec$). These measures are defined similarly to those for target prices and EPS forecasts, with recommendation data available from December 1993 to December 2021.[27] We then sort these three metrics in reverse order, and as many stocks end up with the same recommendation scores, we form tercile instead of quintile portfolios. Table OA.9 in Online Appendix reports statistics for tercile portfolios and their long-short portfolios. In line with the findings from previous literature (e.g., Barber et al., 2001), a favorable consensus recommendation predicts higher subsequent returns. Interestingly, despite potential concerns about the informativeness of analysts' relative ranking of recommendations, we still document more sizable returns from high-minus-low portfolios when switching from consensus to ranking measures of recommendations. The return spreads remain significant in many scenarios and resemble those obtained from analysts' relative forecasts for prices and earnings. Overall, the

[27] When calculating $CRRec$, we assume that for tied stocks, they both receive the lowest possible scaled rank value. For example, if an analyst issues the recommendation values of $\{3, 3, 1\}$ for stocks in her portfolio, these stocks receive the scaled rank value of $\{1/3, 1/3, 1\}$. Our results are largely invariant if instead assigning the highest possible scaled rank to tied stocks (i.e., $\{2/3, 2/3, 1\}$).

evidence by exploring three most common forecasts from sell-side analysts points to consistent skills in ranking stocks.

6 Conclusion

Sell-side security analysts are important information intermediaries in the stock market. They process public and private information and communicate their research with the market by issuing forecasts for individual stocks. Despite their prominent role in financial data processing and information provision, whether analysts' forecasts actually contain useful information for investors is still debated. Our results provide a strong and novel yes to this question, with the qualification that analysts are good at relative valuation, but not absolute valuation. Formulated like this, our results are not particularly surprising. Most analysts specialize on certain types of firms or industries, which should provide some ability to rank the stocks of the firms they cover. On the other hand, analysts are generally not macro-finance experts with superior abilities to forecast the overall direction of the market, which constitutes a large part of the absolute level of any individual stock return forecast. The job-related incentives also tend to bias absolute forecasts, because the forecast target company might have business relationships with the brokerage firms issuing the forecast. In short, we should expect analysts to be good at ranking stocks but less good at giving forecasts of the equity premium. Our empirical findings verify this conjecture.

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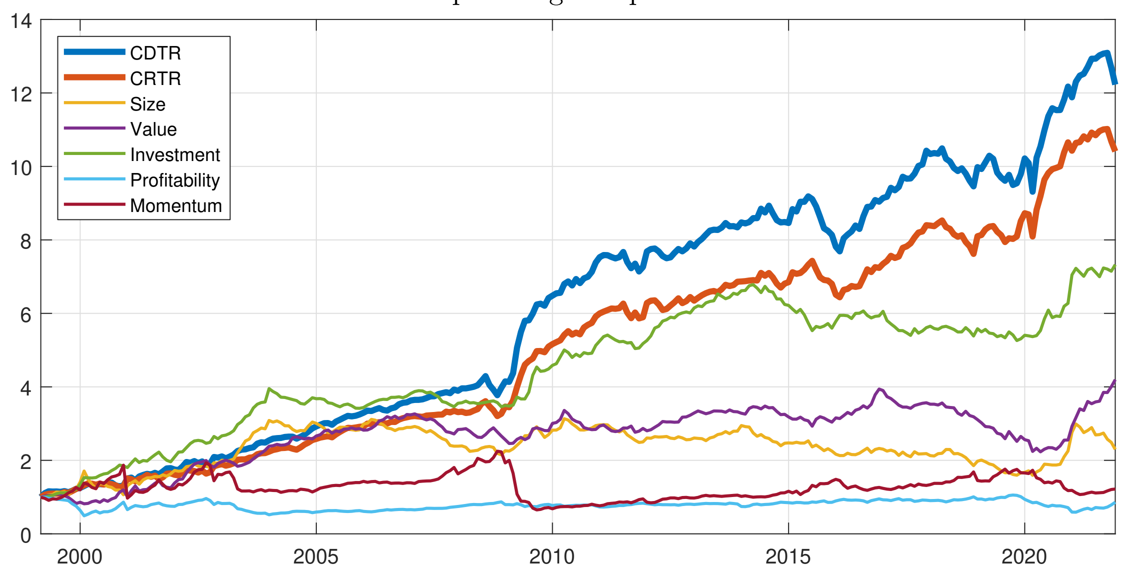
Figure 1: Cumulative return on long-short strategies

The graphs show the growth of $1 invested in various anomaly trading strategies. The strategies are constructed using the two extreme portfolios from equal-weighted (Panel A) or value-weighted (Panel B) quintile sorts. $CDTR$ and $CRTR$ correspond to our measures based on within-analyst demeaned forecasts and within-analyst rankings of forecasts, respectively. Returns on the long and short quintile portfolios for other characteristics are obtained from Kenneth French's data library.

A. Equal-weighted portfolios



B. Value-weighted portfolios

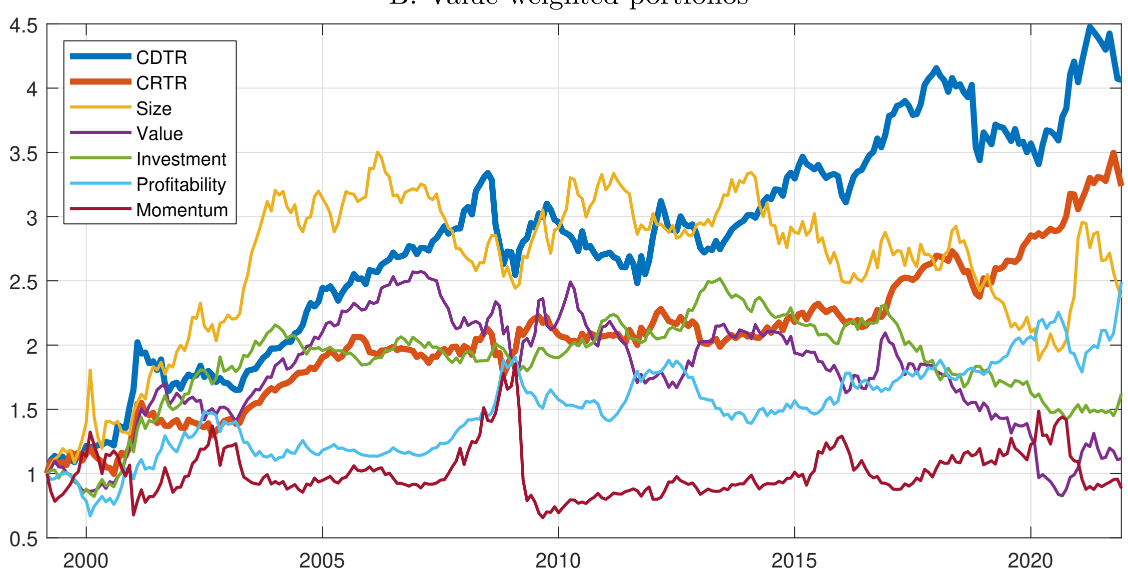


Figure 2: Distribution of t-statistics on time-series alphas

The graphs show histograms of the t-statistics on α estimates from $R_{CDTR,t} = \alpha + \beta R_{X,t} + \epsilon_t$, where $R_{CDTR,t}$ is the monthly return on the long-short quintile strategy based on $CDTR$, while $R_{X,t}$ is the return on the long-short quintile strategy based on one of 140 anomaly variables at a time. The anomaly variables come from the March 2022 release of the asset pricing dataset connected to Chen and Zimmermann (2021). In Panel A (Panel B), the t-statistics come from regressions where both $R_{CDTR,t}$ and $R_{X,t}$ correspond to equal-weighted (value-weighted) portfolios. The sample period ranges from March 1999 to December 2021.

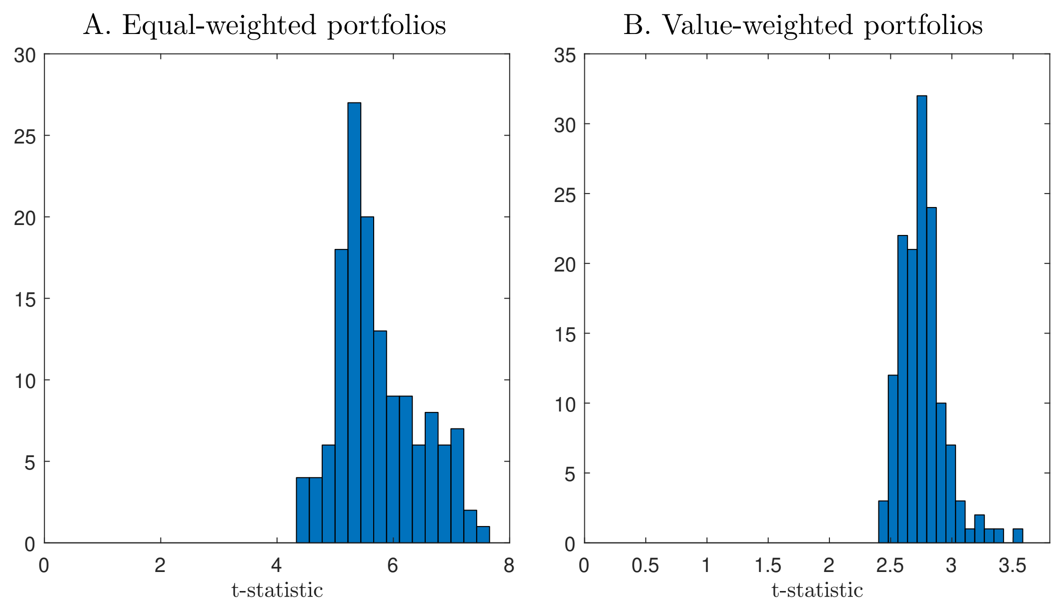


Figure 3: Distribution of t-statistics from Fama-MacBeth regressions

The graph shows the histogram of Newey-West t-statistics on the β_1 estimates from Fama-MacBeth regressions of the type $R_{j,t+1} = \alpha + \beta_1 CDTR_{j,t} + \beta_2 X_{j,t} + \epsilon_{j,t}$, where $R_{j,t+1}$ is the return on stock j in month $t+1$, $CDTR_{j,t}$ is our measure based on within-analyst demeaned return forecasts from month t, and $X_{j,t}$ is one of 140 anomaly variables at a time. The anomaly variables come from the March 2022 release of the asset pricing dataset connected to Chen and Zimmermann (2021). The sample period ranges from March 1999 to December 2021.

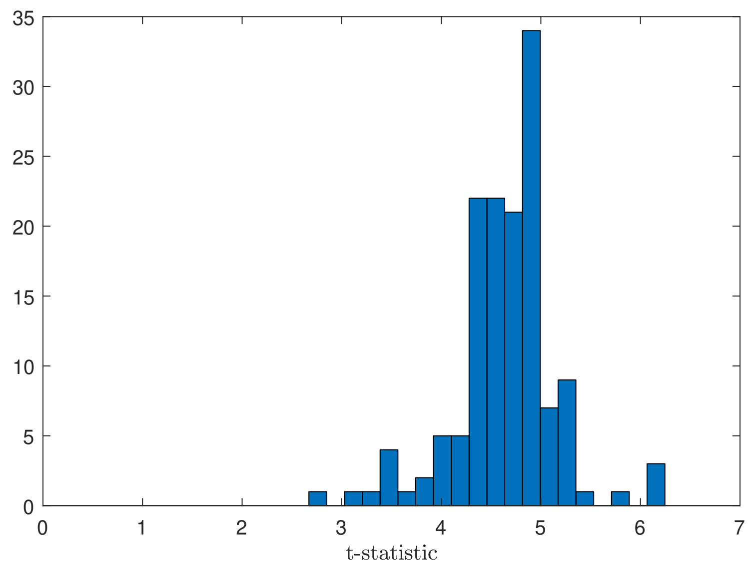
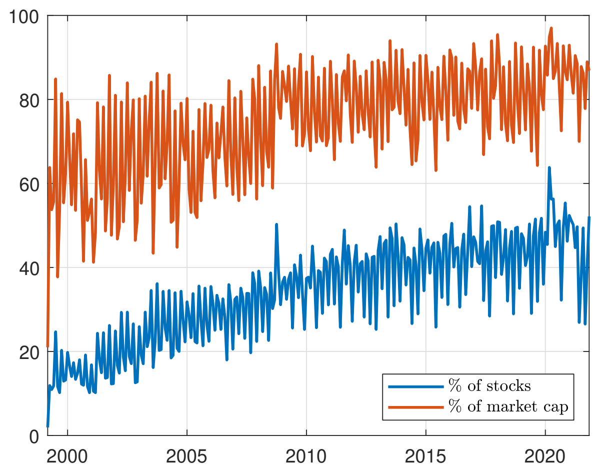


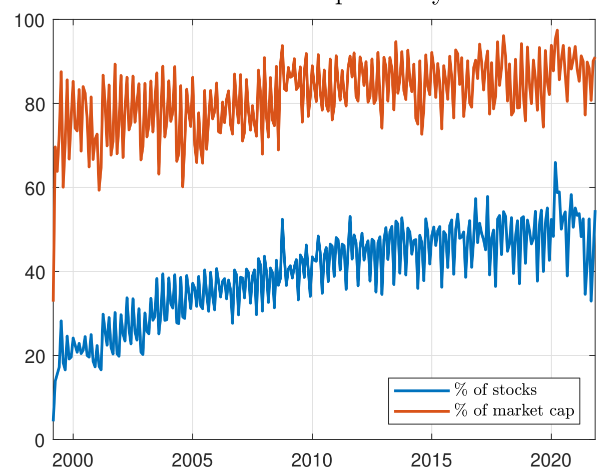
Figure 4: Coverage in terms of number of stocks and market capitalization

The graphs show the monthly cross-sectional coverage of $CDTR$ in terms of the percentage of unique PERMNO-s covered from the CRSP universe (*% of stocks*), and the fraction of total CRSP capitalization covered (*% of market cap*).

A. Baseline implementation of $CDTR$



B. No minimum requirement on number of announcements per analyst



C. Announcements from last 3 months

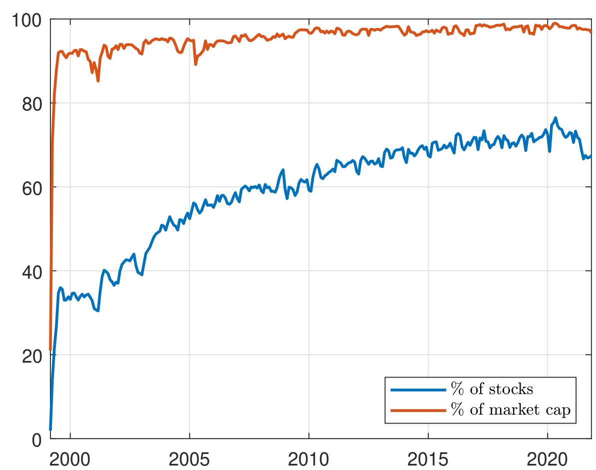


Table 1: Excess returns and alphas on *CDTR*- and *CRTR*-sorted portfolios

The table reports average monthly excess returns (R^e, in percentage) on quintile portfolios sorted on *CDTR* or *CRTR*. The table also reports the average returns on the zero-cost investment strategy that buys the highest and sells the lowest quintile portfolio (*H-L*). In addition, we report the alpha of each portfolio with respect to the five-factor model of Fama and French (2015) (*FF5*), its six-factor extension that adds the momentum factor (*FF6*), the q-factor model of Hou et al. (2015) (*HXZ*), and the behavioral factor model of Daniel et al. (2020) (*DHS*). The sample ranges from March 1999 to December 2021. Newey-West t-statistics are in parenthesis.

	Sorting on *CDTR*						Sorting on *CRTR*					
	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L
A. Equal-weighted portfolios												
R^e	0.48	0.95	1.04	1.20	1.44	0.96	0.54	0.85	1.07	1.20	1.44	0.89
	(1.13)	(2.79)	(3.10)	(3.28)	(2.66)	(5.27)	(1.50)	(2.34)	(2.81)	(2.92)	(3.03)	(5.31)
α_{FF5}	-0.33	0.14	0.18	0.30	0.49	0.83	-0.29	0.04	0.21	0.30	0.50	0.79
	(-3.11)	(1.52)	(2.60)	(3.40)	(2.49)	(5.88)	(-4.01)	(0.47)	(2.19)	(2.63)	(3.36)	(5.89)
α_{FF6}	-0.27	0.16	0.19	0.33	0.61	0.89	-0.26	0.07	0.25	0.37	0.58	0.84
	(-2.79)	(1.81)	(2.59)	(3.76)	(4.06)	(6.89)	(-3.81)	(0.87)	(2.67)	(3.70)	(4.58)	(6.66)
α_{HXZ}	-0.12	0.28	0.31	0.48	0.81	0.93	-0.14	0.19	0.39	0.54	0.74	0.88
	(-1.21)	(2.66)	(3.53)	(4.02)	(3.70)	(5.73)	(-1.85)	(2.19)	(3.43)	(4.00)	(4.15)	(5.81)
α_{DHS}	0.00	0.30	0.34	0.54	1.01	1.00	-0.05	0.22	0.48	0.64	0.89	0.94
	(0.02)	(2.23)	(2.52)	(3.89)	(3.60)	(5.60)	(-0.38)	(1.71)	(3.30)	(3.78)	(3.60)	(5.47)
B. Value-weighted portfolios												
R^e	0.39	0.68	0.72	0.69	0.96	0.57	0.42	0.58	0.72	0.72	0.89	0.47
	(1.16)	(2.54)	(2.71)	(2.43)	(2.46)	(2.78)	(1.43)	(2.03)	(2.40)	(2.38)	(2.79)	(2.69)
α_{FF5}	-0.17	0.01	0.08	0.03	0.26	0.43	-0.24	0.01	0.10	0.06	0.25	0.49
	(-1.39)	(0.18)	(0.92)	(0.42)	(1.70)	(2.21)	(-2.32)	(0.12)	(1.05)	(0.71)	(1.98)	(2.72)
α_{FF6}	-0.14	0.01	0.05	0.05	0.31	0.44	-0.24	0.01	0.11	0.08	0.28	0.51
	(-1.13)	(0.12)	(0.60)	(0.56)	(2.12)	(2.28)	(-2.33)	(0.10)	(1.15)	(0.91)	(2.18)	(2.88)
α_{HXZ}	0.03	0.17	0.12	0.17	0.45	0.42	-0.08	0.12	0.23	0.20	0.39	0.47
	(0.26)	(2.19)	(1.35)	(1.93)	(2.71)	(2.08)	(-0.78)	(1.43)	(2.28)	(2.36)	(2.72)	(2.49)
α_{DHS}	-0.11	0.01	-0.02	0.00	0.41	0.52	-0.21	-0.05	0.06	0.03	0.29	0.50
	(-0.78)	(0.08)	(-0.25)	(0.04)	(2.67)	(2.31)	(-2.00)	(-0.56)	(0.68)	(0.32)	(1.92)	(2.45)

Table 2: Characteristics of $CDTR$- and $CRTR$-sorted portfolios

The table reports the average characteristic rank of the stocks in quintile portfolios sorted on $CDTR$ or $CRTR$, our baseline measures of analysts' relative forecasts. *Low* (*High*) denotes the portfolio containing the stocks with lowest (highest) $CDTR$ and $CRTR$, respectively. The values of each characteristic are cross-sectionally transformed month-by-month to reflect the stocks' rank within the CRSP universe with respect to that variable and are mapped into the $[0, 1]$ interval (from low to high). Characteristic values come from the March 2022 release of the asset pricing dataset connected to Chen and Zimmermann (2021). The characteristics are (the acronym used by Chen and Zimmermann in parenthesis): *Size* is the market value of equity (Size), *B/M* is the book-to-market ratio (BMdec), *Inv* is the annual growth rate of total assets (AssetGrowth), *RoE* is net income over book equity (RoE), *Mom* is 12-month momentum (Mom12m), *SRev* is the stock return over the previous month (STreversal), and *Illiq* is the bid-ask-spread (BidAskSpread). The sample ranges from March 1999 to December 2021.

	Sorting on $CDTR$					Sorting on $CRTR$				
	Low	2	3	4	High	Low	2	3	4	High
Size	0.68	0.75	0.76	0.74	0.61	0.70	0.75	0.74	0.73	0.63
B/M	0.41	0.43	0.44	0.44	0.44	0.43	0.42	0.42	0.44	0.45
Inv	0.55	0.55	0.56	0.56	0.55	0.54	0.56	0.56	0.57	0.55
RoE	0.54	0.61	0.62	0.60	0.48	0.58	0.60	0.59	0.57	0.51
Mom	0.54	0.57	0.57	0.55	0.45	0.55	0.56	0.55	0.53	0.49
SRev	0.48	0.52	0.54	0.54	0.51	0.49	0.52	0.53	0.53	0.52
Illiq	0.45	0.35	0.34	0.37	0.53	0.39	0.37	0.39	0.40	0.48

Table 3: Portfolios sorted on alternative measures of analyst expectations

The table reports average monthly excess returns on the portfolios containing stocks from the lowest (*Low*) to highest (*High*) quintiles when sorting on various characteristics monthly. The average returns to the strategy that buys the Low portfolio and sells the High portfolio is also reported (*H-L*). The characteristics considered are our measure of analysts' relative forecasts ($CDTR$), the consensus return forecast (CTR), the consensus return forecast demeaned at the industry level ($ICTR$), and the informative component of return expectations ($Info$) following Loudis (2022). In the column labeled $\hat{\alpha}$, alpha estimates from $R_{CDTR,t} = \alpha + \beta R_{X,t} + \epsilon_t$ are reported, where $R_{CDTR,t}$ is the monthly return on the long-short quintile strategy based on $CDTR$, while $R_{X,t}$ is the return on the long-short quintile strategy based on the characteristic presented in the same row of the table. The sample ranges from March 1999 to December 2021 in general; for the results that rely on the variable *Info*, the sample starts on September 1999. Newey-West t-statistics are in parenthesis.

	Low	2	3	4	High	H-L	$\hat{\alpha}$
A. Equal-weighted portfolios							
$CDTR$	0.48	0.95	1.04	1.20	1.44	0.96	
	(1.13)	(2.79)	(3.10)	(3.28)	(2.66)	(5.27)	
CTR	0.68	0.97	1.10	1.23	1.14	0.46	0.79
	(1.96)	(3.08)	(3.17)	(2.92)	(1.89)	(1.29)	(5.99)
$ICTR$	0.56	0.95	0.95	1.14	1.35	0.80	0.41
	(1.38)	(2.72)	(2.85)	(3.05)	(2.45)	(3.49)	(4.68)
$Info$	0.80	0.96	1.01	1.11	1.35	0.55	0.75
	(1.89)	(2.87)	(2.92)	(3.18)	(3.03)	(3.42)	(3.90)
B. Value-weighted portfolios							
$CDTR$	0.39	0.68	0.72	0.69	0.96	0.57	
	(1.16)	(2.54)	(2.71)	(2.43)	(2.46)	(2.78)	
CTR	0.56	0.64	0.78	0.63	0.72	0.16	0.54
	(2.07)	(2.52)	(2.70)	(1.74)	(1.41)	(0.46)	(2.63)
$ICTR$	0.36	0.86	0.85	0.69	0.68	0.33	0.40
	(1.17)	(3.03)	(3.15)	(2.33)	(1.56)	(1.19)	(2.79)
$Info$	0.63	0.60	0.54	0.82	0.91	0.27	0.52
	(1.91)	(2.17)	(1.88)	(2.89)	(2.54)	(1.39)	(2.41)

Table 4: Fama-MacBeth regressions

The table reports the average coefficients and Newey-West t-statistics from Fama-MacBeth regressions at the stock-level. The dependent variable is the stock return in the following month, and the independent variables are characteristics constructed from analyst target return forecasts. A constant is included in the regressions, but its estimate is omitted from the table. The average number of stocks in the regressions is also reported. The sample is from March 1999 to December 2021 in general; for the specifications that includes the variable *Info*, the sample starts on September 1999.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CDTR$	0.13		0.17		0.16		0.14	0.16
	(4.61)		(3.97)		(5.06)		(4.41)	(4.14)
CTR		0.07	-0.03					0.03
		(2.10)	(-0.66)					(0.20)
$ICTR$				0.08	-0.02			-0.02
				(2.72)	(-0.41)			(-0.15)
$Info$						0.18	0.12	0.08
						(3.49)	(2.18)	(1.37)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg R^2	0.01	0.01	0.02	0.01	0.01	0.004	0.01	0.04
Avg #obs	1403	1403	1403	1366	1366	1251	1089	1064

Table 5: Strategy performance with variations in the definition of $CDTR$

The table reports the performance of long-short quintile strategies. The strategies are constructed from portfolios sorted month-by-month on analysts' relative return forecasts, i.e., based on our baseline $CDTR$ measure and its variations. The particular variation considered is described in the first column. The performance measures reported in the table are the average monthly return (*Mean*) with the associated t-statistic (t), the monthly volatility (*Vol*), the annualized Sharpe ratio (*SR*), and then rank of this Sharpe ratio among the Sharpe ratios of 140 long-short strategies based on anomaly characteristics from previous literature (*SR rank*). The sample ranges from March 1999 to December 2021.

Change compared to the baseline measure	Mean	t	Vol	SR	SR rank
A. Equal-weighted portfolios					
baseline measure; no change	0.96	5.27	2.77	1.20	2nd
at least 2 announcements per analyst per month	0.85	4.57	2.77	1.06	3rd
no minimum on announcements per analyst per month	0.86	4.84	2.60	1.14	2nd
2-month announcement collection window	0.88	4.37	3.01	1.01	5th
3-month announcement collection window	0.80	3.39	3.17	0.87	13th
drop announcements from last 5 days of the month	0.78	4.36	2.76	0.98	6th
B. Value-weighted portfolios					
baseline measure; no change	0.57	2.78	3.39	0.58	3rd
at least 2 announcements per analyst per month	0.64	3.03	3.41	0.65	3rd
no minimum on announcements per analyst per month	0.48	2.51	2.96	0.56	3rd
2-month announcement collection window	0.73	3.27	3.42	0.74	1st
3-month announcement collection window	0.42	1.75	3.72	0.39	17th
drop announcements from last 5 days of the month	0.49	2.44	3.39	0.50	5th

Table 6: The information sources of relative forecasts

The table reports the average coefficients and Newey-West t-statistics from Fama-MacBeth regressions at the individual stock return forecast level. The dependent variable is next month's realized return on the stock for which the target price was issued for. $TR - \overline{TR}$ is the individual return forecast minus the average forecast of the issuing analyst in the given month. The specification in column 2 includes the following z-transformed stock characteristics: log market value of equity ($Size$), book-to-market ratio (BM), investment measured by asset growth (AG), return-on-equity (RoE), and momentum (Mom). $EAwindow$ is a dummy variable indicating if the target return announcement falls into the $[-3, +3]$ day window around an earnings announcement of the given stock. $Bold$ is a dummy variable indicating bold (as opposed to herding) forecasts following Clement and Tse (2005). $LowCover$ is a dummy variable indicating that the return forecast is issued for a stock with low analyst coverage. A constant is included in the regressions, but its estimate is omitted from the table. The sample is from September 1999 to December 2021.

	(1)	(2)	(3)	(4)	(5)
$TR - \overline{TR}$	0.087	0.091	0.094	0.003	0.051
	(4.03)	(5.13)	(4.03)	(0.07)	(2.14)
$Size$		-0.284			
		(-2.35)			
BM		-0.103			
		(-0.71)			
AG		-0.217			
		(-3.21)			
RoE		0.209			
		(2.98)			
Mom		-0.033			
		(-0.20)			
$EAwindow$			0.001		
			(0.01)		
$(TR - \overline{TR}) \times EAwindow$			-0.047		
			(-1.48)		
$Bold$				0.216	
				(2.17)	
$(TR - \overline{TR}) \times Bold$				0.145	
				(3.77)	
$LowCover$					-0.010
					(-0.08)
$(TR - \overline{TR}) \times LowCover$					0.067
					(2.13)
Constant	Yes	Yes	Yes	Yes	Yes
Avg R^2	0.004	0.067	0.008	0.007	0.010
Avg #obs	3783	3492	3783	3276	3783

Table 7: Understanding analysts' average forecasts

The table reports the average coefficients and Newey-West t-statistics from Fama-MacBeth regressions at the analyst level. The dependent variable, $\overline{TR}$, is the average return forecast across stocks for a given analyst in a given month. $\overline{X}$ denotes the average value of a stock-specific variable across all the stocks that a given analyst covers in month; the following underlying variables are used: log market value of equity ($Size$), book-to-market ratio (BM), investment measured by asset growth (AG), return-on-equity (RoE), and momentum (Mom). $\overline{OCTR}$ aggregates prior forecasts (from previous 6 months) of other analysts for all the stocks that are covered by the analyst in question. $PA\overline{TR}$ is the average $\overline{TR}$ of a given analyst over all *prior* months in the sample. A constant is included in all the regressions. The average number of observations in the regressions is also reported. The sample period is from September 1999 to December 2021.

	(1)	(2)	(3)	(4)	(5)
$\overline{Size}$	-1.188				-0.291
	(-8.76)				(-9.83)
$\overline{BM}$	-0.379				-0.035
	(-4.32)				(-1.30)
$\overline{AG}$	0.262				0.017
	(7.12)				(0.96)
$\overline{RoE}$	-0.810				-0.125
	(-13.57)				(-3.81)
$\overline{Mom}$	-0.224				-0.077
	(-1.99)				(-2.39)
$\overline{OCTR}$		0.765		0.474	0.424
		(29.76)		(26.69)	(23.45)
$PA\overline{TR}$			0.823	0.556	0.532
			(14.55)	(23.20)	(22.74)
Constant	Yes	Yes	Yes	Yes	Yes
Avg R^2	0.195	0.319	0.353	0.438	0.462
Avg #obs	662	663	640	640	639

Table 8: Consensus forecasts calculated from a restricted set of target returns

The table reports some characteristics of consensus target returns, CTR, when different sets of individual target returns are used for its construction. The first column, labeled "baseline", uses the baseline implementation. In the rest of the columns, return forecasts from analysts with $PA\overline{TR}_{kt}$ values above the x-th percentile (and from analysts with missing $PA\overline{TR}_{kt}$) are deleted before calculating the CTR_{jt} measure for the stocks in month t. The row labeled "cap%" reports the average fraction of stocks covered by the specific CTR implementation, as measured by market capitalization. The rest of the rows, in order, show the time-series average of (i) the cross-sectional mean CTR across all stocks, (ii) the cross-sectional mean of next month's return across all stocks with a CTR value, and (iii) the difference of the two. The sample period is from September 1999 to December 2021. Newey-West t-statistics are in parenthesis.

	baseline	Drop analysts with $PA\overline{TR}$ above the x-th percentile		
		$x = 95$	$x = 90$	$x = 75$
cap%	74.9	73.0	72.4	69.8
CTR	2.20	1.88	1.75	1.50
	(11.04)	(10.84)	(10.09)	(8.91)
R_{t+1}	1.15	1.19	1.21	1.21
	(2.87)	(3.02)	(3.10)	(3.20)
$CTR - R_{t+1}$	1.05	0.69	0.54	0.30
	(2.55)	(1.71)	(1.36)	(0.77)

Table 9: Excess returns and alphas for portfolios sorted on ranking of earnings forecasts

The table reports average monthly excess returns (R^e, in percentage) on quintile portfolios sorted on CEP, $CDEP$ or $CREP$. The table also reports the average returns on the zero-cost investment strategy that buys the highest and sells the lowest quintile portfolio (*H-L*). In addition, we report the alpha of each portfolio with respect to the five-factor model of Fama and French (2015) (*FF5*), its six-factor extension that adds the momentum factor (*FF6*), the q-factor model of Hou et al. (2015) (*HXZ*), and the behavioral factor model of Daniel et al. (2020) (*DHS*). The sample ranges from January 1983 to December 2021. Newey-West t-statistics are in parentheses.

	Sorting on CEP						Sorting on $CDEP$						Sorting on $CREP$					
	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L
A. Equal-weighted portfolios																		
R^e	0.25	0.74	0.91	1.00	1.33	1.09	0.36	0.76	0.91	1.01	1.18	0.82	0.40	0.70	0.85	1.00	1.27	0.87
	(0.57)	(2.42)	(3.78)	(4.21)	(4.47)	(3.62)	(0.93)	(2.94)	(3.64)	(3.87)	(3.96)	(5.31)	(1.12)	(2.44)	(3.15)	(3.88)	(4.54)	(5.50)
α_{FF5}	-0.35	-0.00	-0.02	0.03	0.25	0.60	-0.47	-0.04	0.10	0.10	0.23	0.70	-0.38	-0.12	0.01	0.10	0.29	0.66
	(-1.79)	(-0.05)	(-0.35)	(0.52)	(2.50)	(2.98)	(-3.11)	(-0.52)	(1.23)	(1.31)	(2.44)	(5.75)	(-3.00)	(-1.29)	(0.17)	(1.53)	(3.58)	(6.00)
α_{FF6}	-0.08	0.12	0.05	0.09	0.30	0.38	-0.26	0.05	0.17	0.19	0.33	0.59	-0.19	0.01	0.11	0.18	0.36	0.55
	(-0.49)	(1.59)	(1.03)	(1.67)	(2.95)	(1.86)	(-2.26)	(0.69)	(2.21)	(3.74)	(4.39)	(4.92)	(-2.02)	(0.20)	(2.01)	(3.44)	(5.09)	(5.08)
α_{HXZ}	0.19	0.22	0.09	0.12	0.37	0.17	-0.07	0.16	0.25	0.24	0.40	0.47	-0.01	0.13	0.20	0.25	0.42	0.43
	(0.91)	(2.24)	(1.16)	(1.29)	(2.95)	(0.71)	(-0.51)	(1.59)	(2.53)	(2.91)	(4.26)	(3.64)	(-0.09)	(1.27)	(2.25)	(3.27)	(4.62)	(3.77)
α_{DHS}	0.29	0.36	0.25	0.26	0.54	0.25	0.10	0.24	0.33	0.39	0.62	0.51	0.12	0.23	0.32	0.38	0.63	0.51
	(1.05)	(2.85)	(2.65)	(2.42)	(3.15)	(0.94)	(0.47)	(2.22)	(2.98)	(3.51)	(4.33)	(3.45)	(0.62)	(1.79)	(2.90)	(3.75)	(4.62)	(3.64)
B. Value-weighted portfolios																		
R^e	0.48	0.75	0.78	0.91	0.92	0.44	0.57	0.75	0.77	0.75	0.97	0.40	0.58	0.80	0.75	0.77	0.94	0.36
	(1.22)	(2.90)	(3.88)	(4.59)	(3.82)	(1.42)	(1.89)	(3.62)	(3.86)	(3.50)	(4.07)	(2.13)	(2.38)	(3.87)	(3.56)	(3.69)	(4.43)	(3.00)
α_{FF5}	0.41	0.65	0.71	0.87	0.87	0.46	0.51	0.63	0.72	0.68	0.93	0.42	0.52	0.69	0.70	0.70	0.88	0.36
	(1.07)	(2.43)	(3.56)	(4.36)	(3.48)	(1.54)	(1.72)	(2.97)	(3.51)	(3.12)	(3.89)	(2.42)	(2.17)	(3.20)	(3.20)	(3.32)	(4.12)	(3.10)
α_{FF6}	0.35	0.61	0.68	0.84	0.83	0.48	0.43	0.59	0.70	0.65	0.88	0.45	0.48	0.65	0.66	0.68	0.85	0.37
	(0.88)	(2.20)	(3.30)	(4.10)	(3.20)	(1.50)	(1.37)	(2.71)	(3.31)	(2.96)	(3.63)	(2.37)	(1.87)	(2.91)	(2.94)	(3.11)	(3.87)	(3.00)
α_{HXZ}	0.33	0.63	0.61	0.80	0.83	0.50	0.42	0.57	0.69	0.63	0.89	0.47	0.46	0.63	0.65	0.66	0.82	0.36
	(0.80)	(2.24)	(2.81)	(3.60)	(3.12)	(1.44)	(1.37)	(2.61)	(3.04)	(2.67)	(3.56)	(2.46)	(1.79)	(2.79)	(2.81)	(2.88)	(3.65)	(2.93)
α_{DHS}	0.11	0.56	0.57	0.76	0.87	0.76	0.45	0.52	0.63	0.58	0.77	0.32	0.47	0.56	0.59	0.58	0.78	0.31
	(0.25)	(1.80)	(2.61)	(3.63)	(3.22)	(2.19)	(1.30)	(2.27)	(2.84)	(2.38)	(3.10)	(1.52)	(1.69)	(2.44)	(2.49)	(2.43)	(3.33)	(2.38)

Appendix A - Notation and definitions

The variables defined in the paper use the following underlying data:

TP_{jkt}	**Target Price** is the latest 12-month price target issued by analyst k for stock j in month t.
P^{-}_{jkt}	**Price on previous day** is the split-adjusted closing price of stock j on the day before TP_{jkt} was announced.
TR_{jkt}	**Target Return** of analyst k for stock j in month t, expressed in monthly terms; see (1).
R_{jt}	**Return** on stock j in month t.
X_{jt}	Value of characteristic **X** for stock j at the end of month t.

To help defining the variables used in the paper, we use the following definitions of sets (S). Note that $n(S)$ denotes the number of elements in a set.

S^A_{jt}	**Set** of **Analysts** who issued a price target for stock j during month t.
S^S_{kt}	**Set** of **Stocks** for which analyst k issued a price target during month t.
S^I_{jt}	**Set** of **Industry peers** of stock j in month t, including the stock itself.
S^H_{kt}	**Set** of **History** for analyst k, i.e., the set of previous months (relative to month t) when analyst k appears in the sample of target prices.

The variables we derive from the individual target returns are:

CTR_{jt} **Consensus Target Return** is the average of the target returns for stock j across the analysts who cover the stock in month t:

$$CTR_{jt} = \frac{1}{n\left(S^A_{jt}\right)} \sum_{k \in S^A_{jt}} TR_{jkt} \tag{A1}$$

$CDTR_{jt}$ **Consensus Demeaned Target Return** is the average *demeaned* target return for stock j across the analysts who cover the stock during month t, where the issuing analyst's average target return is subtracted from each individual return forecast before taking the cross-sectional average:

$$CDTR_{jt} = \frac{1}{n\left(S^A_{jt}\right)} \sum_{k \in S^A_{jt}} \left(TR_{jkt} - \overline{TR}_{kt}\right) \tag{A2}$$

where

$$\overline{TR}_{kt} = \frac{1}{n\left(S^S_{kt}\right)} \sum_{j \in S^S_{kt}} TR_{jkt} \tag{A3}$$

$CRTR_{jt}$ **Consensus Ranked Target Return** is calculated by taking the average of the within-analyst scaled ranks of the target returns announced for stock j across the analysts who cover the stock during month t:

$$CRTR_{jt} = \frac{1}{n\left(S_{jt}^{A}\right)} \sum_{k \in S_{jt}^{A}} \frac{Rank\left(TR_{jkt}\right) - 1}{n\left(S_{kt}^{S}\right) - 1}\ , \tag{A4}$$

where $Rank\left(\cdot\right)$ denotes the ranking function that assigns the value of one to the lowest element in the set of target returns corresponding to the stocks in S_{kt}^{S}, two to the second lowest element, etc.

ITR_{jt} **Industry Target Return** is the average month-t consensus target return across all the stocks that belong to the same industry as stock j:

$$ITR_{jt} = \frac{1}{n\left(S_{jt}^{I}\right)} \sum_{i \in S_{jt}^{I}} CTR_{it} \tag{A5}$$

$ICTR_{jt}$ **Industry adjusted Consensus Target Return** is the consensus target return of stock j in month t minus the average consensus target return in the stock's industry:

$$ICTR_{jt} = CTR_{jt} - ITR_{jt} = \frac{1}{n\left(S_{jt}^{A}\right)} \sum_{k \in S_{jt}^{A}} \left(TR_{jkt} - ITR_{jt}\right) \tag{A6}$$

$\overline{X}_{kt}$ **analyst average characteristic X** is the average characteristic value (taken from the *end of month* $t-1$) across the stocks covered by analyst k in month t:

$$\overline{X}_{kt} = \frac{1}{n\left(S_{kt}^{S}\right)} \sum_{j \in S_{kt}^{S}} X_{jt-1} \tag{A7}$$

$PA\overline{TR}_{kt}$ **Past Analyst average Target Return** is the average of the $\overline{TR}_{k\tau}$-s for analyst k over the months prior to month t (i.e., $\tau < t$):

$$PA\overline{TR}_{kt} = \frac{1}{n\left(S_{kt}^{H}\right)} \sum_{\tau \in S_{kt}^{H}} \overline{TR}_{k\tau} \tag{A8}$$

Online Appendix for
"Analysts Are Good at Ranking Stocks"

November 27, 2023

This Online Appendix contains additional details and results that are omitted from the main text for brevity.

Anomaly variables from Chen and Zimmermann (2021)

We use anomaly variables from Chen and Zimmermann (2021) to represent the wide range of variables that have predictive power in the cross-section of US stock returns. The anomaly variables come from the March 2022 release of the replication dataset connected to Chen and Zimmermann (2021).[1] In order for a variable to enter in our comparison sample, we require that (i) it is classified as "continuous", (ii) it has values for at least 10 stocks in each month throughout our sample period, and (iii) it has coverage for at least 40% of the CRSP market capitalization on average over our sample period. 140 of the 207 predictors of Chen and Zimmermann (2021) satisfy these criteria. The complete list of the 140 anomaly variables can be found in Table OA.1.

In addition, Figure OA.1 shows the annualized Sharpe ratio of the long-short strategies based on one of the 140 anomaly variables at a time, in terms of their ranks. For each anomaly variable, the long-short strategy is constructed using the two extreme portfolios of its quintile sorts.

Replicating results from the main text using $CRTR$

Results in Figures 2 to 3 and Tables 3 to 6 of the main text are generated using *within-analyst demeaned forecasts* and the corresponding stock-level measure of *Consensus Demeaned Target Returns* ($CDTR$). Figures OA.2 to OA.3 and Tables OA.3 to OA.6 replicate the same results using the *within-analyst ranking of forecasts* and the corresponding stock-level measure of *Consensus Ranked Target Returns* ($CRTR$).

Variations in the construction of CTR and $ICTR$

Table 3 of the main text reports portfolio sorting results for the consensus return forecast (CTR) and the industry-adjusted consensus forecast ($ICTR$). To ensure comparability with $CDTR$, we

[1] The data are available at https://www.openassetpricing.com

make some non-standard choices when constructing these measures. The results in Table OA.7 show that these choices do not considerably change the performance of the measure.

Let us start with the consensus return forecast, CTR. The first row in in each panel of Table OA.7 replicates the results obtained via the baseline version of CTR from the main text. When constructing the baseline version, we require an analyst to have at least three announcements in a month to enter our sample. In the second row of each panel, CTR is calculated without this requirement so that return forecasts from all analysts are used. The consensus forecast is often constructed by taking the median instead of the mean of analysts' forecasts. In the third row of each panel, CTR is constructed using the median and using the return forecasts from all analysts. The results are very similar across the three variations of CTR presented in Table OA.7.

Turning to the industry-adjusted consensus forecast, the fourth row in each panel shows the results using the baseline version of $ICTR$ from the main text. In the fifth row, we construct $ICTR$ without the requirement that an analyst has to have at least three announcements in a month and use all the return forecast issued in a given month. In the next row industries are defined by the first three GICS digits (as opposed to only the first two as in the baseline version). Instead of subtracting the industry average consensus forecast as in $ICTR$, Da and Schaumburg (2011) consider a different implementation of industry-adjustment by ranking the stocks based on their consensus forecasts within an industry. Our next implementation follows the same idea: month-by-month we first calculate the scaled rank (i.e., mapped into the $[0, 1]$ interval from lowest to highest) of the stocks' consensus forecast within their respective industries, and then pick the stocks with the highest (lowest) values of these scaled ranks to from the High (Low) portfolios. The results corresponding to this implementation are presented in the seventh row in each panel of Table OA.7. In the last row of each panel, the industry-adjusted consensus forecast is constructed using (i) forecasts from all analysts, (ii) industries defined by the first three GICS digits, and (iii) the within-industry ranking based portfolio sorting. Overall, the results are very similar across the five variations of $ICTR$ presented in Table OA.7.

Stock-level Fama-MacBeth regressions with characteristic controls

Table 4 of the main text reports the results from Fama-MacBeth regressions of next month's stock returns on $CDTR$ and related variables constructed from analysts' return forecasts. Table OA.8 reports the results from the same regressions by adding stock characteristics as control variables.

Figure OA.1: Sharpe ratios of long-short strategies

The graphs plot the annualized Sharpe ratio of 140 anomaly trading strategies in terms of their ranks. For each anomaly variable, a long-short strategy is constructed using the two extreme portfolios of its quintile sorts. The 140 anomaly characteristics come from the March 2022 release of the asset pricing dataset connected to Chen and Zimmermann (2021). Panel A uses equal-weighted portfolios, while Panels B uses value-weighted portfolios. The sample period is from March 1999 to December 2021.

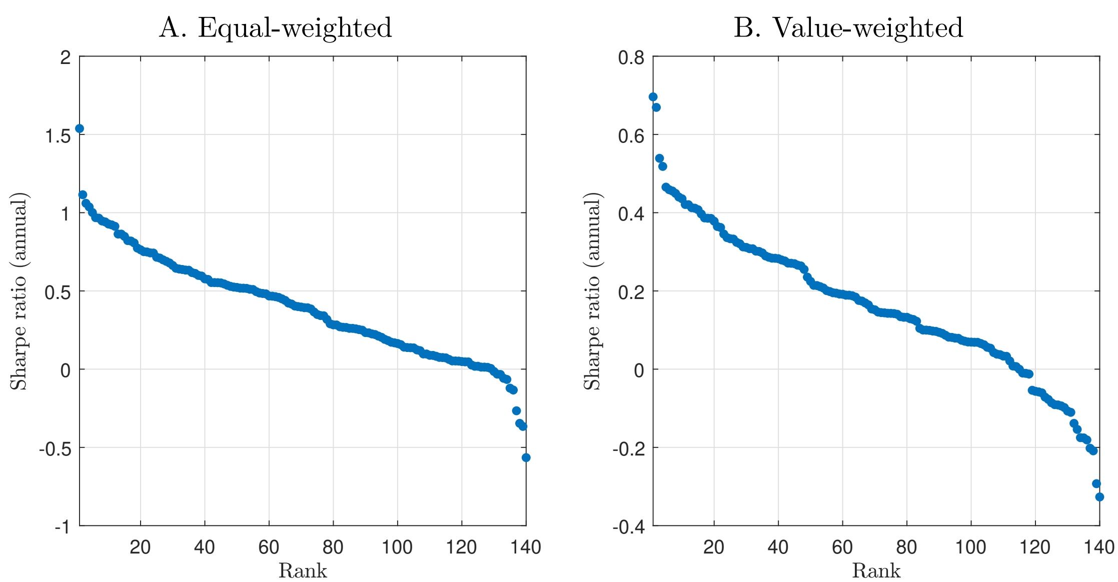


Figure OA.2: Distribution of t-statistics on time-series alphas for the $CRTR$-based strategy

The graphs show histograms of the t-statistics on α estimates from $R_{CRTR,t} = \alpha + \beta R_{X,t} + \epsilon_t$, where $R_{CRTR,t}$ is the monthly return on the long-short quintile strategy based on $CRTR$, while $R_{X,t}$ is the return on the long-short quintile strategy based on one of 140 anomaly variables at a time. The anomaly variables come from the March 2022 release of the asset pricing dataset connected to Chen and Zimmermann (2021). In Panel A (Panel B), the t-statistics come from regressions where both $R_{CRTR,t}$ and $R_{X,t}$ correspond to equal-weighted (value-weighted) portfolios. The sample period ranges from March 1999 to December 2021.

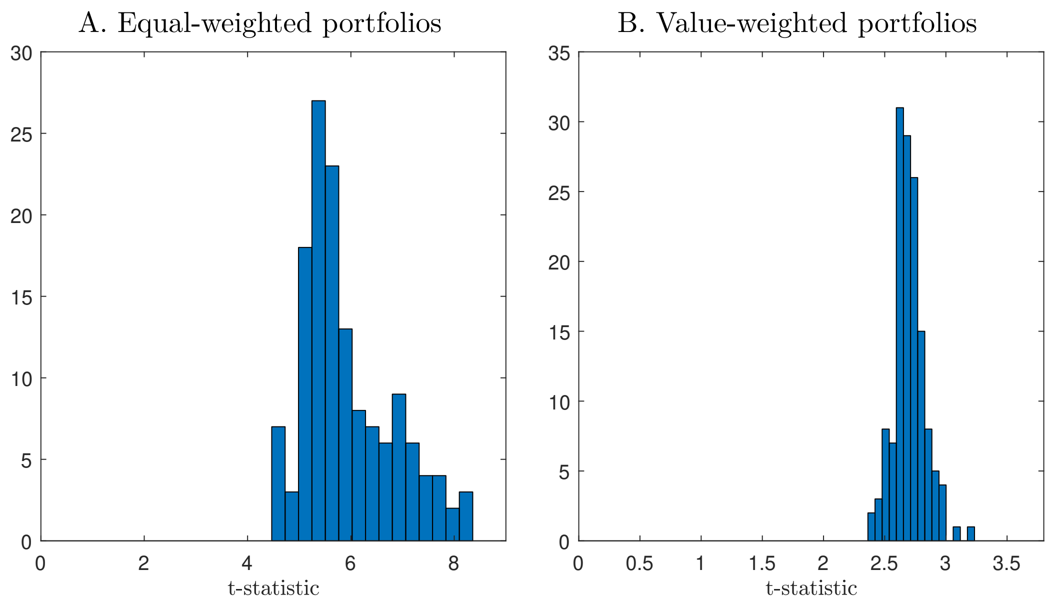


Figure OA.3: Distribution of t-statistics from Fama-MacBeth regressions with $CRTR$

The graph shows the histogram of Newey-West t-statistics on the β_1 estimates from Fama-MacBeth regressions of the type $R_{j,t+1} = \alpha + \beta_1 CRTR_{j,t} + \beta_2 X_{j,t} + \epsilon_{j,t}$, where $R_{j,t+1}$ is the return on stock j in month $t+1$, $CRTR_{j,t}$ is our measure based on the within-analyst ranking of return forecasts from month t, and $X_{j,t}$ is one of 140 anomaly variables at a time. The anomaly variables come from the March 2022 release of the asset pricing dataset connected to Chen and Zimmermann (2021). The sample period ranges from March 1999 to December 2021.

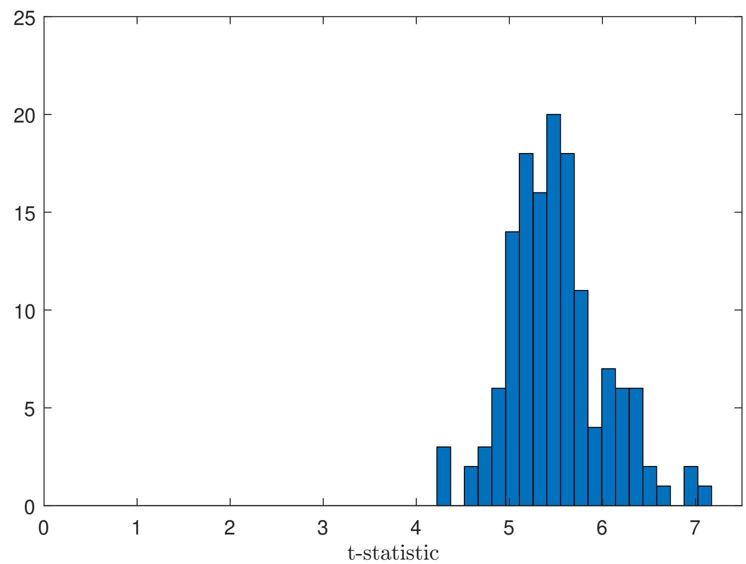


Table OA.1: List of anomaly variables

The table provides the list of 140 anomaly variables from the March 2022 release of the asset pricing dataset connected to Chen and Zimmermann (2021) that are used in this paper. "Acronym" refers to the acronym of the anomaly characteristic used by Chen and Zimmermann (2021). "Sign" refers to the sign of the cross-sectional return predictability by the anomaly from the original paper, as reported by Chen and Zimmermann (2021); if $Sign = 1$ ($Sign = -1$), the long-short strategy based on the characteristic is constructed as the High-Low (Low-High) portfolio. "Rebalancing Frequency" refers to the required frequency of portfolio sorting (in months), as reported by Chen and Zimmermann (2021). In a few cases we depart from the rebalancing frequency of Chen and Zimmermann (2021); these values are indicated by a $*$ superscript.

Acronym	Description	Sign	Rebalancing Frequency
AbnormalAccruals	Abnormal Accruals	-1	12
Accruals	Accruals	-1	12
AdExp	Advertising Expense	1	12
AM	Total assets to market	1	12
AnalystRevision	EPS forecast revision	1	1
AnalystValue	Analyst Value	1	12
AnnouncementReturn	Earnings announcement return	1	1
AOP	Analyst Optimism	-1	12
AssetGrowth	Asset growth	-1	12
Beta	CAPM beta	1	1
BetaFP	Frazzini-Pedersen Beta	1	1
BetaTailRisk	Tail risk beta	1	12
BidAskSpread	Bid-ask spread	1	1
BM	Book to market using most recent ME	1	1
BMdec	Book to market using December ME	1	12
BookLeverage	Book leverage (annual)	-1	12
BPEBM	Leverage component of BM	-1	12
Cash	Cash to assets	1	1
CashProd	Cash Productivity	-1	1
CBOperProf	Cash-based operating profitability	1	12
CF	Cash flow to market	1	12
cfp	Operating Cash flows to price	1	12
ChangeInRecommendation	Change in recommendation	1	1
ChAssetTurnover	Change in Asset Turnover	1	12
ChEQ	Growth in book equity	-1	12
ChInv	Inventory Growth	-1	12
ChInvIA	Change in capital inv (ind adj)	-1	12
ChNNCOA	Change in Net Noncurrent Op Assets	-1	12
ChNWC	Change in Net Working Capital	-1	12
ChTax	Change in Taxes	1	3
CompEquIss	Composite equity issuance	-1	1
CompositeDebtIssuance	Composite debt issuance	-1	12
Coskewness	Coskewness	-1	1
DelCOA	Change in current operating assets	-1	12
DelCOL	Change in current operating liabilities	-1	12
DelEqu	Change in equity to assets	-1	12
DelFINL	Change in financial liabilities	-1	12
DelLTI	Change in long-term investment	-1	12
DelNetFin	Change in net financial assets	1	12
dNoa	change in net operating assets	-1	1

Table OA.1: List of anomaly variables (continued)

Acronym	Description	Sign	Rebalancing Frequency
DolVol	Past trading volume	-1	1
EarningsConsistency	Earnings consistency	1	12
EarningsForecastDisparity	Long-vs-short EPS forecasts	-1	1
EarningsStreak	Earnings surprise streak	1	1
EarningsSurprise	Earnings Surprise	1	1
EBM	Enterprise component of BM	1	12
EntMult	Enterprise Multiple	-1	12
EP	Earnings-to-Price Ratio	1	1
EquityDuration	Equity Duration	-1	12
ExclExp	Excluded Expenses	-1	12
FEPS	Analyst earnings per share	1	1
fgr5yrLag	Long-term EPS forecast	-1	3
FirmAge	Firm age based on CRSP	-1	1
ForecastDispersion	EPS Forecast Dispersion	-1	1
FR	Pension Funding Status	1	12
Frontier	Efficient frontier index	1	12
GP	gross profits / total assets	1	12
GrAdExp	Growth in advertising expenses	-1	1
grcapx	Change in capex (two years)	-1	12
grcapx3y	Change in capex (three years)	-1	12
GrLTNOA	Growth in long term operating assets	1	12
GrSaleToGrInv	Sales growth over inventory growth	1	12
GrSaleToGrOverhead	Sales growth over overhead growth	1	12
Herf	Industry concentration (sales)	-1	1
HerfAsset	Industry concentration (assets)	-1	1
HerfBE	Industry concentration (equity)	-1	1
High52	52 week high	1	1*
hire	Employment growth	-1	12
IdioRisk	Idiosyncratic risk	-1	1
IdioVol3F	Idiosyncratic risk (3 factor)	-1	1
IdioVolAHT	Idiosyncratic risk (AHT)	-1	12*
Illiquidity	Amihuds illiquidity	1	12
IndMom	Industry Momentum	1	1*
IntanBM	Intangible return using BM	-1	1
IntanCFP	Intangible return using CFtoP	-1	1
IntanEP	Intangible return using EP	-1	12
IntanSP	Intangible return using Sale2P	-1	12
IntMom	Intermediate Momentum	1	1
Investment	Investment to revenue	-1	12
InvestPPEInv	change in ppe and inv/assets	-1	1
InvGrowth	Inventory Growth	-1	12
Leverage	Market leverage	1	12
LRreversal	Long-run reversal	-1	1
MaxRet	Maximum return over month	-1	1
MeanRankRevGrowth	Revenue Growth Rank	1	12
Mom12m	Momentum (12 month)	1	1*
Mom12mOffSeason	Momentum without the seasonal part	1	1
Mom6m	Momentum (6 month)	1	1*
MomOffSeason	Off season long-term reversal	-1	1
MomOffSeason06YrPlus	Off season reversal years 6 to 10	-1	1

Table OA.1: List of anomaly variables (continued)

Acronym	Description	Sign	Rebalancing Frequency
MomOffSeason11YrPlus	Off season reversal years 11 to 15	-1	1
MomOffSeason16YrPlus	Off season reversal years 16 to 20	-1	1
MomSeason	Return seasonality years 2 to 5	1	1
MomSeason06YrPlus	Return seasonality years 6 to 10	1	1
MomSeason11YrPlus	Return seasonality years 11 to 15	1	1
MomSeason16YrPlus	Return seasonality years 16 to 20	1	1
MomSeasonShort	Return seasonality last year	1	1
MRreversal	Medium-run reversal	-1	12
NetDebtFinance	Net debt financing	-1	12
NetEquityFinance	Net equity financing	-1	12
NetPayoutYield	Net Payout Yield	1	12
NOA	Net Operating Assets	-1	1
NumEarnIncrease	Earnings streak length	1	1
OperProf	operating profits / book equity	1	12
OperProfRD	Operating profitability R&D adjusted	1	12
OPLeverage	Operating leverage	1	12
OrgCap	Organizational capital	1	12
PayoutYield	Payout Yield	1	12
PctAcc	Percent Operating Accruals	-1	12
PctTotAcc	Percent Total Accruals	-1	12
PredictedFE	Predicted Analyst forecast error	-1	12
Price	Price	-1	1
PriceDelayRsq	Price delay r square	1	12
PriceDelaySlope	Price delay coeff	1	12
PriceDelayTstat	Price delay SE adjusted	1	12
RD	R&D over market cap	1	12
RDS	Real dirty surplus	1	12
ResidualMomentum	Momentum based on FF3 residuals	1	1
ReturnSkew	Return skewness	-1	1
ReturnSkew3F	Idiosyncratic skewness (3F model)	-1	1
RevenueSurprise	Revenue Surprise	1	1
roaq	Return on assets (qtrly)	1	1
RoE	net income / book equity	1	12
ShareIss1Y	Share issuance (1 year)	-1	12
ShareIss5Y	Share issuance (5 year)	-1	12
ShortInterest	Short Interest	-1	1
Size	Size	-1	12
SP	Sales-to-price	1	12
STreversal	Short term reversal	-1	1
Tax	Taxable income to income	1	12
TotalAccruals	Total accruals	-1	12
TrendFactor	Trend Factor	1	1
VarCF	Cash-flow to price variance	-1	12
VolMkt	Volume to market equity	-1	12
VolSD	Volume Variance	-1	1
VolumeTrend	Volume Trend	-1	12
XFIN	Net external financing	-1	12
zerotrade	Days with zero trades	1	1
zerotradeAlt1	Days with zero trades	1	12
zerotradeAlt12	Days with zero trades	1	1

Table OA.3: Portfolios sorted on alternative measures of analyst expectations

The table reports average monthly excess returns on the portfolios containing stocks from the lowest (*Low*) and highest (*High*) quintiles when sorting on various characteristics monthly. The average returns to the strategy that buys the Low portfolio and sells the High portfolio is also reported (*H-L*). The characteristics considered are our measure of analysts' ranked forecasts ($CRTR$), the consensus return forecast (CTR), the consensus return forecast demeaned at the industry level ($ICTR$), and the informative component of return expectations ($Info$) following Loudis (2022). In the column labeled $\hat{\alpha}$, alpha estimates from $R_{CRTR,t} = \alpha + \beta R_{X,t} + \epsilon_t$ are reported, where $R_{CRTR,t}$ is the monthly return on the long-short quintile strategy based on $CRTR$, while $R_{X,t}$ is the return on the long-short quintile strategy based on the characteristic presented in the same row of the table. The sample ranges from March 1999 to December 2021 in general; for the results that rely on the variable *Info*, the sample starts on September 1999. Newey-West t-statistics are in parenthesis.

	Low	2	3	4	High	H-L	$\hat{\alpha}$
A. Equal-weighted portfolios							
$CRTR$	0.54	0.85	1.07	1.20	1.44	0.89	
	(1.50)	(2.34)	(2.81)	(2.92)	(3.03)	(5.31)	
CTR	0.68	0.97	1.10	1.23	1.14	0.46	0.72
	(1.96)	(3.08)	(3.17)	(2.92)	(1.89)	(1.29)	(6.79)
$ICTR$	0.56	0.95	0.95	1.14	1.35	0.80	0.40
	(1.38)	(2.72)	(2.85)	(3.05)	(2.45)	(3.49)	(4.98)
$Info$	0.80	0.96	1.01	1.11	1.35	0.55	0.72
	(1.89)	(2.87)	(2.92)	(3.18)	(3.03)	(3.42)	(3.88)
B. Value-weighted portfolios							
$CRTR$	0.42	0.58	0.72	0.72	0.89	0.47	
	(1.43)	(2.03)	(2.40)	(2.38)	(2.79)	(2.69)	
CTR	0.56	0.64	0.78	0.63	0.72	0.16	0.45
	(2.07)	(2.52)	(2.70)	(1.74)	(1.41)	(0.46)	(2.58)
$ICTR$	0.36	0.86	0.85	0.69	0.68	0.33	0.37
	(1.17)	(3.03)	(3.15)	(2.33)	(1.56)	(1.19)	(2.49)
$Info$	0.63	0.60	0.54	0.82	0.91	0.27	0.40
	(1.91)	(2.17)	(1.88)	(2.89)	(2.54)	(1.39)	(2.35)

Table OA.4: Fama-MacBeth regressions

The table reports the average coefficients and Newey-West t-statistics from Fama-MacBeth regressions at the stock-level. The dependent variable is the stock return in the following month, and the independent variables are characteristics constructed from analyst target return forecasts. A constant is included in the regressions, but its estimate is omitted from the table. The average number of stocks in the regressions is also reported. The sample is from March 1999 to December 2021 in general; for the specifications that includes the variable *Info*, the sample starts on September 1999.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CRTR$	1.03		0.87		0.85		0.87	0.59
	(5.43)		(5.95)		(6.60)		(4.79)	(4.21)
CTR		0.07	0.03					0.04
		(2.10)	(0.82)					(0.27)
$ICTR$				0.08	0.04			0.03
				(2.72)	(1.33)			(0.24)
$Info$						0.18	0.13	0.07
						(3.49)	(2.42)	(1.33)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg R^2	0.003	0.01	0.02	0.01	0.01	0.004	0.01	0.04
Avg #obs	1403	1403	1403	1366	1366	1251	1089	1064

Table OA.5: Strategy performance with variations in the definition of $CRTR$

The table reports the performance of long-short quintile strategies. The strategies are constructed from portfolios sorted month-by-month on analysts' relative return forecasts, i.e., based on our baseline $CRTR$ measure and its variations. The particular variation considered is described in the first column. The performance measures reported in the table are the average monthly return (*Mean*) with the associated t-statistic (t), the monthly volatility (*Vol*), the annualized Sharpe ratio (*SR*), and then rank of this Sharpe ratio among the Sharpe ratios of 140 long-short strategies based on anomaly characteristics from previous literature (*SR rank*). The sample ranges from March 1999 to December 2021.

Change compared to the baseline measure	Mean	t	Vol	SR	SR rank
A. Equal-weighted portfolios					
baseline measure; no change	0.89	5.31	2.61	1.19	2nd
at least 2 announcements per analyst per month	0.78	4.75	2.43	1.11	3rd
no minimum on announcements per analyst per month	0.81	5.15	2.42	1.16	2nd
2-month announcement collection window	0.80	4.24	2.81	0.98	6th
3-month announcement collection window	0.78	3.67	3.07	0.88	13th
drop announcements from last 5 days of the month	0.74	4.40	2.60	0.98	6th
B. Value-weighted portfolios					
baseline measure; no change	0.47	2.69	2.88	0.57	3rd
at least 2 announcements per analyst per month	0.31	2.35	2.31	0.47	5th
no minimum on announcements per analyst per month	0.44	3.15	2.29	0.66	3rd
2-month announcement collection window	0.60	3.74	2.49	0.83	1st
3-month announcement collection window	0.53	2.88	2.94	0.63	3rd
drop announcements from last 5 days of the month	0.41	2.44	2.80	0.50	5th

Table OA.6: The information sources of relative forecasts

The table reports the average coefficients and Newey-West t-statistics from Fama-MacBeth regressions at the individual stock return forecast level. The dependent variable is next month's realized return on the stock for which the target price was issued for. RTR **is ...** . The specification in column 2 includes the following z-transformed stock characteristics: log market value of equity ($Size$), book-to-market ratio (BM), investment measured by asset growth (AG), return-on-equity (RoE), and momentum (Mom). $EAwindow$ is a dummy variable indicating if the target return announcement falls into the $[-3, +3]$ day window around an earnings announcement of the given stock. *Bold* is a dummy variable indicating bold (as opposed to herding) forecasts following Clement and Tse (2005). $LowCover$ is a dummy variable indicating that the return forecast is issued for a stock with low analyst coverage. A constant is included in the regressions, but its estimate is omitted from the table. The sample is from September 1999 to December 2021.

	(1)	(2)	(3)	(4)	(5)
RTR	0.554	0.488	0.546	0.178	0.333
	(4.79)	(5.50)	(4.42)	(0.82)	(3.08)
$Size$		-0.296			
		(-2.40)			
BM		-0.104			
		(-0.72)			
AG		-0.219			
		(-3.25)			
RoE		0.205			
		(2.90)			
Mom		-0.039			
		(-0.24)			
$EAwindow$			0.068		
			(0.54)		
$RTR \times EAwindow$			-0.138		
			(-1.16)		
$Bold$				-0.042	
				(-0.33)	
$RTR \times Bold$				0.491	
				(2.51)	
$LowCover$					-0.276
					(-2.07)
$RTR \times LowCover$					0.550
					(3.73)
Constant	Yes	Yes	Yes	Yes	Yes
Avg R^2	0.002	0.066	0.005	0.005	0.007
Avg #obs	3783	3492	3783	3276	3783

Table OA.7: Variations in the construction of CTR and $ICTR$

The table reports average monthly excess returns on the portfolios containing stocks from the lowest (*Low*) and highest (*High*) quintiles when sorting on various characteristics monthly. The average returns to the strategy that buys the Low portfolio and sells the High portfolio is also reported (*H-L*). The characteristics considered are variations of baseline versions of the consensus return forecast (CTR) and the industry adjusted consensus forecast ($ICTR$). The specific variation is described in each row of the table. In the column labeled $\hat{\alpha}$, alpha estimates from $R_{CDTR,t} = \alpha + \beta R_{X,t} + \epsilon_t$ are reported, where $R_{CDTR,t}$ is the monthly return on the long-short quintile strategy based on $CDTR$, while $R_{X,t}$ is the return on the long-short quintile strategy based on the characteristic presented in the same row of the table. The sample ranges from March 1999 to December 2021. Newey-West t-statistics are in parenthesis.

Measure	Description of variation	Low	High	High-Low	$\hat{\alpha}$
A. Equal-weighted portfolios					
CTR	Baseline version from the	0.68	1.14	0.46	0.79
	main text	(1.96)	(1.89)	(1.29)	(5.99)
CTR	No minimum for announcements	0.65	1.06	0.41	0.82
	per analyst in a month [1].	(1.90)	(1.73)	(1.11)	(6.22)
CTR	[1] + Use median instead of	0.64	1.05	0.40	0.82
	mean in the definition of CTR.	(1.89)	(1.74)	(1.12)	(6.08)
$ICTR$	Baseline version from the	0.56	1.35	0.80	0.41
	main text	(1.38)	(2.45)	(3.49)	(4.68)
$ICTR$	No minimum for announcements	0.58	1.26	0.68	0.51
	per analyst in a month [1].	(1.46)	(2.23)	(2.87)	(4.94)
$ICTR$	[1] + Use the first 3 GICS	0.56	1.33	0.78	0.38
	digits to define industries [2].	(1.37)	(2.39)	(3.63)	(4.15)
$ICTR$	[1] + Use within-industry ranking	0.59	1.32	0.74	0.51
	of consensus forecasts [3].	(1.66)	(2.44)	(3.04)	(4.70)
$ICTR$	[1] + [2] + [3]	0.59	1.43	0.84	0.41
		(1.67)	(2.69)	(3.67)	(4.19)
B. Value-weighted portfolios					
CTR	Baseline version from the	0.56	0.72	0.16	0.54
	main text	(2.07)	(1.41)	(0.46)	(2.63)
CTR	No minimum for announcements	0.57	0.51	-0.07	0.58
	per analyst in a month [1].	(2.17)	(0.93)	(-0.18)	(2.92)
CTR	[1] + Use median instead of	0.57	0.54	-0.03	0.58
	mean in the definition of CTR.	(2.18)	(1.03)	(-0.08)	(2.76)
$ICTR$	Baseline version from the	0.36	0.68	0.33	0.40
	main text	(1.17)	(1.56)	(1.19)	(2.79)
$ICTR$	No minimum for announcements	0.45	0.70	0.26	0.46
	per analyst in a month [1].	(1.50)	(1.53)	(0.90)	(2.82)
$ICTR$	[1] + Use the first 3 GICS	0.45	0.85	0.40	0.40
	digits to define industries [2].	(1.58)	(1.89)	(1.40)	(2.47)
$ICTR$	[1] + Use within-industry ranking	0.50	0.79	0.29	0.43
	of consensus forecasts [3].	(1.85)	(1.78)	(1.12)	(2.42)
$ICTR$	[1] + [2] + [3]	0.56	0.78	0.22	0.46
		(2.16)	(1.86)	(0.88)	(2.73)

Table OA.8: Fama-MacBeth regressions

The table reports the average coefficients and Newey-West t-statistics from Fama-MacBeth regressions at the stock-level. The dependent variable is the stock return in the following month, and the independent variables are are our measure of analysts' relative forecasts ($CDTR$), the consensus return forecast (CTR), the consensus return forecast demeaned at the industry level ($ICTR$), the informative component of return expectations ($Info$) following Loudis (2022), as well as commonly used stock characteristics: the market value of equity (*Size*), book-to-market ratio (B/M), annual growth rate of total assets (*Inv*), net income over book equity (*RoE*), 12-month momentum (Mom), stock return over the previous month (*SRev*), and the bid-ask-spread (*Illiq*). A constant is included in the regressions, but its estimate is omitted from the table. The average number of stocks in the regressions is also reported. The sample is from March 1999 to December 2021 in general; for the specifications that includes the variable *Info*, the sample starts on September 1999.The commonly used stock characteristics standardized via the z-score transformation each month.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CDTR$	0.15		0.13		0.13		0.15	0.16
	(6.70)		(3.78)		(4.61)		(6.20)	(5.13)
CTR		0.11	0.03					-0.05
		(4.42)	(0.67)					(-0.44)
$ICTR$				0.11	0.03			0.05
				(4.96)	(1.03)			(0.53)
$Info$						0.19	0.14	0.13
						(4.31)	(3.38)	(3.16)
$Size$	-0.12	-0.12	-0.12	-0.09	-0.10	-0.12	-0.13	-0.10
	(-3.39)	(-3.29)	(-3.32)	(-2.56)	(-2.72)	(-3.56)	(-3.45)	(-2.74)
B/M	-0.01	-0.00	-0.01	-0.01	-0.01	-0.04	-0.05	-0.05
	(-0.22)	(-0.04)	(-0.23)	(-0.17)	(-0.12)	(-0.50)	(-0.54)	(-0.58)
Inv	-0.23	-0.24	-0.23	-0.23	-0.23	-0.16	-0.18	-0.15
	(-4.48)	(-4.67)	(-4.53)	(-4.70)	(-4.66)	(-4.32)	(-4.16)	(-3.89)
RoE	0.05	0.05	0.05	0.05	0.05	0.03	0.06	0.05
	(1.21)	(1.32)	(1.42)	(1.32)	(1.37)	(0.84)	(1.66)	(1.44)
Mom	0.13	0.12	0.13	0.07	0.07	0.11	0.12	0.09
	(1.06)	(1.00)	(1.06)	(0.56)	(0.61)	(0.89)	(0.95)	(0.75)
$STrev$	-0.08	-0.09	-0.10	-0.12	-0.13	-0.25	-0.28	-0.30
	(-0.98)	(-0.99)	(-1.10)	(-1.40)	(-1.46)	(-3.07)	(-3.13)	(-3.42)
$Illiq$	-0.08	-0.10	-0.05	-0.03	-0.01	-0.02	-0.05	0.05
	(-0.52)	(-0.70)	(-0.37)	(-0.20)	(-0.09)	(-0.17)	(-0.36)	(0.43)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg R^2	0.08	0.08	0.08	0.08	0.08	0.08	0.09	0.10
Avg #obs	1267	1267	1267	1236	1236	1251	1089	1063

Table OA.9: Excess returns and alphas for portfolios sorted on ranking of recommendations

The table reports average monthly excess returns (R^e, in percentage) on tercile portfolios sorted on $CRec$, $CDRec$ or $CRRec$. The table also reports the average returns on the zero-cost investment strategy that buys the highest and sells the lowest quintile portfolio (*H-L*). In addition, we report the alpha of each portfolio with respect to the five-factor model of Fama and French (2015) (*FF5*), its six-factor extension that adds the momentum factor (*FF6*), the q-factor model of Hou et al. (2015) (*HXZ*), and the behavioral factor model of Daniel et al. (2020) (*DHS*). The sample ranges from December 1993 to December 2021. Newey-West t-statistics are in parentheses.

	Sorting on $CRec$				Sorting on $CDRec$				Sorting on $CRRec$			
	Low	2	High	H-L	Low	2	High	H-L	Low	2	High	
A. Equal-weighted portfolios												
R^e	0.55	0.82	1.01	0.46	0.66	0.88	1.08	0.43	0.72	0.89	1.15	0.42
	(1.39)	(2.33)	(2.85)	(2.37)	(1.82)	(2.47)	(3.08)	(3.97)	(2.01)	(2.37)	(3.32)	(4.43)
α_{FF5}	-0.48	-0.07	0.17	0.65	-0.28	-0.00	0.18	0.46	-0.17	-0.09	0.26	0.43
	(-2.56)	(-0.70)	(2.12)	(3.42)	(-2.17)	(-0.01)	(2.16)	(3.92)	(-1.51)	(-0.91)	(2.89)	(3.99)
α_{FF6}	-0.26	0.05	0.21	0.47	-0.13	0.09	0.24	0.37	-0.04	-0.01	0.32	0.36
	(-1.45)	(0.45)	(2.71)	(2.61)	(-1.26)	(0.91)	(3.07)	(3.25)	(-0.41)	(-0.03)	(3.92)	(3.31)
α_{HXZ}	-0.06	0.17	0.36	0.42	-0.01	0.24	0.38	0.38	0.08	0.20	0.45	0.37
	(-0.27)	(1.54)	(3.62)	(1.81)	(-0.04)	(2.33)	(3.81)	(2.90)	(0.59)	(1.72)	(4.33)	(3.06)
α_{DHS}	-0.06	0.23	0.43	0.49	0.06	0.33	0.41	0.35	0.18	0.25	0.48	0.31
	(-0.27)	(1.51)	(3.06)	(2.41)	(0.37)	(2.25)	(2.88)	(2.78)	(1.05)	(1.89)	(3.35)	(2.59)
B. Value-weighted portfolios												
R^e	0.60	0.66	0.87	0.27	0.58	0.74	0.85	0.27	0.66	0.73	0.83	0.18
	(2.01)	(2.57)	(3.12)	(1.48)	(2.25)	(2.77)	(3.10)	(2.29)	(2.55)	(2.58)	(3.09)	(1.47)
α_{FF5}	-0.36	-0.06	0.07	0.43	-0.24	0.01	0.06	0.30	-0.13	-0.01	0.04	0.17
	(-2.41)	(-0.74)	(0.89)	(2.45)	(-2.76)	(0.12)	(0.75)	(2.63)	(-1.46)	(-0.10)	(0.46)	(1.46)
α_{FF6}	-0.28	-0.02	0.09	0.36	-0.20	0.04	0.08	0.29	-0.08	0.01	0.06	0.14
	(-1.87)	(-0.22)	(1.02)	(2.03)	(-2.30)	(0.42)	(1.05)	(2.46)	(-0.94)	(0.01)	(0.73)	(1.20)
α_{HXZ}	-0.11	-0.07	0.12	0.23	-0.18	0.01	0.12	0.30	-0.11	-0.02	0.13	0.24
	(-0.56)	(-0.75)	(1.33)	(0.99)	(-1.73)	(0.06)	(1.44)	(2.30)	(-1.11)	(-0.24)	(1.55)	(1.68)
α_{DHS}	-0.22	-0.01	0.12	0.34	-0.17	0.02	0.09	0.27	-0.03	-0.05	0.08	0.11
	(-1.34)	(-0.15)	(1.47)	(1.78)	(-1.81)	(0.21)	(1.11)	(2.39)	(-0.37)	(0.46)	(1.01)	(0.94)