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 document analogous results using analysts' *earnings* forecasts, showing that 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 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.

In a second, alternative, implementation of the relative forecast strategy we use 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 common characteristics used to explain variations in the cross-section of stock returns. Rather, the rankings appear mostly unrelated to these characteristics. Our results thus suggest that analysts bring relevant information to the market via their relative forecasts, and that such information is not related to publicly available information captured by common stock characteristics. We also show that the profitability of the long-short strategies is robust to variations in the construction of the stock-level relative valuation measure, and that the strategies remain profitable after adjusting for transaction costs.

It is important to understand the difference between stock-level aggregates of absolute forecasts (which leads to the standard consensus measure) and 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 analyst-specific biases (e.g., consistent over-optimism or a faiblesse for growth stocks). To use the language of regression analysis, within-analyst demeaning can identically be thought of as controlling for individual 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.

We show that upwards of two thirds of the cross-sectional variation in these analyst fixed effects can be explained by (i) the prior forecasts of *other* analysts' covering the same stocks, (ii) the average of the analyst's *own* history of forecasts, and (iii) brokerage-specific unobserved factors.[1] This suggests that the biases in consensus forecasts are to a large extent either inherent to the analyst (consistently optimistic or pessimistic), a result of herding between analyst peers, or stem from the incentives and working environment set up by the analyst's workplace. While it is interesting to identify the potential sources of the analyst-level bias, the advantage of analyst fixed effects is that

[1]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.

they have the potential to capture this bias *regardless of its source*. Therefore, by getting rid of the analyst-level fixed effects, the relative forecasts provide a very general and comprehensive way of controlling for the optimistic bias of individual analysts, the negative "learning" effect from other analysts' forecasts, and also for various *unobservable* factors that may be detrimental to analysts' ability to provide accurate forecasts.[2] 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.

To the best of our knowledge, our study is the first to emphasize the strong information content in the relative ranking of analysts' stock returns forecasts.[3] 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 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.

[2]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.

[3]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.

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.[4] 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.[5]

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 analyst 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

[4]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.

[5]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.

"private" information when ranking the returns of stocks.

Finally, we extend our analysis to encompass two additional important outputs from sell-side analysts: earnings forecasts 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-short return spreads are sizable and significant under both equal- and value-weighted schemes. Furthermore, these results also remain robust after controlling for common risk factors. 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 mask code (AMASKCD) 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 for stock j by analyst k 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

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

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.[6]

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

[6]Consensus target returns could also be defined as the *median*, rather than mean, forecast across analysts. As shown in the Online Appendix, our results are robust to using the median instead of the mean.

$CDTR_{jt}$; 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.[7]

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 value of one.[8] 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 the comparative analysis

[7]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.

[8]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.

in Section 3. A complete set of results for the ranking-based measure, $CRTR$, is found in the Online Appendix.

2.2 Portfolios sorted on relative valuation

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 target returns (high $CDTR$) earn an average excess return of 1.44% per month, while those with low demeaned target 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 (alphas) 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. Stocks in the two extreme portfolios tend to be somewhat 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 4 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.[9] 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.

[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 these alternative measures, and

[9]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.

look at the alpha estimates. In particular, we estimate

$$R_{CDTR,t} = \alpha + \beta R_{X,t} + \epsilon_t \ , \tag{2}$$

where $R_{CDTR,t}$ is the monthly return on the long-short quintile strategy based on $CDTR$, while $R_{X,t}$ 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).[10] Comparing equations (A2) and (A6) from Appendix A, it is straightforward to see that $CDTR$ and $ICTR$ are related: while the former adjusts individual 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

[10] 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 the 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.

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 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.[11] 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 long-short strategy to a general set of 140 strategies from the "factor zoo".[12] We estimate the same

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

[12] 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.

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 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. Section 2.5.3 considers the implications of strategy turnover and transaction costs.

2.5.1 Coverage statistics of the relative valuation measure

Panel A of Figure 4 plots the coverage statistics of our baseline $CDTR$ measure.[13] 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 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;

[13] 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.

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. In the main specification, we collect target prices announced during month t when calculating the values of $CDTR$ corresponding to the end of month t. Panels C and D of Figure 4 show that coverage considerably improves if we instead collect announcements issued over the two-month period covering months $t-1$ and t (Panel C) or the four-month period covering months $t-3$ to t (Panel D). 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 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 for value-weighted portfolios.[14] The table reports

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

both gross and transaction-cost adjusted (net) Sharpe ratios. Here we comment on the before-cost (gross) Sharpe ratios, and leave the analysis of the net Sharpe ratios to Section 2.5.3.

[Table 5 about here]

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 third among the 140 value-weighted strategies that are used for comparison.[15]

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 or 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. In the case of 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 four months from its baseline value of one month. Nevertheless, the $CDTR$-based strategy using a 4-month window would still be ranked 21st among the 140 comparison strategies in terms of its Sharpe ratio. In the case of value-weighted portfolios, using longer

[15]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.

announcement collection windows leads to similar performance to the baseline implementation. Interestingly, 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.

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.

2.5.3 Turnover and transaction costs

A practical implementation of a trading strategy based on the $CDTR$ or $CRTR$ signals would need to take into account turnover and transaction costs. To be clear, the main purpose of this study is to test whether analysts' forecasts contain relevant, and not elsewhere available, information on future stock returns. Our results above strongly suggest that the relative forecasts are informative in this sense. Whether this information can be profitably used in a real-world strategy, accounting for transaction costs, is a somewhat distinct question, but still of independent interest. In this subsection, we analyze this aspect using detailed measures of transaction costs.

Consider first the amount of trading required to implement the $CDTR$-based strategies. Table 5 reports what percentage of the long and short portfolios that has to be turned over each month on average (in the column TO).[16] The turnover of the equal- and corresponding value-weighted strategies are similar. All implementations using a one-month announcement collection window, including the baseline strategy, turn over more than 80% of their long and short portfolios each month. This high turnover is not surprising, since the signal relies on a completely new set of return forecasts every month. As a comparison, a short-term reversal strategy (i.e., a long-short strategy based on quintile portfolios formed on previous month's returns) has a similar turnover during our sample period.

The turnover is considerably reduced if a longer announcement collection window is used. Using the two-month window reduces the turnover to around 55%. This is similar to the turnover of the long-short quintile-based strategies using the idiosyncratic volatility of Ang et al. (2006) or the maximum daily return of Bali et al. (2011). Finally, the turnover is around 35% when the four-month announcement collection window is used, which is similar to that of a momentum strategy. The advantage of the $CDTR$-based strategies, compared to those mentioned above, is that it trades larger stocks on average (as the $CDTR$ is typically not available for very small stocks), and thus the associated transaction costs will be somewhat lower in comparison.

The last two columns of Table 5 show the strategies' transaction-cost adjusted Sharpe ratios and their rank among the net Sharpe ratios of the 140 comparison strategies.[17] As expected, given the high turnover, the Sharpe ratios of all the equal-weighted strategies are greatly reduced after the adjustment for trading costs. However, there are two observations worth highlighting. First, all

[16]To calculate the number reported in the column TO of Table 5, we take the time-series average of the monthly turnover for both the long and the short portfolios, and then take the average across the two portfolios.

[17]To adjust for transaction costs, we track portfolio weights, and assume that the effective half spread is paid each time a stock position is changed, entered, or exited. This notion of transaction costs is also used, among others, by Korajczyk and Sadka (2004), Novy-Marx and Velikov (2016), and Chen and Velikov (2023). Following Chen and Velikov (2023), we measure the effective spreads from high-frequency intraday data using the TAQ database. Chen and Velikov (2023) show that effective spreads calculated from low-frequency data (e.g., from daily CRSP data) are upward biased in the post-2003 period, and argue that it is important to use high-frequency data to examine trading costs in this period, which constitutes most of our sample. In Online Appendix, we describe how we calculate effective spreads from high-frequency data.

the Sharpe ratios remain positive, indicating that the average strategy returns stay positive after the cost-adjustment. Second, some implementations are still relatively successful, e.g., the baseline implementation remains in the top 20% in terms of its net Sharpe ratio among the 140 strategies used for comparison.

Since value-weighted strategies are associated with lower trading costs than their equal-weighted counterparts, the net Sharpe ratios in Panel B of Table 5 all end up higher than the corresponding values from Panel A, in contrast with the reverse pattern seen in the before-cost Sharpe ratios. $CDTR$-based long-short strategies can lead to sizable net Sharpe ratios. For example, the 0.40 net Sharpe ratio associated with the baseline $CDTR$ measure would rank the value-weighted long-short strategy tenth among the 140 comparison strategies, while the 0.60 net Sharpe ratio corresponding to the $CDTR$ constructed using a 2-month announcement collection window would be ranked second.

3 Relative forecasts remove analyst fixed effects

The results in Section 2 show that analysts' *relative* return forecasts ($CDTR$) strongly predict the cross-section of future stock returns, while analysts' *absolute* return forecasts (CTR) fail to produce a significant return spread in sorted portfolios. Recall that CTR_{jt} for stock j in month t is the average of the individual target returns (TR_{jkt}) for stock j across the analysts who cover the stock in month t. $CDTR_{jt}$ 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*. To make this more precise, consider regressing all individual target returns on the complete set of analyst dummies in a given month t:

$$TR_{jkt} = \sum_k \delta_{kt} \times AnalystDummy_{jkt} + \varepsilon_{jkt} \ , \tag{4}$$

where t is fixed (the chosen month), $AnalystDummy_{jkt}$ is a dummy variable taking the value one if TR_{jkt} was issued by analyst k, and the sum runs over all the analysts who issued a target return forecast during month t. It is straightforward that the residuals from this regression can be calculated as $\hat{\varepsilon}_{jkt} = TR_{jkt} - \hat{\delta}_{kt} = TR_{jkt} - \overline{TR}_{kt}$, where $\overline{TR}_{kt}$ is the average target return of analyst k across the stocks she covered during month t. Hence, $CDTR_{jt}$ can be equivalently viewed as the average of the residuals ($\hat{\varepsilon}_{jkt}$) for stock j across the analysts who cover the stock in month t. That is, $CDTR$ 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 corrects 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.

Figure 5 documents that analyst fixed effects explain a considerable part of the cross-sectional variation in individual target returns by showing the R^2 from the regression in (4), estimated each month throughout our sample period. The R^2 fluctuates in the 25%-60% range, and the average R^2 is 42%. That is, almost half of the variation in individual target returns can be explained by analyst fixed effects on average. It is precisely this variation that is removed when constructing the $CDTR$ measure.

[Figure 5 about here]

In the remainder of this section, we highlight some of the factors that explain analysts' average forecasts. Table 6 presents the results from *analyst-level* Fama-MacBeth regressions, where the dependent variable is $\overline{TR}_{kt}$, the average forecast across stocks for a given analyst in a given month; i.e., the analyst fixed effect.[18] The first factor we consider is related to analyst herding. It has been

[18]There are explanatory variables in Table 6 that rely on previously issued price targets (see $\overline{OCTR}$ and

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). We 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. Our fist explanatory variable in Table 6 is $\overline{OCTR}_{kt}$, calculated as 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.

[Table 6 about here]

The first column in Table 6 shows that $\overline{OCTR}$ strongly predicts the analyst fixed effect; for every percentage point increase in the aggregated prior forecasts of other analysts, $\overline{TR}$ 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 herding 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.

Second, we study if there are analysts who consistently have higher (or lower) return forecasts compared to other analysts. 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 (A7) in Appendix A. A high value of $PA\overline{TR}$ thus indicates that the analyst had typically issued high return forecasts in the past (prior to month t), irrespective of market conditions or possible changes in the set of stocks covered.

Column 2 of Table 6 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

$PA\overline{TR}$ introduced later in this section). Therefore, the first six months of the overall sample period are omitted when estimating the results in Table 6.

return forecasts in the past continue to have high (low) average forecasts going forward. This effect likely reflects some general tendency of analysts to be either consistently over-optimistic or over-pessimistic. 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 3 of Table 6 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%.

Third, we consider broker fixed effects. Analysts' average forecasts might be influenced by their work environment (e.g., a common input they receive from macro analysts within the firm) or by common incentives that a firm sets up for all its analysts. To the extent that such broker-specific factors similarly affect all analysts working at the same firm, their effect will be captured by broker fixed effects. Columns 4-6 of Table 6 add broker fixed effects to the previous specifications. The coefficients on $\overline{OCTR}$ and $PA\overline{TR}$ only slightly decrease when adding the broker fixed effects, and their statistical significance remains essentially unchanged. The average R^2 values increase, reaching 61% in column 6, where $\overline{OCTR}$, $PA\overline{TR}$, and broker fixed effects are all used.

In the Online Appendix Note, we also consider an additional set of factors, namely stock-level anomaly characteristics. Previous research has 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). We study whether the type of stocks covered by an analyst, measured as the average value of a stock characteristic calculated over the stocks that she covers, has an effect on her average forecasts.[19] Our results show that adding the anomaly-related measures only marginally increases the explanatory power of the specifications in Table 6: the average R^2 of the specification in column 3 increases

[19] We use the most prominent anomaly characteristics: size, value (book-to-market ratio), investment (asset growth), profitability (return on equity), and momentum (return over the previous year).

from 44% to 46%, while the R^2 of the specification in column 6 increases from 61% to 63%.

The results in Table 6 indicate that almost two thirds of the cross-sectional variation in the within-analyst average forecasts (i.e., in the analyst fixed effects) are explained, on average, by (i) aggregated prior forecasts of other analysts covering the same stocks, (ii) the average of a given analyst's own previous forecasts (across all stocks the analyst has ever covered), and (iii) broker-specific factors.[20] The first two 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).

While these factors shed light on the potential sources of the analyst-level bias, it should be emphasized that the advantage of the within-analyst demeaning of target returns (i.e., getting rid of the analyst fixed effects) is the ability to capture this bias *regardless of its source*. Therefore, analysts' relative forecasts, constructed either via within-analyst demeaning or ranking, provide a very general and comprehensive way of controlling for both observable and unobservable analyst-specific factors that may be detrimental to analysts' ability to provide accurate forecasts.

4 Information sources of relative valuation

In this section, we study where the predictive ability of analysts' *relative* forecasts stems from. Table 7 presents the results from *individual forecast-level* Fama-MacBeth regressions, i.e., the cross-

[20] We show in the Online Appendix that if individual target returns are only partially adjusted, by the part of $\overline{TR}$ that is explained by (a combination of) the explanatory variables from Table 6, the ability of these adjusted target returns to predict future stock returns is better than that of unadjusted individual target returns. These results in the Online Appendix therefore confirm that the factors highlighted in this section are indeed detrimental to the ability of absolute forecasts, and hence the consensus target return, to predict future returns.

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 target return (TR_{jkt}) for that stock minus the average of all the analyst's forecasts ($\overline{TR}_{kt}$) 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 7 establishes that $TR - \overline{TR}$ is a strong predictor of future returns, as we have already seen before.[21]

[Table 7 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 underlying stock j, taken from the end of month $t-1$ to ensure that it is available for the analyst when making her announcement.[22]

[21]The sample period used in Table 7 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.

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

Column 2 of Table 7 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.[23] 46% of all individual forecasts fall in the above-defined windows. Column 3 of Table 7 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.[24] Overall, this evidence suggests that the profitability of analyst-level relative valuation is not driven by the public information from earnings 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

[23] 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).

[24] 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 7. Inclusion or omission of these level effects does not affect the interaction coefficients in any meaningful way.

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 7 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 7 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 suggests 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.

5 Relative earnings forecasts and recommendations

Target price forecasts are not the only 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] Similarly, stocks receiving relatively higher recommendations should also yield higher returns.

We start by considering analysts' earnings forecasts. 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) forecasts 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. Since EPS forecasts are not directly comparable across stocks, we normalize them by stock prices from the end of the preceding year (on the same per-share basis as the unadjusted EPS forecasts). We then evaluate whether subsequent returns align with analysts' relative EPS per price ratio (E/P) forecasts.[26]

In particular, for each stock in each month, we compute three metrics: (i) Consensus E/P (CEP), derived as the mean of predicted earnings-price ratios across analysts covering the stock within that month; (ii) Consensus Demeaned E/P ($CDEP$), calculated by subtracting the analyst-level mean from the forecasts before aggregating across analysts, analogous to $CDTR$ outlined in Section 2.1; (iii) Consensus Ranked E/P ($CREP$), calculated as the mean of within-analyst scaled

[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.

[26] To mitigate the influence of stock price reversals on our findings, we do not use stock prices from the end of the preceding month in our normalization. This is because stocks with recently lower prices often exhibit higher subsequent returns. Since our objective is to evaluate whether higher normalized earnings forecasts predict higher subsequent returns, we want to exclude the potential predictive power from stock prices in the denominator.

rank values of the E/P forecasts, analogous to $CRTR$ described in Section 2.1. Similar to our baseline specification for target returns, we use a one-month announcement collection window and require an analyst to have E/P forecasts for at least three firms within the month to enter our sample. The sample period spans from January 1983 to December 2021.[27]

At the end of each month, we sort all stocks into quintile portfolios based on one of the three aforementioned metrics. We then form long-short portfolios using the two extreme quintiles (high minus low). Table 8 presents the average excess returns for the two extreme quintiles and the long-short portfolio, and alphas from regressing the long-short portfolio returns on the same sets of factors that were used previously in the paper. Results using the consensus E/P forecasts (sorting on CEP) align with the findings in Elgers et al. (2001): stocks in the highest CEP quintile outperform those in the lowest by 1.02% per month (t-statistic is 3.38) under the equal-weighted scheme. However, the outperformance is largely explained by exposures to factors in the $FF6$, HXZ, and DHS models, since the long-short α-s from these models are insignificant. Additionally, sorting on CEP fails to produce a significant long-short return spread in the value-weighted case.

[Table 8 about here]

The results from sorting on relative forecasts are stronger. When portfolios are sorted on $CDEP$ or $CREP$, the long-short return spread is around 0.80% per month (t-statistic above 5) in the equal-weighted case, and all the long-short α-s are significant. In the value-weighted case, the long-short return spread is around 0.40% per month and is significant for both $CDEP$ and $CREP$. The corresponding long-short α-s are also significant, with the only exception being the DHS α after sorting on $CDEP$. These results largely resemble those in Table 1, indicating that analysts demonstrate skill in relative valuation when forecasting earnings-price ratios. The evidence that common risk factors fail to capture the predictive power of $CDEP$ and $CREP$ suggests that the

[27] 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.

information embedded in relative forecasts is different from the information reflected in absolute forecasts represented by CEP.

Analysts also issue recommendations that take values on a five-point scale. Similar to Jegadeesh et al. (2004), we code the data so that more favorable recommendations receive a higher score (e.g., 5=Strong Buy and 1=Strong Sell).[28] Recommendations are less ideal for studying analysts' relative forecasts, than the other two analyst outputs, for at least two reasons. First, there are fewer recommendation announcements than target price announcements: on average, there are 654 analysts who announce target prices for at least three firms in a given month, but only an average of 191 analysts announce at least three recommendations. Therefore, we only require an analyst to announce a recommendation for at least two stocks within the month to enter our sample, which raises the average monthly number of analysts to 420. Second, and most pertinently, as has been previously documented by, e.g., Barber et al. (2001), the majority of the recommendations fall on the three-point scale from Hold to Strong Buy, which limits the informativeness of the within-analyst ranking of these recommendations. In fact, almost 90% of all analyst-month observations in our sample are such that the analyst announced at most two distinct recommendation values during the month.

Despite these considerations, and for the sake of completeness, we proceed with a similar analysis by calculating Consensus Recommendations ($CRec$), Consensus Demeaned Recommendations ($CDRec$), and Consensus Ranked Recommendations ($CRRec$). These measures are defined analogously to those for target returns and EPS forecasts.[29] In line with data availability, the sample period spans from November 1993 to December 2021 when using recommendations. Table 8 al-

[28] The full set of possible recommendation values constitutes 5=Strong Buy, 4=Buy, 3=Hold, 2=Sell, and 1=Strong Sell.

[29] When calculating the within-analyst ranked recommendations, the procedure for dealing with tied values becomes important. If there are tied recommendation values within a given analyst-month, we assign the average rank to each of the tied values. For example, if an analyst issues the same recommendation value to all the stocks she covers during the month (e.g., only 4=Buy recommendations), then all the stocks receive the scaled rank value of 0.5. If the analyst issues the recommendations of $\{3, 4, 4, 4, 5, 5\}$ for the stocks in her portfolio, the corresponding scaled rank values are $\{0, 0.4, 0.4, 0.4, 0.9, 0.9\}$.

so presents the results from sorting stocks into quintile portfolios based on $CRec$, $CDRec$, and $CRRec$. In line with the findings from previous literature (e.g., Barber et al., 2001), sorting on consensus recommendations leads to a statistically significant long-short return spread in the equal-weighted case. However, similar to the case when sorting on consensus E/P forecasts, the spread becomes insignificant when value-weighted portfolios are considered. Interestingly, despite our concerns about the informativeness of the within-analyst relative recommendations, we document considerable long-short returns when the sorting is based on $CDRec$ and $CRRec$: the long-short return spreads are sizable and statistically significant in both the equal- and value-weighted cases, and all the corresponding α-s remain statistically significant. Overall, our exploration of the three most common forecasts from sell-side analysts (target prices, E/P forecasts, and recommendations) consistently highlights their skill 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 (and recommendations) 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 better at relative valuation than at absolute valuation. Formulated like this, our results are not particularly surprising. Most analysts specialize on certain types of firms, 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.

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 for stock j by analyst k 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 $\mathbf{X}$ 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 $n\left(S\right)$ 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:

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

where

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

$CRTR_{jt}$ **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 $Rank(\cdot)$ 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:

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

$PA\overline{TR}_{kt}$ **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., $\tau < t$):

$$PA\overline{TR}_{kt} = \frac{1}{n\left(S_{kt}^{H}\right)} \sum_{\tau \in S_{kt}^{H}} \overline{TR}_{k\tau} \tag{A7}$$

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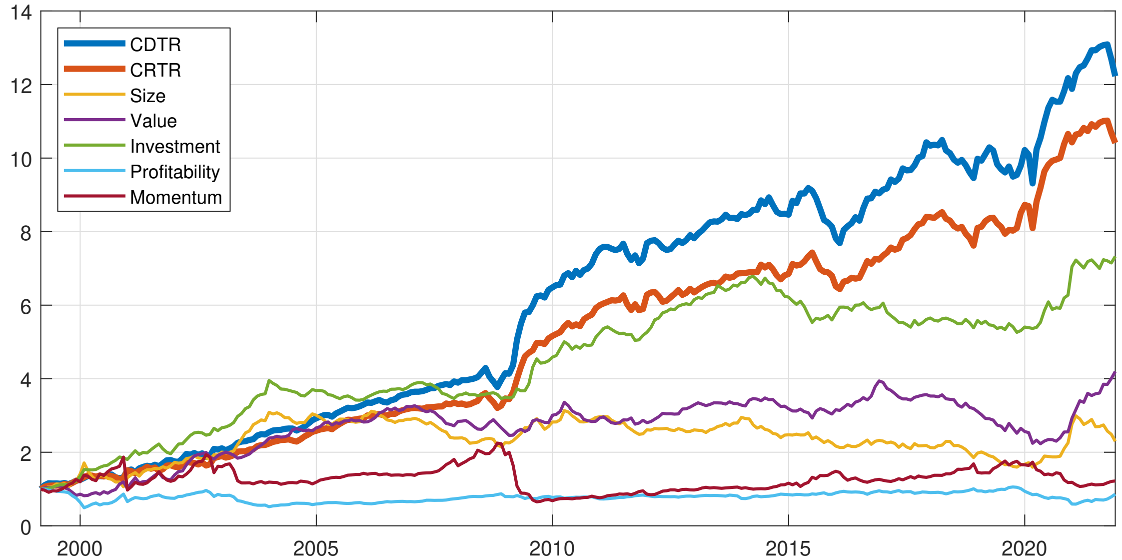
Figure 1: Cumulative return on long-short strategies

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

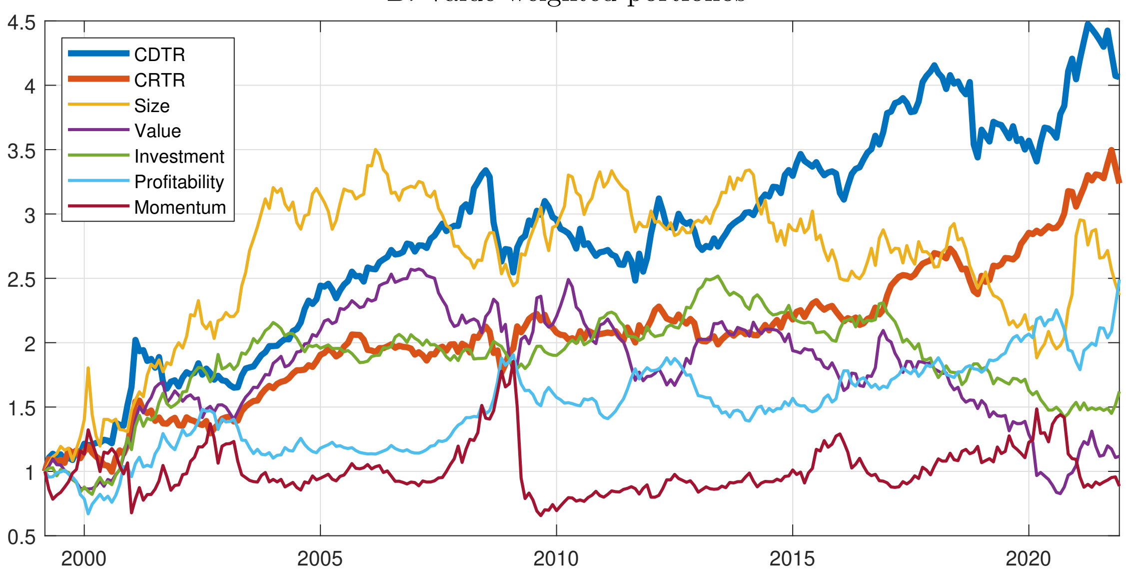


Figure 2: Distribution of t-statistics on time-series alphas

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.

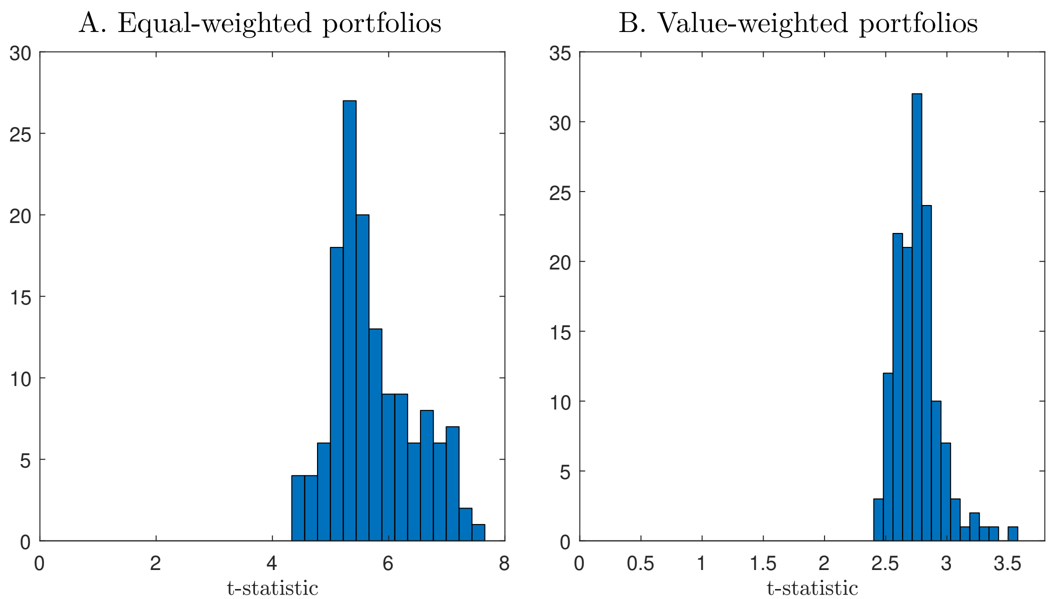


Figure 3: Distribution of t-statistics from Fama-MacBeth regressions

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.

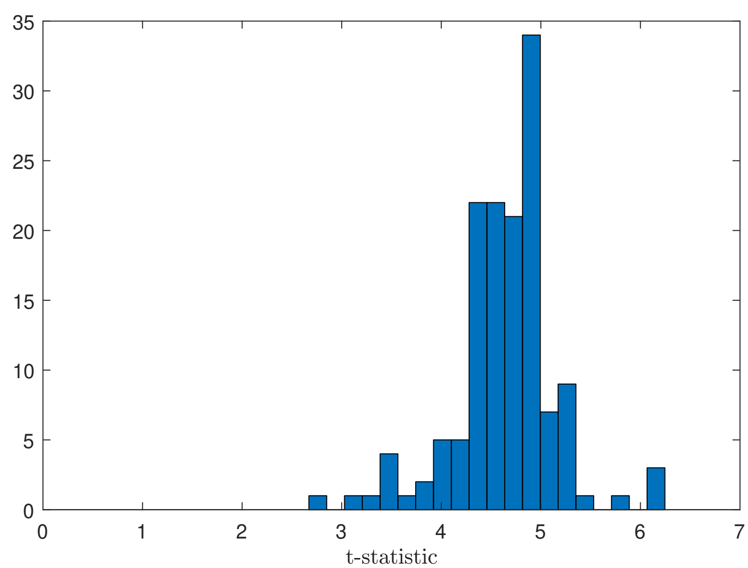


Figure 4: Coverage in terms of number of stocks and market capitalization

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*).

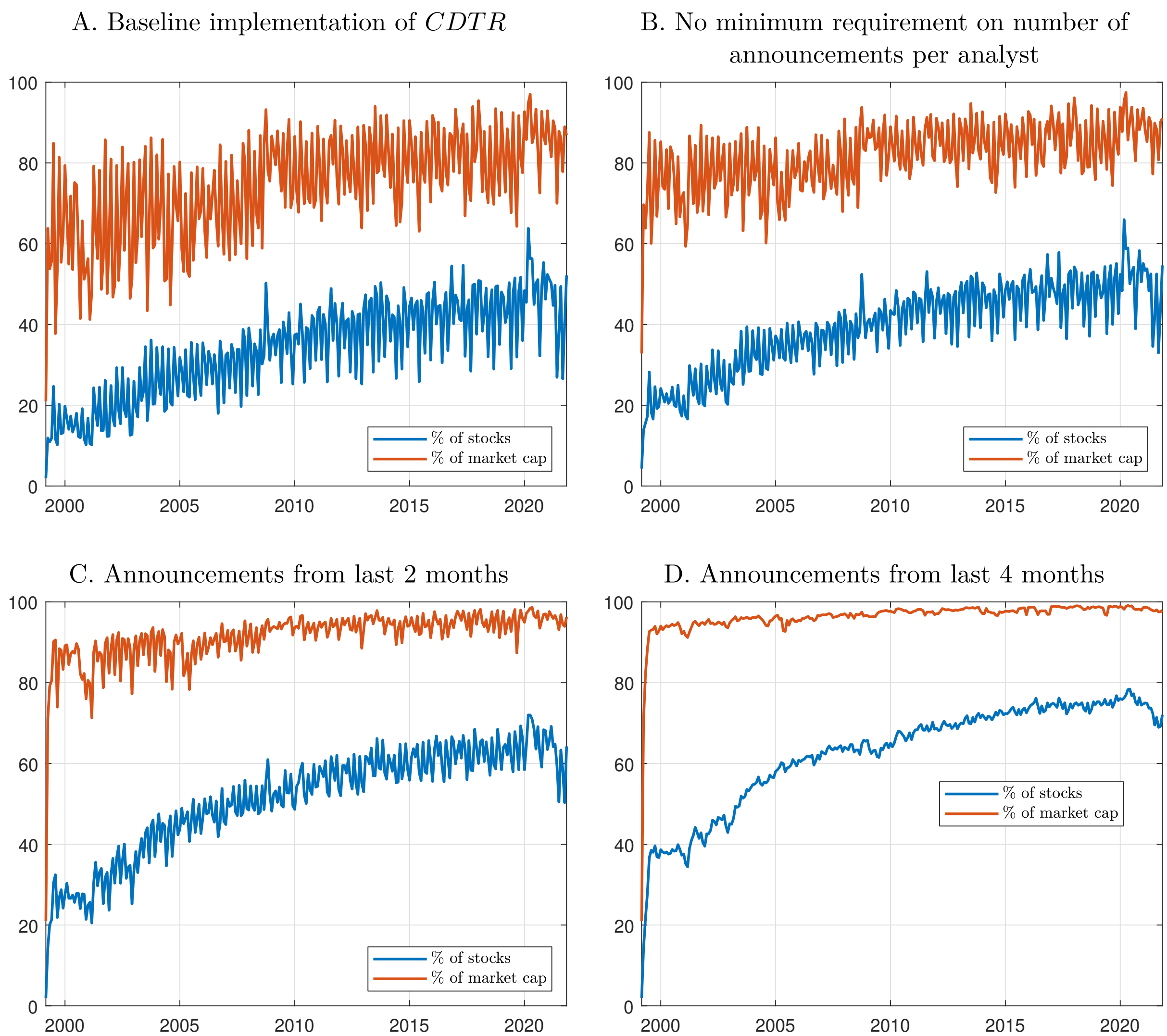


Figure 5: Target return variation explained by analyst fixed effects

The graph shows the R^2 (in %) from monthly cross-sectional regressions, where individual target returns are regressed on analyst dummies. More specifically, the regression in (4) is estimated every month t throughout the sample, and the graph shows the R^2 from these regressions. The sample period is from September 1999 to December 2021.

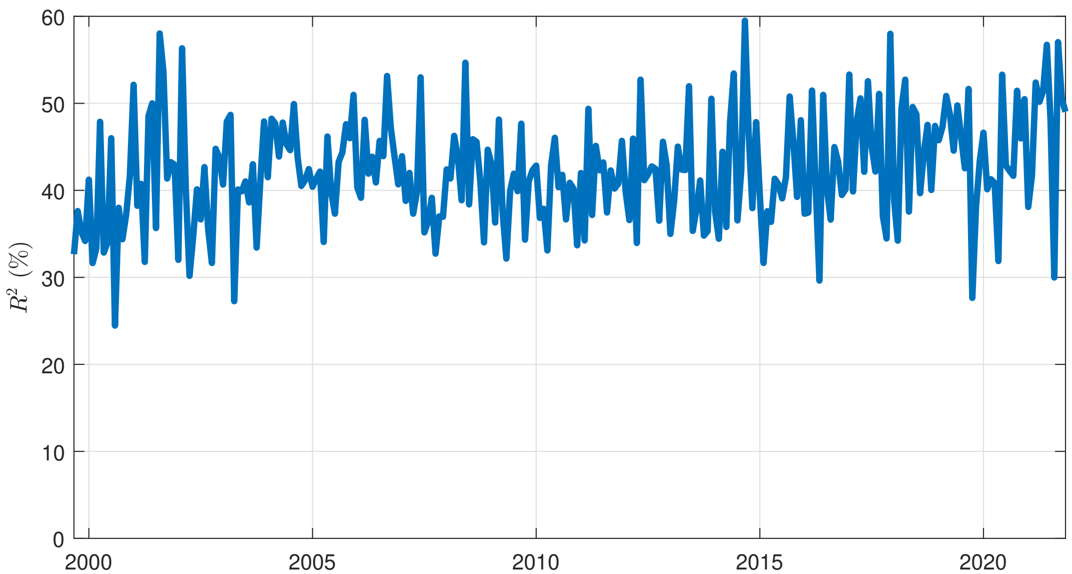


Table 1: Excess returns and alphas on $CDTR$- and $CRTR$-sorted portfolios

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 (*AvgRet*) with the associated t-statistic (*t-stat*), the annualized Sharpe ratio (*SR*), and the rank of this Sharpe ratio among the Sharpe ratios of 140 long-short strategies based on anomaly characteristics from previous literature (*SRrank*). *SR* and *SRrank* are reported both in gross and in net (after transaction costs) terms. The sample ranges from March 1999 to December 2021.

			gross			net	
Change compared to the baseline measure	AvgRet	t-stat	SR	SRrank	TO(%)	SR	SRrank
A. Equal-weighted portfolios							
baseline measure; no change	0.96	5.27	1.20	2nd	84.5	0.29	28th
at least 2 announcements per analyst	0.85	4.57	1.06	3rd	83.2	0.10	47th
at least 1 announcement per analyst	0.86	4.84	1.14	2nd	82.3	0.15	42nd
2-month announcement collection window	0.88	4.37	1.01	5th	55.2	0.36	19th
4-month announcement collection window	0.68	2.86	0.76	21st	34.0	0.29	28th
drop announcements from last 5 days	0.78	4.36	0.98	6th	86.3	0.09	52nd
B. Value-weighted portfolios							
baseline measure; no change	0.57	2.78	0.58	3rd	80.7	0.40	10th
at least 2 announcements per analyst	0.64	3.03	0.65	3rd	80.5	0.47	4th
at least 1 announcement per analyst	0.48	2.51	0.56	3rd	79.7	0.35	18th
2-month announcement collection window	0.73	3.27	0.74	1st	58.3	0.60	2nd
4-month announcement collection window	0.50	2.15	0.46	7th	37.6	0.35	20th
drop announcements from last 5 days	0.49	2.44	0.50	5th	82.4	0.32	22nd

Table 6: Understanding analysts' average forecasts

The table reports the average coefficients and Newey-West t-statistics (in parenthesis) 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. $\overline{OCTR}$ 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. 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)	(6)
$\overline{OCTR}$	0.765		0.474	0.623		0.445
	(29.76)		(26.69)	(21.91)		(21.58)
$PA\overline{TR}$		0.823	0.556		0.698	0.463
		(14.55)	(23.20)		(14.28)	(25.30)
Constant	Yes	Yes	Yes	No	No	No
Broker FE	No	No	No	Yes	Yes	Yes
Avg R^2	0.319	0.353	0.438	0.563	0.558	0.612
Avg #obs	663	640	640	663	640	640

Table 7: 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 8: Portfolios sorted on measures from earnings forecasts and recommendations

The table reports average excess returns on quintile portfolios sorted on measures calculated from analysts' earning forecasts (CEP, $CDEP$, and $CREP$) and recommendations ($CRec$, $CDRec$, and $CRRec$). The first three columns present the average excess returns for the two extreme quintiles (Low and High) and 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 the long-short 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*). All the returns and alphas are in monthly percentage terms. The sample period for the measures from earnings forecasts ranges from January 1983 to December 2021. The sample period for the measures from recommendations ranges from November 1993 to December 2021. Newey-West t-statistics are in parentheses.

	Avg. excess return			α-s on the H-L portfolio			
	Low	High	H-L	α_{FF5}	α_{FF6}	α_{HXZ}	α_{DHS}
A. Equal-weighted portfolios							
CEP	0.32	1.34	1.02	0.55	0.32	0.14	0.19
	(0.73)	(4.49)	(3.38)	(2.80)	(1.62)	(0.57)	(0.72)
$CDEP$	0.42	1.22	0.79	0.69	0.57	0.48	0.48
	(1.08)	(4.09)	(5.00)	(5.81)	(4.96)	(3.97)	(3.18)
$CREP$	0.45	1.29	0.84	0.64	0.52	0.43	0.47
	(1.24)	(4.62)	(5.12)	(5.67)	(4.72)	(3.64)	(3.22)
$CRec$	0.41	1.12	0.71	0.82	0.61	0.54	0.64
	(1.02)	(3.18)	(3.49)	(3.65)	(2.88)	(2.33)	(3.10)
$CDRec$	0.50	1.15	0.65	0.63	0.56	0.58	0.52
	(1.42)	(3.32)	(5.89)	(5.12)	(4.48)	(4.64)	(3.98)
$CRRec$	0.62	1.22	0.60	0.63	0.57	0.57	0.49
	(1.71)	(3.52)	(6.17)	(6.12)	(5.74)	(5.42)	(4.63)
B. Value-weighted portfolios							
CEP	0.43	0.92	0.49	0.06	-0.10	-0.28	-0.20
	(1.10)	(3.82)	(1.66)	(0.28)	(-0.45)	(-1.13)	(-0.95)
$CDEP$	0.52	0.89	0.37	0.55	0.49	0.39	0.23
	(1.77)	(3.67)	(2.39)	(3.29)	(2.96)	(2.29)	(1.27)
$CREP$	0.49	0.92	0.43	0.48	0.49	0.42	0.44
	(2.00)	(4.19)	(3.83)	(4.14)	(4.08)	(3.46)	(3.46)
$CRec$	0.55	0.82	0.27	0.38	0.31	0.30	0.35
	(1.68)	(2.92)	(1.20)	(1.73)	(1.43)	(1.38)	(1.36)
$CDRec$	0.49	0.97	0.48	0.57	0.53	0.52	0.37
	(1.70)	(3.60)	(3.14)	(3.45)	(3.34)	(3.02)	(2.43)
$CRRec$	0.48	0.90	0.42	0.50	0.47	0.47	0.38
	(1.79)	(3.30)	(3.28)	(3.75)	(3.75)	(3.70)	(3.09)

Online Appendix for
"Analysts Are Good at Ranking Stocks"

April 16, 2024

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 gorss and net (after transaction costs) Sharpe ratio of the long-short strategies based on one of the 140 anomaly variables at a time, sorted on their ranks. For each anomaly variable, the long-short strategy is constructed using the two extreme portfolios of its quintile sorts.

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

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 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 measures.

Let us start with the consensus return forecast, CTR. The first row 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. Comparing the results in Table OA.8 and Table 4 of the main text, it is evident that the coefficients on $CDTR$ are not much affected by controlling for stock characteristics and $CDTR$ remain strongly statistically significant in all specifications. In Table OA.8, compared to in Table 4 of the main text, CTR and $ICTR$ come out as more strongly significant in specifications (2) and (4), respectively, where these measures are included without $CDTR$. However, in specifications (3) and (5), where $CDTR$ is also included, the stock characteristics make no significant difference. The only qualitative difference of note, between Table OA.8 and Table 4 of the main text, is that $Info$ is significant in the final joint regression (specification (8)) in Table OA.8.

Further specifications for analysts' average forecasts

Table 6 of the main text presents the results from *analyst-level* Fama-MacBeth regressions, where the dependent variable is $\overline{TR}_{kt}$. Table OA.9 present similar results using further explanatory variables, anomaly characteristics of stocks. Similar to Section 4 of the main text, we find the value of characteristic X, at the end of month $t-1$, for the underlying stock j (denoted X_{jt-1}). We then define $\overline{X}_{kt}$ as the average of these characteristic values across all the stocks that analyst k covers in month t:

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

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 4 of the main text: $Size$, book-to-market ratio (BM), investment (AG), profitability (RoE), and momentum (Mom).

In Column 1 of Table OA.9, 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 the bias in the consensus forecast.

However, when adding these $\overline{X}$ variables to the explanatory variables that are already considered in the main text, their additional explanatory power is marginal. Column 2 of Table OA.9 shows the coefficient estimates when the $\overline{X}$ variables are added to the specification with $\overline{OCTR}$ and $PA\overline{TR}$. The coefficients on $\overline{OCTR}$ and $PA\overline{TR}$ barely change (compare column 2 of Table OA.9

to column 3 of Table 6 from the main text), but the coefficients on the anomaly characteristics are only small fractions of those reported in column 1 of Table OA.9. Moreover, adding the anomaly characteristics to the regression with $\overline{OCTR}$ and $PA\overline{TR}$ only marginally increases the R^2, from 44% to 46%. The conclusions are similar if broker fixed effects are also included (compare column 3 of Table OA.9 to column 6 of Table 6 from the main text): the R^2 increases from 61% (without the anomaly characteristics) to 63% (with the anomaly characteristics).

Partial adjustment of target returns based on observed analyst-specific factors

As emphasized in the main text, the analyst fixed effects make up the difference between the consensus forecast, CTR, and the relative forecast, $CDTR$. The former is a weak predictor of subsequent returns, whereas the latter is a strong predictor. Section 3 of the main text identifies factors that explain, to a large extent, the cross-sectional variation in the analyst fixed effects. These factors should therefore be helpful in adjusting the bias in the consensus forecast. In this section, we explicitly verify this conjecture.

Table OA.10 shows the results from *individual forecast level* Fama-MacBeth regressions, where the dependent variable is next month's realized return on the stock for which the target return (TR) was issued. The first column of Table OA.10 shows that TR has a positive but insignificant association with the subsequent realized return. This finding aligns with the result that sorting stocks on CTR produces a positive but insignificant return spread between the high and low CTR portfolios. The second column, on the other hand, shows that the demeaned (by within-analyst mean) target return, $TR - \overline{TR}$, is a highly significant predictor of next month's return, which is in line with our finding that $CDTR$ is a strong cross-sectional predictor of next month's stock returns.

The rest of Table OA.10 uses adjusted target returns, where the adjustment is done with *predicted TR values*. In particular, in each month t, the following analyst-level cross-sectional regression can be estimated:

$$\overline{TR}_{kt} = \alpha_t + \beta_t' \mathbf{Z}_{kt} + \varepsilon_{kt} \ , \tag{OA.2}$$

where $\mathbf{Z}_{kt}$ denotes a set of analyst-level explanatory variables. The results from such regressions are presented in Table 6 of the main text. After running the above regression in month t, the resulting predicted values can be denoted by $\hat{\overline{TR}}_{\{\mathbf{Z}\},kt}$. Table OA.10 presents specifications where next month's realized return is predicted by $TR_{jkt} - \hat{\overline{TR}}_{\{\mathbf{Z}\},kt}$, for different sets of variables in $\mathbf{Z}$.[2] That is, instead of subtracting the actual analyst-specific mean from the individual target returns (as in $TR - \overline{TR}$), we only subtract the part of $\overline{TR}$ that is explained by the set of variables in $\mathbf{Z}$.

An example might be useful to demonstrate what these specifications reveal. Consider the case where the single explanatory variable in the regression (OA.2) is the *Past Analyst average Target Return* ($PA\overline{TR}_{kt}$), i.e., the average $\overline{TR}$ of analyst k over all months *prior to month* t. Column 2 of Table 6 from the main text shows that $PA\overline{TR}$ is a very strong predictor of $\overline{TR}$ in the cross-section: analysts who had high (low) average return forecasts prior to month t continue to have high (low) average forecasts in month t as well. The adjusted individual target return in this specific example can then be written as

$$TR_{jkt} - \hat{\overline{TR}}_{\{PA\overline{TR}\},kt} = TR_{jkt} - \hat{\alpha}_t - \hat{\beta}_t \times PA\overline{TR}_{kt} \ . \tag{OA.3}$$

Since $\hat{\beta}_t$ in (OA.3) is positive (on average), individual target returns issued by analysts with high $PA\overline{TR}$ receive a bigger downward adjustment compared to target returns that are issued by low $PA\overline{TR}$ analysts. That is, individual target returns are adjusted with the part of the analyst fixed effect that is explained by $PA\overline{TR}$. Comparing columns 1 and 3 of Table OA.10 shows that $TR - \hat{\overline{TR}}_{\{PA\overline{TR}\}}$ is a better predictor of next month's realized return than the unadjusted individual

[2] In any specific month t, there might be missing values for $\hat{\overline{TR}}_{\{\mathbf{Z}\},kt}$, due to missing values in $\mathbf{Z}_{kt}$. There are typically only a few missing values (see the average number of observations for the different specifications in Table 6 of the main text). However, to have the same sample across all specifications in Table OA.10, we use the average $\hat{\overline{TR}}_{\{\mathbf{Z}\},kt}$ in that month instead of the missing values.

target return, TR.

Columns 4 to 7 of Table OA.10 show that similar adjustments using $OCTR$, broker fixed effects (BFE), or a combination of these variables all improve the ability of individual target returns to predict future realized returns. These results confirm that the factors identified in Section 3 of the main text to explain variation in analyst fixed effects do indeed contribute to the poor cross-sectional predictive performance of *absolute* return forecasts, and hence to the poor performance of CTR.

Table OA.10 also reveals that the strongest predictor of future returns is $TR - \overline{TR}$, i.e., when individual target returns are adjusted with the actual within-analyst mean. That is, there are further, unobserved, factors captured by analyst fixed effects that contribute to the poor predictive performance of absolute return forecasts. The fixed-effects transformation that leads to the construction of our $CDTR$ measure provides a comprehensive way to control for a wide range of observable *and unobservable* analyst-specific factors that may be detrimental to analysts' ability to provide informative forecasts.

Measuring trading costs: high-frequency effective bid-ask spreads

To assess the tradability of our strategies, we account for trading costs by using high-frequency effective bid-ask spreads, as suggested by e.g., Chen and Velikov (2023). Using the NYSE daily and monthly TAQ datasets directly, we initially utilize the DOW loop provided by WRDS, a widely accessible resource for WRDS users. The DOW loop offers an efficient methodology for screening, merging, and deriving statistics from trades and quotes data.[3] After this step, we get the matched bid-offer prices (from the quote files) for each trade in the trade files.

We then calculate the high-frequency effective bid-ask spreads for each stock-month. To begin,

[3]Rather than subscribing through WRDS, we procure TAQ data directly from the NYSE, obtaining separate trade files and quote files (national best bid-offer). See more details about the DOW loop: `https://wrds-www.wharton.upenn.edu/pages/wrds-research/applications/microstructure-research/sas-dow-loop-approach/`

for each trade k of stock i within day τ, we initially compute the effective relative bid-ask spread:

$$\text{Effective Relative Spread}_{k,i} = \frac{2D_{k,i}(P_k - M_{k,i})}{M_{k,i}}, \tag{OA.4}$$

with $D_{k,i} = +1$ (-1) if trade k is a buy (sell). $M_{k,i}$ is the mid-price from the matched quotes, and $P_{k,i}$ is the transacted price. We follow the methodology outlined by Lee and Ready (1991) to infer the trade direction (buy vs. sell). Then for a given day τ, we compute the dollar value-weighted effective relative bid-ask spread across all trades for stock i as follows:

$$\text{VW Effective Relative Spread}_{i,\tau} = \sum_{k=1}^{n} w_{k,i} \times \text{Effective Relative Spread}_{k,i}, \tag{OA.5}$$

where the value weight $w_{k,i} = \frac{P_{k,i} \times SHR_{k,i}}{\sum_{k=1}^{n} P_{k,i} \times SHR_{k,i}}$ is calculated from the transacted price and volume (SHR). Note that the WRDS Intraday Indicator (IID) provides this statistic directly, when accessing TAQ via WRDS. Finally, the monthly spread for stock i is determined as the average of all daily effective spreads within that month.[4]

References

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Da, Z., & Schaumburg, E. (2011). Relative valuation and analyst target price forecasts. Journal of Financial Markets, 14(1), 161-192.

[4]For this step we use the SAS code from Andrew Chen `https://github.com/chenandrewy/hf-spreads-all`.

Lee, C. M., & Ready, M. J. (1991). Inferring trade direction from intraday data. The Journal of Finance, 46(2), 733-746.

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

The graphs plot the annualized gross and net Sharpe ratios of 140 anomaly trading strategies, sorted on 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.

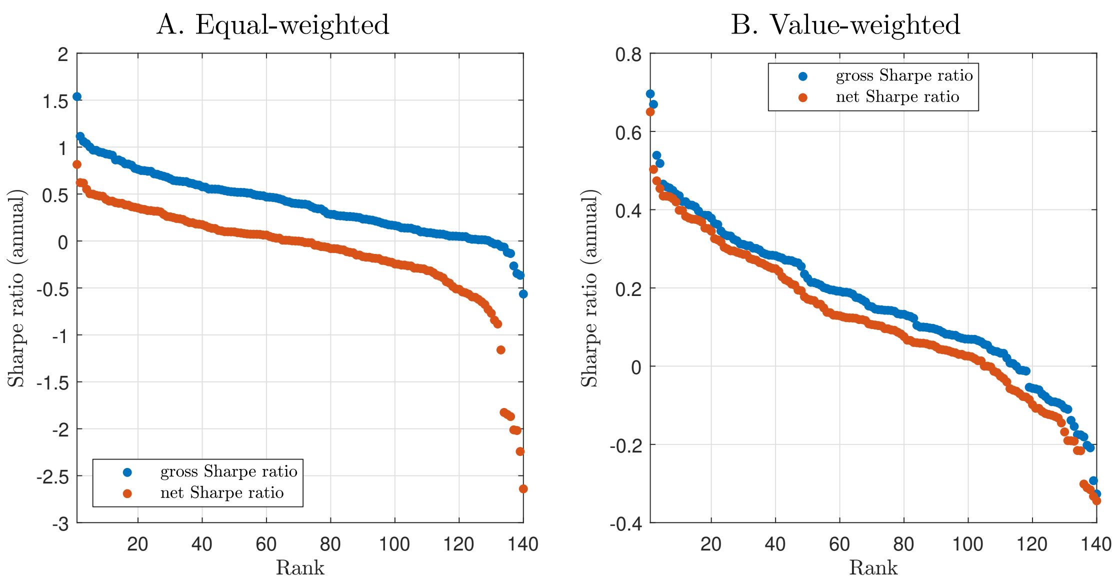

Figure OA.2: Distribution of t-statistics on time-series alphas for the $CRTR$-based strategy

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.

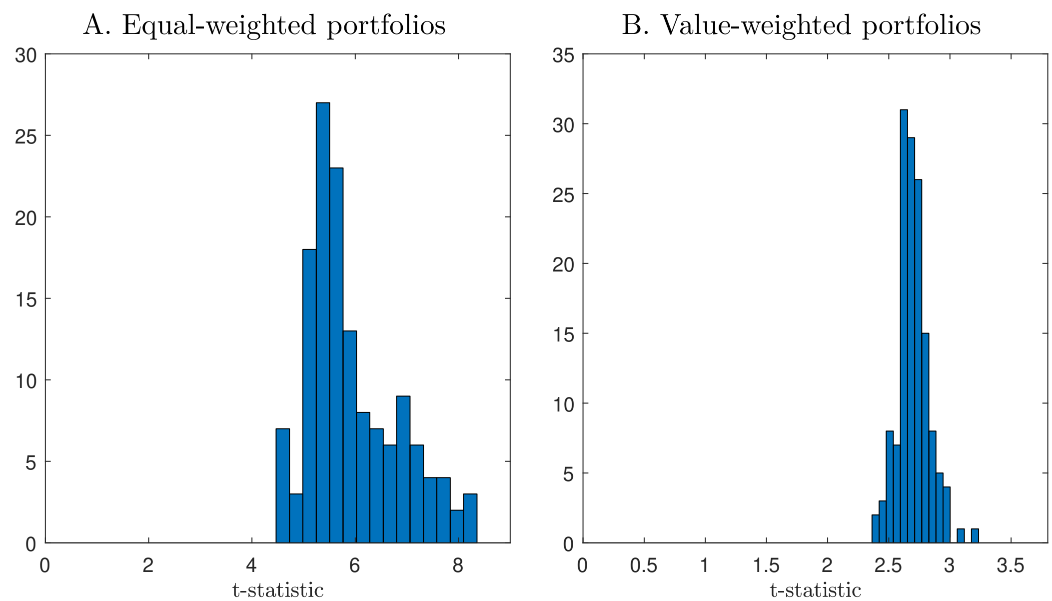

Figure OA.3: Distribution of t-statistics from Fama-MacBeth regressions with $CRTR$

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.

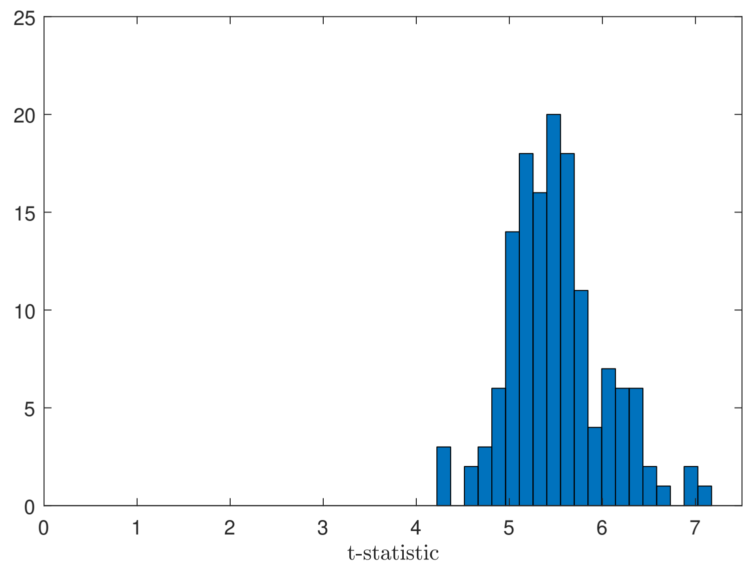

Table OA.1: List of anomaly variables

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 (*AvgRet*) with the associated t-statistic (*t-stat*), the annualized Sharpe ratio (*SR*), and the rank of this Sharpe ratio among the Sharpe ratios of 140 long-short strategies based on anomaly characteristics from previous literature (*SRrank*). *SR* and *SRrank* are reported both in gross and in net (after transaction costs) terms. The sample ranges from March 1999 to December 2021.

			gross			net	
Change compared to the baseline measure	AvgRet	t-stat	SR	SRrank	TO(%)	SR	SRrank
A. Equal-weighted portfolios							
baseline measure; no change	0.90	5.31	1.19	2nd	86.3	0.27	29th
at least 2 announcements per analyst	0.78	4.75	1.11	3rd	85.8	0.05	62nd
at least 1 announcement per analyst	0.81	5.15	1.16	2nd	84.7	0.12	45th
2-month announcement collection window	0.80	4.24	0.98	6th	58.6	0.29	28th
4-month announcement collection window	0.67	3.14	0.75	21st	36.7	0.28	29th
drop announcements from last 5 days	0.74	4.40	0.98	6th	88.0	0.10	49th
B. Value-weighted portfolios							
baseline measure; no change	0.47	2.69	0.57	3rd	83.4	0.37	16th
at least 2 announcements per analyst	0.31	2.35	0.47	5th	84.8	0.21	45th
at least 1 announcement per analyst	0.44	3.15	0.66	3rd	83.0	0.41	10th
2-month announcement collection window	0.60	3.74	0.83	1st	61.5	0.64	2nd
4-month announcement collection window	0.55	3.03	0.65	3rd	41.0	0.52	2nd
drop announcements from last 5 days	0.41	2.44	0.50	5th	84.5	0.31	24th

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 relative target return made by individual analysts. 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 main text	0.68	1.14	0.46	0.79
		(1.96)	(1.89)	(1.29)	(5.99)
CTR	No minimum for announcements per analyst in a month [1].	0.65	1.06	0.41	0.82
		(1.90)	(1.73)	(1.11)	(6.22)
CTR	[1] + Use median instead of mean in the definition of CTR.	0.64	1.05	0.40	0.82
		(1.89)	(1.74)	(1.12)	(6.08)
$ICTR$	Baseline version from the main text	0.56	1.35	0.80	0.41
		(1.38)	(2.45)	(3.49)	(4.68)
$ICTR$	No minimum for announcements per analyst in a month [1].	0.58	1.26	0.68	0.51
		(1.46)	(2.23)	(2.87)	(4.94)
$ICTR$	[1] + Use the first 3 GICS digits to define industries [2].	0.56	1.33	0.78	0.38
		(1.37)	(2.39)	(3.63)	(4.15)
$ICTR$	[1] + Use within-industry ranking of consensus forecasts [3].	0.59	1.32	0.74	0.51
		(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 main text	0.56	0.72	0.16	0.54
		(2.07)	(1.41)	(0.46)	(2.63)
CTR	No minimum for announcements per analyst in a month [1].	0.57	0.51	-0.07	0.58
		(2.17)	(0.93)	(-0.18)	(2.92)
CTR	[1] + Use median instead of mean in the definition of CTR.	0.57	0.54	-0.03	0.58
		(2.18)	(1.03)	(-0.08)	(2.76)
$ICTR$	Baseline version from the main text	0.36	0.68	0.33	0.40
		(1.17)	(1.56)	(1.19)	(2.79)
$ICTR$	No minimum for announcements per analyst in a month [1].	0.45	0.70	0.26	0.46
		(1.50)	(1.53)	(0.90)	(2.82)
$ICTR$	[1] + Use the first 3 GICS digits to define industries [2].	0.45	0.85	0.40	0.40
		(1.58)	(1.89)	(1.40)	(2.47)
$ICTR$	[1] + Use within-industry ranking of consensus forecasts [3].	0.50	0.79	0.29	0.43
		(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 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 stock characteristics are 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: Understanding analysts' average forecasts (additional explanatory variables)

The table reports the average coefficients and Newey-West t-statistics (in parenthesis) 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 a given 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. The average number of observations in the regressions is also reported. The sample period is from September 1999 to December 2021.

	(1)	(2)	(3)
$\overline{Size}$	-1.188	-0.291	-0.227
	(-8.76)	(-9.83)	(-6.82)
$\overline{BM}$	-0.379	-0.035	-0.028
	(-4.32)	(-1.30)	(-1.09)
$\overline{AG}$	0.262	0.017	0.027
	(7.12)	(0.96)	(1.63)
$\overline{RoE}$	-0.810	-0.125	-0.143
	(-13.57)	(-3.81)	(-4.20)
$\overline{Mom}$	-0.224	-0.077	-0.086
	(-1.99)	(-2.39)	(-3.05)
$\overline{OCTR}$		0.424	0.404
		(23.45)	(21.00)
$PA\overline{TR}$		0.532	0.452
		(22.74)	(24.87)
Constant	Yes	Yes	No
Broker FE	No	No	Yes
Avg R^2	0.195	0.462	0.627
Avg #obs	662	639	639

Table OA.10: Predicting future returns: various adjustments to individual target returns.

The table reports the average coefficients and Newey-West t-statistics from Fama-MacBeth regressions at the individual return forecast level. The dependent variable is next month's realized return on the stock for which the target price was issued for. TR denotes the individual return forecast, while $TR-\overline{TR}$ is the individual return forecast minus the average forecast of the issuing analyst in the given month. $\hat{\overline{TR}}_{\{\mathbf{Z}\}}$ denotes the predicted values from the cross-sectional regression in equation (OA.2), where $\mathbf{Z}$ is a specific set of explanatory variables that may include $\overline{OCTR}$, $PA\overline{TR}$, or the complete set of broker fixed-effects (BFE). 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)	(6)	(7)
TR	0.035						
	(1.20)						
$TR-\overline{TR}$		0.087					
		(4.03)					
$TR-\hat{\overline{TR}}_{\{PA\overline{TR}\}}$			0.049				
			(1.93)				
$TR-\hat{\overline{TR}}_{\{\overline{OCTR}\}}$				0.046			
				(1.93)			
$TR-\hat{\overline{TR}}_{\{\overline{OCTR},PA\overline{TR}\}}$					0.051		
					(2.19)		
$TR-\hat{\overline{TR}}_{\{BFE\}}$						0.048	
						(1.84)	
$TR-\hat{\overline{TR}}_{\{\overline{OCTR},PA\overline{TR},BFE\}}$							0.057
							(2.49)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg R^2	0.011	0.004	0.006	0.007	0.006	0.007	0.005
Avg #obs	3783	3783	3783	3783	3783	3783	3783