The Effect of Dispersion on the Informativeness of Analyst Target Prices

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ABSTRACT: Consensus analyst target prices are widely available online at no cost to investors. In this paper we examine how the amount of dispersion in the individual target prices comprising the consensus affects the predictive relationship between the consensus target price and future returns. We find some evidence that when dispersion is low, returns predicted by consensus target prices are more positively associated with realized future returns. However, we document a strong *negative* association between predicted and realized returns for stocks with high target price dispersion. Further analyses suggest that this effect of dispersion reflects distortions from analysts being slow to update price targets after bad news. As a stock performs poorly and some analysts are slow to update their target prices, dispersion increases and the consensus target price becomes too high. This has important implications for the informativeness of the consensus analyst target price. Finally, we show that the negative correlation between consensus-based predicted returns and future realized returns for high-dispersion stocks exists mainly for stocks with high retail interest, suggesting that unsophisticated investors are misled by inflated target prices available freely online.

Keywords: analyst forecast, target price, stock return, dispersion, retail investors
JEL: G11, G12, G14, G23, G41, M41

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1. Introduction

Publicly traded stocks with significant market capitalization typically receive dedicated coverage from multiple financial analysts who provide periodic research reports and valuation estimates after considering various sources of information about the company. Because they are straightforward to understand, target prices are one of the primary end products of analysts' research reports (Bradshaw et al. 2016). Any investor, even an unsophisticated one, can easily compare the stock's current price with a future price target to calculate its predicted return (e.g., Bilinski et al. 2013; Ho et al. 2018).[1] Prior research has revealed mixed results about the predictive value of target prices, finding in particular that price targets tend to be positively biased and that a large proportion of stocks do not reach their price targets (e.g., Dimson and Marsh 1984; Brown et al. 1991; Brav and Lehavy 2003; Asquith et al. 2005; Bradshaw et al. 2013; Joos et al. 2016). This apparent lack of target price informativeness is surprising in light of the large industry of analysts devoted to generating target prices as one of their primary outputs. In this paper, we consider the potential moderating role played by an important but underexplored feature of a collection of individual analysts' price targets: their dispersion.

Dispersion in analysts' target prices likely has important implications for their informativeness.[2] Conceptually, dispersion in target prices might emerge for two different reasons, each of which carries its own implications for informativeness. On one hand, target price dispersion may represent genuine differences in opinion among analysts about the expected value of the firm; we refer to this type of dispersion as "disagreement". On the other hand, dispersion may stem from analysts

[1] Analysts' stock recommendations (e.g., sell/hold/buy) are also available and straightforward. However, while recommendations capture "discrete rather than continuous assessments of security mispricing,…the *degree of mispricin*g is important to investors" (Francis and Soffer 1997, p. 194, emphasis added; also see Asquith et al. 2005 and Bradshaw et al. 2013). Prior literature also argues that target prices and recommendations are not identical sources of information (Brav and Lehavy 2003; Bradshaw et al. 2013; Gleason et al. 2013; Engelberg et al. 2019).
[2] By informativeness, we mean the degree to which target prices are useful for predicting future realized stock returns.

responding differently to their own incentives to avoid issuing negative opinions about firms, or from some analysts being slow or partial when updating their target prices (e.g., McNichols and O'Brien 1997; Bradshaw 2002; Diether et al. 2002; Bonini et al. 2010); we refer to this type of dispersion as "distortion". For example, if incentives cause some analysts to be slower than others in updating their target prices after negative news is revealed about a firm's prospects, dispersion will be higher because of incentive- and behavior-driven distortions rather than true differences in opinion.

When both types of dispersion are low, target prices ought to be more informative about future returns. When dispersion comes from disagreement, low dispersion among analysts' target prices would suggest a more accurate consensus price target (Malkiel 1982; Fisher and Raman 1996; Barron and Stuerke 1998; Guar et al. 2007; Barron et al. 2009; Engelberg et al. 2019; Gaba et al. 2019). Similarly, low distortion would suggest timelier and less biased target prices (Diether et al. 2002). Either way, low target price dispersion suggests that analysts' price targets should be more informative about future stock price (i.e., price targets should be more positively correlated with future returns for these stocks).

Conversely, high dispersion may impair the informativeness of target prices. High disagreement would point to greater uncertainty about the value of the firm, meaning that consensus target prices would be noisier, less helpful signals for predicting the future stock price (i.e., the correlation between price targets and future returns might plausibly be closer to zero for stocks with high disagreement). High distortion might result in more optimistically biased and stale target prices, which could in turn lead to overpriced stocks if investors are attracted to stocks with high target prices (Diether et al. 2002). As a result, the correlation between price targets and future returns could become negative for stocks with high distortion.

Consistent with these predictions, we find that predicted returns based on consensus target prices are more positively correlated with future realized returns when dispersion is low, with dispersion measured as the standard deviation of the target prices comprising the consensus (scaled by the current stock price). This result suggests that when analysts agree with each other and incentive-based distortions are low, target prices are generally more informative about future stock prices, in line with the view that analysts provide value to the capital markets. Still, we note that this result tends to hold only for very low-dispersion stocks, meaning that the target price inaccuracies reported in prior research cannot be overcome entirely by conditioning on low dispersion.

On the other hand, predicted returns based on consensus target prices exhibit a strong *negative* correlation with future returns when dispersion is high. This striking reversal of the predictive association between low- and high-dispersion stocks suggests that both disagreement and distortion contribute to the overall weak informativeness of target prices documented in prior literature. Moreover, the economic magnitude of these effects is large. Utilizing the predictable mispricing patterns from both low- and high-dispersion cases, a hedge portfolio that takes a long (short) position in the stocks from the highest decile of predicted returns within the lowest (highest) dispersion decile earns over 10% annually. This result is robust to 4-factor model, 5-factor model, and regression frameworks.

We next consider the question of *why* the information content of target prices differs between low- and high-dispersion stocks. In light of the earlier discussion, we consider both disagreement and distortion as potential reasons for the negative correlation between predicted returns based on target prices and future realized returns when dispersion is high. Conceptually, disagreement only suggests larger errors in target prices and does not explain the negative correlation between predicted returns and realized future returns. However, distortion does provide an explanation for the negative association. Conceivably, some analysts' incentives may lead them to delay target price revisions when firm fundamentals deteriorate, which simultaneously increases dispersion across analysts and leaves the target price too high.

While our overall results point to a larger role for distortion than disagreement, we consider each channel in turn. To explore the effect of disagreement on target price informativeness, we construct a current-month consensus predicted return and its dispersion using only individual target prices issued in month *t* (as opposed to the IBES-constructed consensus employed in our main tests). By construction, these alternative variables are based on less stale information than our primary measures and thus are more likely to capture genuine disagreement among analysts. As expected, we find the results based on current-month forecasts to be weaker than our primary results. When we include both versions of predicted returns and dispersion in the regression model, the current-month variables become statistically insignificant. To explore the distortion explanation, we examine past stock returns and analysts' revision time across low- and high-dispersion stocks. We find that high-dispersion stocks tend to exhibit very poor recent stock returns, and tend to include coverage from analysts who are slowest in updating their target prices, especially for high-dispersion stocks with high predicted returns. Taken together, the findings suggest that distortion is the primary driver of the negative association between target-price-based predicted returns and future returns for high-dispersion stocks, while disagreement plays a smaller role.

Finally, we consider the implications of our findings for retail investors because prior research finds that retail investors pay attention to target prices (Lawrence et al. 2017) and tend to take analysts' opinions at face value without adjusting for analysts' incentives to publish biased information (Malmendier and Shanthikumar 2007). As a result, we expect retail investors to be more affected by high price targets and to contribute more to the negative association between predicted and realized returns we document for high-dispersion stocks. From a limits-to-arbitrage perspective, if retail investors place too much confidence in high target prices, the dispersion in *investors'* (i.e., not analysts') expectations about future returns will increase, thereby inflating stock prices which reflect the opinions of investors with the most positive outlook (Miller 1977; Diether et al. 2002). In other words, if retail investors are ignorant of target price dispersion and naively follow artificially inflated target prices for high-dispersion stocks, and if arbitrageurs cannot arbitrage away the mispricing, the pattern we observe for our main results should be stronger for stocks with more retail interest.

Consistent with these arguments, we find that the negative correlation between predicted returns and future realized returns for high-dispersion stocks is driven by stocks with low institutional ownership. This result is consistent with the view that retail investors are more likely to be misled by inflated target prices than institutional investors who have access to more data and more information about firms.

This paper makes several contributions to the literature. We extend the target price informativeness literature by considering the effects of target price dispersion and the implications of these effects for retail investors. Our evidence that the dispersion of individual analysts' target prices plays an important moderating role and flips the informativeness of consensus target prices between low- and high-dispersion stocks sheds light on the mixed results from prior research on target price informativeness. By documenting the effect of dispersion on the informativeness of *consensus* target prices, we also extend the literature examining the complementary usefulness of various aspects of *individual* analysts' target prices such as their scenario-based valuations (Joos et al. 2016, 2017) or valuation techniques (Gleason et al. 2013). Moreover, our findings are distinct from existing results about dispersion and stock returns. Prior studies (e.g., Diether et al. 2002) find that dispersion is negatively correlated with future returns and conclude that stock prices reflect the views of the most optimistic investors when pessimistic investors do not trade. These papers study the average effect of dispersion, showing that dispersion correlates directly with future stock returns. In contrast, we focus on the *interaction* between dispersion and predicted returns based on target prices and show that the correlation between predicted returns and future realized returns changes sign for low- versus high-dispersion stocks. These findings extend the literature on target prices by providing a more complete understanding of the information content of target prices and their implications for future returns.

Our results could be of interest to academics, practitioners, regulators, and particularly retail investors who rely on target price information. Practitioners will be interested in our findings as they provide a road map for portfolio management based on consensus target prices. Regulators could be concerned that retail investors appear to be fooled by optimistic target prices when dispersion is high and may want to encourage the disclosure of more information about the dispersion and staleness of consensus target prices provided freely online.

The rest of the paper is organized as follows: Section 2 discusses related literature and our research question, Section 3 describes the sample data, Section 4 presents our research design and main empirical findings, Section 5 explores potential explanations and considers retail investors, and Section 6 concludes.

2. Background and research question

2.1. Institutional background

Along with the earnings forecast and stock recommendation, the target price is one of the primary components of an analyst's research report (Asquith et al. 2005; Bradshaw et al. 2013; Bradshaw et al. 2016). In practice, the vast majority of target prices have a 12-month horizon and represent the analyst's opinion about the stock price 12 months in the future.[3] As Brav and Lehavy (2003) note, "Target prices provide market participants with analysts' most concise and explicit statement on the magnitude of the firm's expected value" (p. 1933). For the last 20 years, it has been common for sell-side analysts' reports to include target prices in support of their stock recommendations (Bradshaw 2002; Brav and Lehavy 2003; Gleason et al. 2013). Schipper (1991, p. 106) calls stock recommendations "the ultimate analyst judgment," and target prices are critical because they form the basis of these recommendations (Bradshaw 2004; Gleason et al. 2013). The fact that target price disclosure is explicitly regulated in FINRA Rule 2241 (and its predecessors NASD Rule 2711 and NYSE Rule 472) provides additional support for the view that target prices are important in capital markets.

[3] Of the 5.85 million observations in the IBES Target Price Detail History file, 89% have a 12-month horizon, and according to WRDS, all target price summary statistics calculated by IBES are based on the 12-month horizon.

However, analysts' incentives should not be ignored when contemplating their disclosed target prices. While much analyst-focused accounting research tends to focus on quantitative accuracy (for commentary, see Schipper 1991; Bradshaw 2011; Bradshaw et al. 2016), it is unclear whether analysts (or their employers) care very much about forecast accuracy (e.g., Francis and Philbrick 1993; Groysberg et al. 2011; Bradshaw 2011; Brown et al. 2015). For example, consider the bank research director quoted in Groysberg et al. (2011) who stated, "I don't think [forecast accuracy] is any kind of acid test for whether an analyst has keen insight. If the clients pay attention to and pay for the services of an analyst, then that is a 'good' analyst, whether or not they get the earnings, or for that matter, stock prices, right" (p. 985).[4] Moreover, the literature has identified many potential conflicts of interest relating to analysts. For example, Bradshaw (2011) lists incentives related to investment banking fees, currying favor with management, trade generation, institutional investor relationships, research for hire, and analysts' own behavioral biases as potential concerns when considering analysts' research, forecasts, and recommendations. These types of conflicts have been discussed as potential drivers of the positively skewed distribution of stock recommendations (e.g., Bradshaw 2002), which suggests they likely also play a role in analysts' target prices.

While prior studies often use individual analysts' target prices (and their revisions) to examine analyst incentives and forecast properties, our focus on the dispersion of individual analysts' price targets motivates the use of consensus target prices in our informativeness tests. In addition to this empirical expediency, our focus on dispersion vis-à-vis consensus price targets is important for several reasons. First, because the consensus target price represents the aggregate opinion of multiple analysts, the "wisdom of crowds" (Surowiecki 2005) suggests that it will generally be more accurate than an individual target price, which may increase the credibility of consensus information in the minds of

[4] Supporting the view that analysts may not focus on forecast accuracy, Engelberg et al. (2019) and Drake et al. (2011) show that analysts' target prices and recommendations do not fully reflect public information related to documented stock return anomalies.

investors.[5] Second, unlike individual analysts' price targets, consensus target price information is commonly provided by financial websites to the investing public at no cost. Relatedly, while consensus target prices are not the only analyst-based information available online, they are perhaps the easiest to interpret.[6] Third, while underlying dispersion is an important characteristic of consensus target prices, detailed information about dispersion is not readily available on financial websites.[7] Collectively, these factors suggest that it is important to understand the informativeness of consensus target prices because they constitute one of the analyst industry's primary and most widely accessible outputs. Moreover, our study of the dispersion underlying consensus price targets carries important implications for investors and the purveyors of financial information.[8]

2.2. Prior literature and research question

Prior research generally supports the view that target price levels and revisions carry some information, even though target prices tend to be positively biased and a large proportion of stocks do not reach their target prices (e.g., Dimson and Marsh 1984; Brown et al. 1991; Brav and Lehavy 2003; Asquith et al. 2005; Bonini et al. 2010; Bradshaw et al. 2013; Joos et al. 2016). Analysts' target prices and recommendations are related to their forecasts of earnings and long-term growth (e.g., Bandyopadhyay et al. 1995; Bradshaw 2004), and analysts' target price revisions are influenced by recent market performance, stock returns, and other analysts' revisions (Ho et al. 2018). Target price

[5] As we discuss in Section 5.2, we are particularly interested in unsophisticated/retail investors' use of consensus target price information. Thus, we appeal to these arguments of perceived credibility of the consensus. However, we also acknowledge prior research that documents bias in measures aggregated from poll-type settings (such as analysts submitting forecasts) when respondents may behave strategically (e.g., Trueman 1994; Morgan and Stocken 2008). These findings provide additional motivation for understanding the information content of consensus target prices and the resulting implications for investors.

[6] For example, investors can also freely observe earnings, revenue, and/or growth forecasts, but it may be difficult to form specific expectations about how this information maps into a stock price. On the other hand, it is very easy to compare a consensus target price with the current stock price to calculate a forecasted stock return.

[7] Some platforms like Yahoo! Finance and MarketWatch provide the high and low target prices among contributing analysts, but it is not always clear whether these are outliers relative to the majority of the contributing analysts. Other platforms like MSN Money and CNBC only provide a point estimate of the consensus target price.

[8] In Section 5.2, we explicitly consider the implications of retail investors potentially relying on freely available consensus target prices more than sophisticated investors.

accuracy is associated with analyst characteristics, valuation techniques and scenarios, earnings forecast accuracy, firm-specific factors, and aspects of country culture (Bilinksi et al. 2013; Gleason et al. 2013; Imam et al. 2013; Joos et al. 2016, 2017). However, it appears that the market does not respond differentially to analysts' target prices based on their historical target price accuracy (Bradshaw et al. 2013). Researchers have also shown that target prices can be more informative when considered in context with other information such as stock recommendations (Huang et al. 2009), relative rankings within industries (Da and Schaumburg 2011; Da et al. 2016), and the information conveyed by scenario-based valuations (Joos et al. 2016, 2017).

While prior research generally suggests that target prices convey some information, results also show "that target prices are highly inaccurate and biased, and analysts appear to have little skill in forecasting future stock prices" (Dechow and You 2020, p. 127; also see Bradshaw et al. 2013 and Dimson and Marsh 1984). Moreover, as mentioned above, analysts may not care too much about forecast accuracy (e.g., Groysberg et al. 2011; Brown et al. 2015). Perhaps the description of target prices from one online platform (wallmine.com) is an apt summary: "While the average or median … may be predictive and reflect the actual future value, the results are usually not extremely successful."[9] Given these conflicting views and the generally inconclusive evidence about the usefulness of target prices, we argue that one way to improve understanding of target price informativeness is to consider potential moderating factors, particularly those that might provide insight about how particular types of investors could use analysts' target prices. To this end, we consider the research question of whether, when, and to what extent the dispersion in the individual price targets used to construct the consensus affects the informativeness of that consensus target price.

[9] Given that analysts' target prices are closely related to their stock recommendations, Bradshaw's (2009) comment on the stock recommendation literature is also relevant: "Such studies provide mixed evidence at best, with the majority of such studies concluding that recommendations have no investment value" (p. 1073).

As described in the introduction, we choose to focus on dispersion because it likely has implications for the usefulness of consensus target prices in predicting future returns.[10] However, it is ex ante unclear what information is conveyed by dispersion in the target price setting. For example, dispersion may arise due to genuine disagreement about firm value among analysts—perhaps due to differences in their private information. Alternatively, dispersion may reflect distortions arising from individual analysts responding *differently* to the various incentives mentioned previously. When observed dispersion is small, one possibility is that disagreement and incentive-driven biases are both low, suggesting that consensus target prices should be more informative. This reasoning is consistent with both analytical (Gaba et al. 2019) and empirical (Malkiel 1982; Fisher and Raman 1996; Barron and Stuerke 1998; Guar et al. 2007; Barron et al. 2009; Engelberg et al. 2019) analyses suggesting that the dispersion of a set of individual estimates is negatively related to the accuracy of the consensus estimate. However, it is important to note that incentive-driven biases can still exist if observed dispersion is low: If all analysts respond to the same incentives in a similarly biased fashion, then a low-dispersion consensus target price could still be plagued by biases even if genuine disagreement is low. In this case, low dispersion might not result in better consensus target price informativeness.

Similarly, the implications of high dispersion for target price informativeness can differ depending on whether disagreement or distortion dominates. High disagreement stems from authentic uncertainty about firm value among analysts; as a result, consensus target prices characterized by high disagreement might simply be less accurate and less useful for predicting future returns. However, high distortion arises when analysts' differential reactions to incentives result more in dispersed and optimistically biased target prices. For example, some analysts' incentives might lead them to avoid or delay incorporating negative news in their price targets, leading to higher dispersion. In these cases,

[10] Joos et al. (2016, 2017) examine dispersion within individual analysts' own target prices driven by different scenario-based valuations. Their findings suggest that this type of individual-level dispersion carries information, providing additional motivation for the idea that target price dispersion *across analysts* may have important implications for the informativeness of consensus target prices.

stocks with high distortion and high consensus target prices would be expected to experience lower future returns. Ultimately, the manner in which dispersion impacts the informativeness of consensus target prices is an empirical question. Studying the effects of dispersion provides a better understanding of how an important but underemphasized feature of analysts' price targets potentially moderates target price informativeness.

3. Sample data and descriptive statistics

The data for our main sample come from three sources: (1) analysts' target prices, analysts' earnings forecasts, and firms' actual earnings data from IBES; (2) accruals and other financial variables from annual Compustat files; and (3) stock return data from monthly (and daily) CRSP files. Target prices, which are our primary focus, have only been widely available on IBES starting in 1999; our sample covers the period from July 1999 to June 2020. Because IBES releases consensus target price statistics once per month (usually on the third Thursday), our observations occur at the firm-month level. For most analyses, we simply use the consensus target price provided by IBES (rather than constructing our own consensus from individual forecasts) because it closely matches the consensus target price information available online to investors; this choice also facilitates replication by future researchers.[11]

Our main dependent variable is $\text{RET}_{t+1,t+12}$, the 12-month future realized return from month t+1 to month t+12, where t refers to the month in which IBES calculates the consensus target price. Our two primary explanatory variables are the 12-month predicted stock return based on the IBES

[11] The few prior papers that consider the consensus target price create their own consensus measures by screening and aggregating particular analysts' target prices from the IBES detail files (e.g., Li et al. 2021; Dechow and You 2020; Engelberg et al. 2019). To better understand the consensus target price data available online and investigate its correspondence with the IBES database, we tracked a representative sample of 30 stocks each day in the month of April 2019 across Yahoo! Finance, MarketWatch, MSN Money, and CNBC. It was necessary to collect the data every day because unlike IBES, these platforms do not provide historical target price data. After comparing the data to the IBES consensus target prices for the same period, we concluded that the online consensus target prices tend to be very similar to the IBES consensus, providing additional support for our use of the IBES consensus as a proxy for the target price data available to investors online.

consensus analyst target price (PRET) and the dispersion in target prices comprising the consensus (DISP). PRET is defined as the average target price in month t minus stock price in month t, scaled by stock price in month t.[12] DISP is measured as the standard deviation from the IBES summary target price data for month t scaled by stock price in month t.[13] During our analysis, we observed that IBES has some issues with stock split adjustments in target prices. As a precaution, we drop firm-month observations in which the mean target price is different from the median target price by more than 50%. We also follow the finance literature and drop observations with stock prices below \$5. Our main sample includes 523,247 firm-month observations with non-missing $RET_{t+1,t+12}$, PRET, and DISP.

Table 1 presents descriptive statistics and correlations for our three primary variables of interest ($RET_{t+1,t+12}$, PRET, and DISP), along with several other control variables used throughout the analyses. The variable AN records the number of analysts contributing to the consensus target price calculation. Market value of equity (MV), the book-to-market ratio (BM), past realized returns from months t-6 to t-1 ($RET_{t-6,t-1}$), and accruals from the fiscal year prior to month t (ACC) are commonly-used factors that potentially explain stock returns. The appendix provides detailed variable definitions. Panel A presents summary statistics, with all variables except returns winsorized each month at their 1st and 99th percentiles. Comparing $RET_{t+1,t+12}$ with PRET at both the mean (10.0% versus 22.5%) and median (7.5% versus 14.6%), it is clear that analysts' target prices tend to be optimistic, consistent with findings from prior literature (e.g., Bradshaw et al. 2013; Joos et al. 2016; Dechow and You 2020). It is also important to note that there is significant variation in the individual target prices contributing to each consensus calculation, as shown by the mean (median) DISP of 18.1% (13.3%). Of note, we

[12] The monthly stock price is taken from the IBES Summary History Actuals + Pricing and Ancillary File. The value of the stock price is the closing price on the day before the IBES Statistical Period Date each month, which is the day when consensus information is calculated.

[13] We acknowledge that our approach for calculating PRET and DISP does not account for analysts' individual target prices being issued at different times. We make this choice because we are motivated by the availability of consensus information available online, which closely mirrors IBES' consensus calculations. We examine recently issued price targets in Section 5.1.

include in our dataset only firm-month observations with a minimum of four analysts, in order to ensure that DISP captures meaningful dispersion among analysts. The average (median) number of individual analysts contributing to the consensus is 9.61 (8).

Panel B of Table 1 presents Pearson (above the diagonal) and Spearman (below the diagonal) correlations among the key variables in Panel A. Given our interest in the informativeness of target prices, we first note the *negative* correlation between target-price-based predicted returns (PRET) and future realized returns ($\text{RET}_{t+1,t+12}$). This counterintuitive result suggests that when analysts issue more optimistic target prices relative to prevailing stock prices, actual stock performance tends to be worse, indicating little overall informativeness of target prices. Consistent with the prior literature using other dispersion measures (e.g., Diether et al. 2002), we also observe that $\text{RET}_{t+1,t+12}$ is negatively correlated with DISP, suggesting that stocks with higher dispersion in individual analysts' target prices tend to perform worse.[14] Finally, we note the large positive correlation between PRET and DISP, which is consistent with Engelberg et al. (2019) and demonstrates that stocks with higher predicted returns also tend to have higher dispersion among the individual analysts contributing to the consensus prediction. This large correlation also emphasizes the need to understand the implications of high dispersion for informativeness given that investors may be drawn to stocks with high consensus target prices.

Panel C of Table 1 provides evidence about the revision frequency of three major analyst outputs: annual earnings forecasts, target prices, and stock recommendations. We first calculate average revision frequencies by analyst in each firm's fiscal year; we then calculate summary statistics for approximately 43,000 firm-year observations. The results show that on average, annual earnings

[14] Li et al. (2021) study dispersion in analysts' target prices and find that their various measures of dispersion are *positively* associated with future stock returns and conclude that their measures of target price dispersion are correlated with stock riskiness. They do not measure dispersion using IBES' consensus calculations. Moreover, they find that the correlations between earnings forecast dispersion and their measures of target price dispersion "are close to zero" (p. 4), which contradicts the (untabulated) strong positive correlation between DISP and earnings forecast dispersion in our sample (Pearson and Spearman correlation coefficients are above 0.353 and 0.386, respectively). As a result, it appears that their measures of dispersion capture something quite different from our DISP measure.

forecasts are updated 3.85 times per year, consistent with updates happening around quarterly earnings announcements. Target prices are updated less frequently at 2.82 times per year (on average), and recommendations are updated only 1.33 times per year (on average). Given that recommendations are more coarse than target prices, it is not unexpected to see recommendations being updated less frequently than target prices. The fact that target prices tend to be updated fewer than three times per year suggests that many consensus target prices could be stale, an issue we discuss in Section 5.1 in the context of distortion-driven dispersion.

Panel D reports the time-series averages of mean future realized returns ($RET_{t+1,t+12}$) across 10 PRET deciles, where we sort stocks into deciles each month based on PRET. Consistent with the sorting process, the average PRET increases monotonically from -5.57% for PRET1 to 84.71% for PRET10.[15] However, the $RET_{t+1,t+12}$ pattern tells a different story. Realized returns for stocks in PRET1 through PRET8 remain fairly stable around 10% or 11% before dropping to 9.16% for PRET9 and 6.27% for PRET10. A hedge strategy that takes a long position in PRET10 stocks and a short position in PRET1 stocks yields a return of -4.24% (t = -2.91). These results are consistent with prior research (Bradshaw et al. 2013; Dechow and You 2020) and the negative correlation between PRET and $RET_{t+1,t+12}$ observed in Panel B. The findings indicate that stocks with the highest predicted returns based on consensus target prices tend to perform the worst on average. Overall, the results from Panel D suggest that consensus target prices are generally not informative about future stock returns due to their inability to meaningfully distinguish future performance among the majority of stocks (PRET1 to PRET8) and the counterintuitive finding that stocks with the highest predicted returns based on the consensus target price (PRET9 and PRET10) have the worst future realized returns.

[15] Throughout the paper, we use the notation of X# to refer to deciles of the sorting variable X, where # can be any value from 1 to 10, with lower (higher) numbers indicating lower (higher) values of the sorting variable X.

4. Main results

4.1 The effect of dispersion on the informativeness of target prices: Portfolio approach

We first use the portfolio approach to examine the potential moderating role of DISP on the association between PRET and $RET_{t+1,t+12}$. Each month, we first sort stocks into deciles based on DISP. Then, within each DISP decile, we further sort stocks into deciles based on PRET. The reason we first sort by DISP is that irrespective of the value of PRET, smaller (larger) values of DISP may indicate less (more) disagreement and/or distortion underlying the consensus-based predicted return. As explained previously, low versus high dispersion suggests possible differences in target price informativeness; thus, our goal is to first condition on dispersion and then examine informativeness (i.e., the association between PRET and $RET_{t+1,t+12}$) among stocks with similar dispersion. This sorting procedure yields 100 portfolios each month, and we take the average realized future stock return ($RET_{t+1,t+12}$) for each portfolio every month. Table 2 presents the time-series average for each portfolio.

The most striking result in Table 2 comes from comparing the stocks with the lowest target price dispersion (DISP1) to those with the highest target price dispersion (DISP10). Within the DISP1 decile, realized future returns tend to increase when moving from PRET1 (9.14%) to PRET10 (11.78%). As shown in the far right column of Table 2, a hedge portfolio that goes long in PRET10 stocks and short in PRET1 stocks within the DISP1 decile earns a return of 2.64% (t = 2.35). In contrast to the overall pattern observed in Panel D of Table 1, Table 2 shows a positive correlation between PRET and $RET_{t+1,t+12}$ when analysts agree about their target prices (i.e., when DISP is lowest). This finding is consistent with consensus target prices being more useful for predicting future stock returns when the consensus does not suffer from disagreement or distortion. Nevertheless, we note that this positive correlation only exists when dispersion is very low (e.g., the DISP1 and DISP2 deciles), consistent with the overall lack of informativeness found in prior studies. This result suggests that while conditioning on low dispersion can be useful, it is not a perfect remedy for overcoming target price inaccuracy.

At the other end of the spectrum, we observe a drastically different pattern within the DISP10 decile. Within this decile, realized future returns *decrease* from 10.94% in PRET1 to 1.52% in PRET10. In other words, among stocks with the highest dispersion, those with the highest predicted returns based on the consensus target price perform *far worse* than those stocks with the lowest predicted returns. A corresponding hedge portfolio that goes long in PRET10 stocks and short in PRET1 stocks within the DISP10 decile yields a -9.42% return (t = -4.68). Moreover, significantly negative hedge portfolio returns are observed for deciles 5, 6, 7, 8, and 9 of DISP, suggesting that the effects of high dispersion on informativeness are not confined to extreme levels of dispersion. Thus, it appears that the negative correlation between PRET and $RET_{t+1,t+12}$ observed in Table 1 is driven by stocks with greater dispersion among individual analysts' target prices (i.e., those with higher values of DISP). Given that future realized returns tend to increase with PRET for the lowest-dispersion stocks but consistently decline with PRET for higher-dispersion stocks, a more promising trading strategy is to go long in stocks with lowest DISP and highest PRET and short stocks with highest DISP and highest PRET. The bottom row in Table 2 reports a hedge return of 10.27% (t = 4.86) for this trading strategy.[16]

4.2 The effect of dispersion on the informativeness of target prices: Factor model approach

To ensure that the portfolio results from the above trading strategy are robust to controls for commonly-used factors, we estimate four-factor and five-factor models for monthly returns on the long (DISP1, PRET10), short (DISP10, PRET10), and hedge portfolios:

$$R_{it} - R_{ft} = a + b_{iM}\left(R_{Mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + m_i MOM_t + \varepsilon_{it} \qquad (1a)$$

$$R_{it} - R_{ft} = a + b_{iM}\left(R_{Mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{it} \qquad (1b)$$

[16] In untabulated analyses, we also examine the time series averages of the sorting variables (DISP and PRET) in each of the 100 portfolios shown in Table 2. Consistent with the large positive correlations between DISP and PRET shown in Table 1 Panel B, these calculations indicate that the highest average values of DISP (79%) and PRET (139%) correspond to stocks in the short (DISP10, PRET10) portfolio. For comparison, DISP averages 5% and PRET averages 33% for stocks in the long (DISP1, PRET10) portfolio.

In equations (1a) and (1b), R_{it} - R_{ft} is the average monthly excess return for each portfolio from month t+1 where month t is the month when target prices and dispersion are measured, R_{Mt} - R_{ft}, *SMB*, and *HML* are as defined in Fama and French (1996); *MOM* is the momentum factor as defined in Carhart (1997); and RMW and CMA are profitability and investment factors as defined in Fama and French (2015).[17] In equations (1a) and (1b), the intercept *a* captures the monthly abnormal return for each hedge portfolio after controlling for commonly-used factors. Results from estimating the models are presented in Table 3. Focusing on the intercept column, we observe that the long position has a positive abnormal return (only significant at the 10% level in Panel A for the four-factor model) and that the short position exhibits strongly negative abnormal returns of -1.659% (t = -3.72) for the four-factor model and -1.238% (t = -2.58) for the five-factor model. The hedge portfolio yields a strong positive abnormal monthly return of 2.000% (t = 4.46) for the four-factor model and 1.391% (t = 2.96) for the five-factor model. Converting these average monthly returns to an annual basis indicates an economically significant annual hedge return between 18.0% and 26.8% to the trading strategy that utilizes both target prices and their dispersion. The hedge returns are higher than those reported in Table 2 mainly because we use future returns in month t+1 in multi-factor models as opposed to 12-month returns in Table 2, a result consistent with the idea that the predictive power of return signals decays over time.

4.3 The effect of dispersion on the informativeness of target prices: Regression approach

We further examine the moderating role of dispersion using regression models and estimate the following equations for each month in the sample period:

$$RET_{t+1,t+12,it} = \beta_0 + \beta_1 PRET_{it} + \beta_2 DISP_{it} + \beta_3 PRET_{it} \times DISP_{it} + \sum_{1}^{k} \beta_{3+k}\, CTRL_k + \varepsilon_{it} \qquad (2)$$

[17] We obtain the factor data from Kenneth French's website.

$$RET_{t+1,t+12,it} = \alpha_0 + \alpha_1 PRET_{it} + \alpha_2 LowDISP_{it} + \alpha_3 HiDISP_{it} + \alpha_4 PRET_{it} \times LowDISP_{it} + \alpha_5 PRET_{it} \times HiDISP_{it} + \sum_{1}^{k} \alpha_{5+k}\, CTRL_k + \varepsilon_{it} \quad (3)$$

In equation (2), we directly regress the future 12-month realized return ($RET_{t+1,t+12}$) on the predicted return based on the consensus target price (PRET) and its dispersion (DISP) as well as their interaction. Equation (3) takes a similar approach except that we replace the continuous measure of DISP with two indicator variables: LowDISP (HiDISP) is an indicator equal to one for observations falling in the bottom (top) quartile of the DISP distribution in month *t*. We take this approach to compare stocks with low or high dispersion against stocks with middle levels of dispersion since Table 2 shows the greatest differences between the smallest and largest deciles of DISP. In both equations (2) and (3), the *k* control variables are the natural log of the market value of equity (SIZE), the book-to-market ratio (BM), past realized stock returns from months *t*-6 to *t*-1 ($RET_{t-6,t-1}$), and total accruals (ACC). All non-indicator independent variables are decile ranks converted to a [0,1] scale. The main variables of interest are the interaction terms in equations (2) and (3).

Table 4 presents the average coefficient estimates after running the models each month, and Fama-MacBeth *t*-statistics are presented in parentheses.[18] In column (1), the interaction of PRET×DISP is highly significant and negative (-0.108, *t* = -8.41). This result is consistent with our prior findings that stocks with high predicted returns *and* high dispersion have the worst future stock performance.[19] Turning to column (2) of Table 4, we continue to observe strong results for the interaction terms, and the indicator variable approach yields results that are consistent with the patterns observed in Table 2. Specifically, PRET×LowDISP has a significantly positive coefficient of 0.046 (*t* = 6.08), showing that for stocks with low dispersion, PRET is more positively associated with future stock returns (relative

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[18] Our inferences are unchanged if we use Newey-West standard errors to adjust for autocorrelations for six or even 12 lags.

[19] In untabulated analyses, we also interact DISP with SIZE and $RET_{t-6,t-1}$ and find that both interactions are statistically insignificant whereas the coefficient on the main variable of interest, PRET×DISP, is largely unchanged at -0.107 (*t* = -7.95).

to stocks with middle levels of dispersion).[20] On the other side, PRET×HiDISP has a significantly negative coefficient of -0.051 (t = -5.61), consistent with the results in column (1) and previous tables showing that stocks with the highest dispersion exhibit a strong negative association between predicted returns based on the consensus target price and future realized returns.

Taken together, the results from Tables 2, 3, and 4 suggest that the informativeness of consensus analyst target prices is moderated strongly by the dispersion of individual target prices. When the dispersion is small (i.e., lower DISP), predicted stock returns generated from the consensus target price are positively correlated with future returns. This result is consistent with our expectations but appears to be concentrated in stocks with very low dispersion and is not uniformly strong across methods. On the other hand, however, when dispersion is large (i.e., higher DISP), the relation flips with predicted stock returns from the consensus target price becoming *negatively* correlated with future stock returns. This strong, robust result suggests that disagreement among analysts and especially their incentive-driven distortions impair the informativeness of target prices to such an extent that, for high-dispersion stocks, the highest target prices predict the worst returns.

5. Additional analyses and robustness checks

5.1. Underlying channels: Disagreement and distortion

We now turn our attention to additional analyses with the aim of providing insight into why we observe such markedly different associations between predicted and future returns depending on the level of dispersion in individual analysts' target prices. The main findings in Tables 2, 3, and 4 show that high dispersion significantly impacts the informativeness of target prices, but the results do not distinguish between dispersion stemming from disagreement and distortion. Given that we find a

[20] An untabulated test shows that the sum of the PRET and PRET×LowDISP coefficients is 0.007 with a Fama-MacBeth t-statistic of 0.66, which is consistent with results in Tables 2 and 3 in that low-dispersion stocks show a *more* positive association between PRET and $RET_{t+1,t+12}$ than stocks with middle or high dispersion, but the positive association is not nearly as strong or robust as the negative association shown for stocks with the highest dispersion.

strong negative association (i.e., in contrast with no association) between predicted and future returns for high-dispersion stocks in our main results, distortion likely plays a larger role, but it is important to better understand the impacts of both disagreement and distortion as we consider the information conveyed by analysts' target prices.

We first test whether dispersion is simply capturing analyst disagreement (e.g., Diether et al. 2002; Li et al. 2021), which would lead to noisier, less useful price targets. To capture genuine disagreement and to tease out (at least some of) the effects of incentive-related distortions, we construct alternative versions of the predicted return and the associated dispersion. Instead of using the consensus numbers calculated by IBES in month *t*, we construct our own consensus and dispersion figures using only individual target prices issued in month *t*, which we call current-month predicted returns (CPRET) and current-month dispersion (CDISP). The logic behind this approach is that analysts might not update stale forecasts after bad news because of their incentives to curry favor with managers and preserve institutional relationships. As a result, very recently issued price targets are more likely to reflect all available information, even if firms have recently announced bad news. In our view, dispersion across a collection of recently issued price targets is more likely to reflect disagreement than differences stemming from incentive-driven biases.

We use CPRET and CDISP in our regression framework from equation (2). This approach allows us to replace PRET and DISP with CPRET and CDISP, and we can also include both versions of the variables simultaneously. Results are presented in Table 5. Column (1) shows a re-estimation of equation (2) since the sample with non-missing CPRET and CDISP results in fewer available firm-months than were used in Table 4. Confirming that our main results still hold in this smaller sample, column (1) of Table 5 shows that PRET×DISP continues to load significantly negative, with a coefficient magnitude similar to the first column of Table 4 (the *t*-statistic is smaller but still significant at $p < 0.01$). When we replace PRET and DISP with CPRET and CDISP in column (2) of Table 5, the interaction term remains significantly negative, but we find a smaller coefficient magnitude (-0.080 versus -0.133) and t-statistic (-3.66 versus -5.14) when compared to column (1). Finally, we include both versions of PRET and DISP in column (3) of Table 5 and find that PRET×DISP continues to load significantly negative with a similar magnitude to the results in the first column (-0.106, t = -3.50), whereas the coefficient on CPRET×CDISP becomes statistically insignificant (-0.039, t = -1.61). Taken together, the results in columns (2) and (3) suggest that disagreement plays a partial role in the negative association between predicted and realized returns, but distortions seem to be a more dominant factor in explaining the patterns observed for high-dispersion stocks.

To provide additional support for this interpretation, we build on the logic underlying the construction of CPRET and CDISP to consider whether stocks with high dispersion and large predicted returns exhibit evidence of analysts ignoring negative information and allowing their price targets to become stale. More specifically, we examine how PRET and DISP vary with (1) past stock performance; (2) the speed and extent of analysts updating their target prices; and (3) the difference between predicted returns from the consensus of all target prices (PRET) and predicted returns from only recently issued target prices (CPRET). For these tests, we create the following measures: $RET_{t\text{-}11,t}$ is the stock return over the 12 months ending with month t; $TPREV_{t\text{-}3,t}$ is the change in the mean analyst target price from month t-3 to month t, scaled by stock price in month t; TPREVTIME is the number of days since each analyst last updated their target price (averaged across all analysts for each firm-month); and (4) PRET-CPRET is the difference between PRET and CPRET, where CPRET is the current-month predicted return based only on individual target prices issued in month t. As CPRET reflects the most recent information, PRET-CPRET captures the staleness in the consensus target prices provided to investors. If target price dispersion reflects distortions from some analysts choosing to delay target price updates after poor performance and/or bad news, we should observe consistent patterns in these four variables ($RET_{t\text{-}11,t}$, $TPREV_{t\text{-}3,t}$, TPREVTIME, and PRET-CPRET) when comparing high-dispersion and low-dispersion stocks.

Using a structure similar to Table 2, Table 6 presents time series means for each of the four variables for each PRET decile in the first, sixth, and tenth DISP deciles (for parsimony we do not show all DISP deciles). We observe a general negative trend for $RET_{t\text{-}11,t}$ moving from PRET1 to PRET10 in all DISP deciles, indicating that stocks with higher predicted returns have experienced worse recent realized returns than stocks with lower predicted returns. However, the magnitude of this negative trend increases dramatically from DISP1 to DISP10, suggesting that the high-DISP, high-PRET stocks tend to be those with particularly poor past performance.[21] $TPREV_{t\text{-}3,t}$ tends to decline from PRET1 to PRET10 for medium- and high-dispersion stocks, but the magnitude of the differences from PRET1 to PRET10 are smaller than those observed for past stock returns. It is also noteworthy that DISP10 stocks have much more negative revisions. This suggests that bad news isn't being ignored entirely for high-DISP, high-PRET stocks, but perhaps some analysts aren't willing to fully adjust their price targets due to their incentives. More importantly, while average target price revision time (TPREVTIME) declines slightly from 133 days in PRET1 to 129 days in PRET10 for the lowest-DISP stocks, it *increases* from 133 days in PRET1 to 156 days in PRET10 for the highest-DISP stocks. In other words, the high-DISP, high-PRET stocks are those with the longest revision times, implying that these stocks have more stale consensus target prices.

Finally, PRET-CPRET, which captures the staleness in predicted returns from consensus target prices, increases from -5.9% in PRET1 to 53.0% in PRET10 for the highest-DISP stocks, whereas it increases only slightly for the lowest-DISP stocks. Taken together, the results in Table 6 suggest that a lack of timely updates to target prices—particularly after bad news—appears to be one key potential

[21] To illustrate the magnitude of the difference in the negative trend for DISP1 versus DISP10, consider the difference between the PRET10 and PRET1 values of $RET_{t\text{-}11,t}$ for stocks in DISP1 at -0.161 (i.e., 0.173 – 0.334) versus stocks in DISP10 at -0.633 (i.e., -0.222 – 0.411).

reason for high dispersion to exist in the first place. That is, if not all analysts update (or partially and/or differently revise) their target prices due to their incentives, dispersion will increase. Moreover, this lack of timely updates also helps explain why high predicted returns are negatively associated with future returns when the dispersion is large. If high dispersion is a signal of stale information, and these stocks also tend to have the worst recent performance, it suggests the consensus target price is simply too high.[22]

Overall, the evidence in Table 6 is in line with prior research suggesting that (1) analysts may not incorporate all public information into their price targets, particularly when the information is negative (Engelberg et al. 2019), and (2) analysts might not update earnings forecasts after receiving bad news due to their incentives and/or conflicts of interest (e.g., McNichols and O'Brien 1997; Hayes 1998; Raedy et al. 2006).[23] In the context of our research question, our results suggest that predicted returns from consensus target prices will be inflated for high-dispersion stocks because target prices are not updated enough after stock prices drop.

5.2. Implications for retail investors

So far, our analyses have shown that the dispersion in analysts' target prices significantly moderates the informativeness of consensus target prices. More specifically, we have shown that an investor can earn significant returns by going long in stocks with low DISP and high PRET while shorting stocks with high DISP and high PRET. This strategy obviously requires access to the cross-section of predicted returns along with underlying dispersion; moreover, only investors who appreciate the potential impact of analysts' incentives on target prices and their dispersion might think to consider

[22] Gleason et al. (2013) focus on individual analysts' target prices in the context of valuation techniques, but consistent with our results, they also note that "stale price targets are negatively related to realized returns" (p. 110).

[23] Ho et al. (2018) find that target price revisions are more sensitive to bad news than good news for UK firms, but their analyses are conditional upon observing a target price revision. Bradshaw et al. (2016) argue that "self-censoring is likely to contaminate studies that draw inferences based on revisions, for example, because some downward revisions may be missing" (p. 142). Our findings suggest that analysts are slower to update target prices after recent poor performance, which is consistent with Ho et al. (2018) in that when analysts do decide to issue a negative target price revision, it is likely to be after observing significant bad news.

such a strategy. These requirements are important to consider because they are unlikely to be satisfied for unsophisticated, retail investors, but these are precisely the sort of investors likely to be swayed by high consensus target prices available freely online. Lawrence et al. (2017) find that retail investors on Yahoo! Finance typically pay more attention to target prices and ratings than earnings forecasts; they also appear to pay much less attention to detailed financial statements and SEC filings than analyst-provided information. Relatedly, Malmendier and Shanthikumar (2007) argue that small investors tend to follow analyst advice literally instead of adjusting for analysts' incentives. As a result, we expect retail/unsophisticated investors to be more affected by inflated consensus target prices and to contribute more to the observed negative relationship between predicted and future realized returns for high-dispersion, high-predicted-return stocks.

The basic idea underlying this prediction is that because consensus target prices are freely available, easy to interpret, and have the guise of credibility, retail investors will simply place too much weight on them, leading them to buy stocks with high predicted returns based on consensus target prices. Prior research supports this intuition, with Barber and Odean (2008) asserting that retail investors are "net buyers of attention-grabbing stocks" (p. 785) and Barber and Odean (2000) contending that retail investors often experience poor investment performance due to overconfidence in their investment decisions. From a limits-to-arbitrage perspective, retail investors relying too much on high consensus target prices increases the dispersion in *investors'* (not analysts') expectations about future returns, thereby inflating stock prices which reflect the opinions of investors with the most positive outlook (Miller 1977; Diether et al. 2002). Stated differently, if retail investors naively follow inflated target prices for high-dispersion stocks and arbitrageurs cannot arbitrage away the mispricing, the pattern we observe for our main results should be exacerbated for stocks with more retail interest.[24]

[24] Recall that predicted returns based on target prices are very positively correlated with target price dispersion (see Table 1 Panel B). This means that even if retail investors are unaware of dispersion, their tendency to buy stocks with high predicted returns based on consensus target prices will also lead them to buy stocks with high dispersion.

To test this idea, we partition our sample into two groups based on institutional ownership (INST). Because institutional ownership is strongly correlated with firm size, we also regress institutional ownership on firm size each month and use the residuals as our measure of institutional ownership to ensure that we are not capturing effects related to firm size. Low institutional ownership implies high retail interest. If retail investors are attracted to stocks with high consensus target prices, we expect our results for high-dispersion stocks to be particularly strong in the low-INST subsample.

Table 7 reports results of equation (3) after we partition the sample based on the median raw (columns 1 and 2) or residual (columns 3 and 4) institutional ownership. Across all partitions, we find a significantly positive coefficient on PRET×LowDISP, which is consistent with our main results. This finding suggests that retail investors do not play a differentiating role in the slightly improved informativeness of target prices observed for low-dispersion stocks. On the other hand, we only observe a significantly negative PRET×HiDISP coefficient for low institutional ownership (both raw and residual), and the coefficient magnitudes are larger than the main sample coefficient on PRET×HiDISP in Table 4. These results suggest that stocks with high retail interest exhibit the most mispricing for high-PRET, high-DISP stocks, plausibly because retail investors exert buying pressure on stocks with high returns based on consensus target prices.

There are two main takeaways from these results. First, from a trading strategy perspective, sophisticated investors can likely earn even more returns if they focus on stocks with high retail interest before going long in low-DISP/high-PRET stocks and shorting high-DISP/high-PRET stocks. To test this conjecture, we recalculate the hedge returns from Tables 2 and 3 after partitioning the sample based on INST. As expected, untabulated results show that the hedge returns are much larger for low-INST stocks (ranging from 11.34% to 37.72%) than for high-INST stocks (ranging from 4.13% to 6.58%) or for the full sample shown in Tables 2 and 3 (ranging from 10.27% to 26.82%). Second, retail investors should exercise caution before buying stocks with high predicted returns based on consensus target prices. As indicated by the correlations between DISP and PRET in Table 1 Panel B, these stocks are likely to also exhibit high dispersion, and this dispersion plausibly indicates significant incentive-based distortion and staleness in the consensus (see Section 5.1). In light of this fact, online financial platforms could consider disclosing more information about the dispersion and staleness underlying consensus target prices. Having said that, some platforms (e.g., Yahoo! Finance and MarketWatch) already provide the range of analyst target prices, which could potentially be used by retail investors to proxy for underlying dispersion. To test this idea, we define RANGE as the highest target price in month *t* minus the lowest target price in month *t*, scaled by the current stock price in month *t* (using IBES data as in our main analyses). We then repeat our main tests using RANGE instead of DISP, and the results are very similar. These findings suggest that retail investors could use ranges to identify problematic stocks with high target-price-based predicted returns and high dispersion.[25]

5.3. Robustness tests

Our first robustness test examines future fundamental performance to test whether we observe patterns similar to what we document for future stock returns. In other words, the purpose of this test is to check whether the patterns in future returns shown in our main results are supported by corresponding future fundamental performance. For these tests, we simply modify equation (3) by replacing $RET_{t+1,t+12}$ with one of three proxies for future fundamental performance: (1) EARET is the average three-day return for earnings announcements occurring during the 12-month window from months *t*+1 to *t*+12 and captures surprises in earnings and other accounting performance; (2) $SURPRISE_{FY1}$ is the annual earnings surprise for the current fiscal year, measured as actual earnings

[25] In terms of potentially useful benchmarks, RANGE averages 301% and PRET averages 138% over time for stocks in the short (RANGE10, PRET10) portfolio. For comparison, RANGE (PRET) averages 13% (38%) for stocks in the long (RANGE1, PRET10) portfolio. The hedge return using RANGE instead of DISP averages 10.99% (*t*=5.20). Recommending that retail investors use the range in analyst target prices to proxy for dispersion echoes the approach used by Joos et al. (2016) in examining the range in individual analysts' scenario-based target prices. Joos et al. (2017) also suggest methods for approximating this type of information when scenario-based target prices are unavailable.

minus the median analyst forecast in month *t* (scaled by stock price on the forecast date); and (3) SURPRISE_{FY2} is the same as SURPRISE_{FY1} except that actual earnings for the following fiscal year are used. EARET captures the market response to firms' announced accounting performance, and the two SURPRISE measures capture the difference between firms' announced future accounting performance and analysts' expectations in month *t*.

Similar to the second column of Table 4, in Table 8 we observe significantly positive estimates of PRET×LowDISP for all three future performance measures (*t*-statistics range from 3.66 to 11.89), while PRET×HiDISP loads significantly negative for all three specifications (*t*-statistics range from -4.84 to -5.42). These results support the conclusion that the patterns in future stock returns observed in Tables 2, 3, and 4 reflect future fundamental performance. In other words, when analysts' target price dispersion is high (low), predicted returns based on the consensus target price are more negatively (positively) associated with future fundamental accounting performance, which helps justify the pattern for future returns documented in Tables 2, 3, and 4.

Our main results indicate that dispersion in analysts' target prices is a critical moderating factor for the informativeness of consensus target prices. We also consider an alternative measure of dispersion common in the accounting and finance literatures: Dispersion in analysts' earnings forecasts (EDISP), measured as the standard deviation of analysts' current year annual earnings forecasts in month *t*, scaled by stock price in month *t*. EDISP is more likely to capture genuine analyst disagreement than our primary measure of target price dispersion (DISP) because analysts update their earnings forecasts more frequently than target prices (see Table 1 Panel C). Thus, we expect EDISP to behave similarly to CDISP in Table 5, where we observe a moderating effect that is weaker than that of DISP.

We consider two empirical models. First, we replace DISP with EDISP in equation (2); second, we include both EDISP and DISP (and their interactions with PRET) in the model. Column (1) of Table 9 presents results when we replace DISP with EDISP. Consistent with expectations, the

PRET×EDISP interaction term is significantly negative (-0.080, t = -3.03), but the magnitude is smaller compared to the PRET×DISP coefficient reported in Table 4 (-0.108, t = -8.41). Moreover, when both EDISP and DISP are included (column [2] of Table 9), PRET×DISP continues to load strongly negative (-0.086, t = -2.94) while PRET×EDISP loads insignificantly (-0.031, t = -1.06). These results are consistent with our expectations and suggest that, although EDISP captures related information, DISP is a stronger moderator of the association between target prices and future realized returns because it captures incentive-based distortions in addition to disagreement among analysts.

Lastly, to ensure that our results are not unduly influenced by outlier individual price targets, we replicate our main findings using median instead of mean target prices when calculating predicted returns (PRET). The (untabulated) results are very similar to the evidence shown in Tables 2, 3, and 4, providing more assurance in the robustness of our inferences.

6. Conclusion

Consistent with prior research, we find that predicted returns based on consensus target prices are generally not informative about future returns, and in fact, stocks with the highest predicted returns tend to have the lowest future realized returns. To shed more light on this lack of target price informativeness, we investigate whether, when, and to what extent the dispersion in analysts' target prices moderates the degree to which consensus-based predicted returns are informative about future stock returns. We show that the dispersion in individual analyst target prices comprising the consensus is a critical moderating factor. When dispersion is low, we observe a more positive association between consensus predicted returns and future realized returns. In other words, when individual analysts agree about the target price and the consensus is less affected by incentive-driven distortions, the consensus prediction tends to correlate more positively with the future stock price. Still, however, we note that conditioning on low dispersion does not eliminate all of the inaccuracies in target prices highlighted in previous work.

On the other hand, when target price dispersion is high, we observe a strong, robust negative association between consensus-based predicted returns and future realized returns. Follow-up analyses suggest that high-dispersion and high-predicted-return stocks tend to exhibit recent poor performance, and analysts are slow to update their target prices to reflect this information. As a result, consensus target prices are inflated for these stocks. In other words, when analysts allow target prices to become distorted by delaying the incorporation of bad news, dispersion increases along with predicted returns becoming too high. We show that an investor can earn significant returns by going long in stocks with low dispersion and high predicted returns based on consensus target prices while shorting stocks with high dispersion and high predicated returns.

We also find that the strong negative correlation between consensus predicted returns and future realized returns manifests mainly for stocks with high retail interest, suggesting that retail/unsophisticated investors are simultaneously misled by high consensus price targets and unaware of the implications of high dispersion. Given that consensus target prices are readily available online at no cost, but the dispersion is *not* freely available, our results suggest that retail investors should use considerable caution before buying stocks with high price targets. Moreover, purveyors of financial information should carefully consider which (incomplete) financial information should be made widely available to investors online. From a regulatory perspective, one potential remedy would be to encourage financial websites to disclose the dispersion, staleness, or other information about the makeup of target prices that underlie the consensus.

References

Asquith, P., M. B. Mikhail, and A. S. Au. 2005. Information content of equity analyst reports. *Journal of Financial Economics* 75(2), 245-282.

Bandyopadhyay, S. P., L. D. Brown, and G. D. Richardson. 1995. Analysts' use of earnings forecasts in predicting stock returns: Forecast horizon effects. *International Journal of Forecasting* 11(3), 429-445.

Barber, B. M., and T. Odean. 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance* 55(2), 773-806.

Barber, B. M., and T. Odean. 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies* 21(2), 785-818.

Barron, O. E., M. H. Stanford, and Y. Yu. 2009. Further evidence on the relation between analysts' forecast dispersion and stock returns. *Contemporary Accounting Research* 26(2), 329–357.

Barron, O. E., and P. S. Stuerke. 1998. Dispersion in analysts' earnings forecasts as a measure of uncertainty. *Journal of Accounting, Auditing & Finance* 13, 245–270.

Bilinski, P., D. Lyssimachou, and M. Walker. 2013. Target price accuracy: International evidence. *The Accounting Review* 88(3), 825-851.

Bonini, S., L. Zanetti, R. Bianchini, and A. Salvi. 2010. Target price accuracy in equity research. *Journal of Business Finance & Accounting* 37(9-10), 1177-1217.

Brav, A., and R. Lehavy. 2003. An empirical analysis of analysts' target prices: Short-term informativeness and long-term dynamics. *Journal of Finance* 58, 1933–1967.

Bradshaw, M. T. 2002. The use of target prices to justify sell-side analysts' stock recommendations. *Accounting Horizons* 16(1), 27-41.

Bradshaw, M. T. 2004. How do analysts use their earnings forecasts in generating stock recommendations? *The Accounting Review* 79(1), 25-50.

Bradshaw, M. T. 2009. Analyst information processing, financial regulation, and academic research. *The Accounting Review* 84(4), 1073-1083.

Bradshaw, M. T. 2011. Analysts' forecasts: What do we know after decades of work? Working paper, Boston College.

Bradshaw, M. T., L. D. Brown, and K. Huang. 2013. Do sell-side analysts exhibit differential target price forecasting ability? *Review of Accounting Studies* 18, 930-955.

Bradshaw, M., Y. Ertimur, and P. O'Brien. 2016. Financial analysts and their contribution to well-functioning capital markets. *Foundations and Trends in Accounting* 11(3), 119-191.

Brown, L. D., G. D. Richardson, and C. A. Trzcinka. 1991. Strong-form efficiency on the Toronto stock exchange: An examination of analyst price forecasts. *Contemporary Accounting Research* 7(2), 323-346.

Brown, L. D., A. C. Call, M. B. Clement, and N. Y. Sharp. 2015. Inside the "black box" of sell-side financial analysts. *Journal of Accounting Research* 53(1), 1-47.

Carhart, M. 1997. On persistence in mutual fund performance. *Journal of Finance* 52, 57-82.

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

Da, Z., K. P. Hong, and S. Lee. 2016. What drives target price forecasts and their investment value? *Journal of Business Finance & Accounting* 43(3-4), 487-510.

Dechow, P. M., and H. You. 2020. Understanding the determinants of analyst target price implied returns. *The Accounting Review* 95(6), 125-149.

Diether, K. B., C. J. Malloy, and A. Scherbina. 2002. Differences of opinion and the cross section of stock returns. *The Journal of Finance* 57(5), 2113-2141.

Dimson, E., and P. Marsh. 1984. An analysis of brokers' and analysts' unpublished forecasts of UK stock returns. *The Journal of Finance* 39(5), 1257-1292.

Drake, M. S., L. Rees, and E. P. Swanson. 2011. Should investors follow the prophets or the bears? Evidence on the use of public information by analysts and short sellers. *The Accounting Review* 86(1), 101-130.

Engelberg, J., R. D. McLean, and J. Pontiff. 2019. Analysts and anomalies. Forthcoming, *Journal of Accounting and Economics*, https://doi.org/10.1016/j.jacceco.2019.101249.
Fama, E. F., and K. R. French. 1996. Multifactor explanations of asset pricing anomalies. *Journal of Finance* 51(1), 55-84.
Fama, E. F., and K. R. French. 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116(1), 1-22.
Fisher, M., and A. Raman. 1996. Reducing the cost of demand uncertainty through accurate response to early sales. *Operations Research* 44(1), 87-99.
Francis, J., and D. Philbrick. 1993. Analysts' decisions as products of a multi-task environment. *Journal of Accounting Research* 31(2), 216-230.
Francis, J., and L. Soffer. 1997. The relative informativeness of analysts' stock recommendations and earnings forecast revisions. *Journal of Accounting Research* 35(2), 193-211.
Gaba, A., D. G. Popescu, and Z. Chen. 2019. Assessing uncertainty from point forecasts. *Management Science* 65(1), 90-106.
Gleason, C. A., W. B. Johnson, and H. Li. 2013. Valuation model use and the price target performance of sell-side equity analysts. *Contemporary Accounting Research* 30(1), 80-115.
Groysberg, B., P. M. Healy, and D. Maber. 2011. What drives sell-side analyst compensation at high-status investment banks? *Journal of Accounting Research* 49(4), 969-1000.
Guar, V., S. Kesavan, A. Raman, and M. L. Fisher. 2007. Estimating demand uncertainty using judgmental forecasts. *Manufacturing & Service Operations Management* 9(4), 480-491.
Hayes, R. M. 1998. The impact of trading commission incentives on analysts' stock coverage decisions and earnings forecasts. *Journal of Accounting Research* 36(2), 299-320.
Ho, T. Q., N. Strong, and M. Walker. 2018. Modelling analysts' target price revisions following good and bad news? *Accounting and Business Research* 48(1), 37-61.
Huang, J., G. M. Mian, and S. Sankaraguruswamy. 2009. The value of combining the information content of analyst recommendations and target prices. *Journal of Financial Markets* 12, 754-777.
Imam, S., J. Chan, and S. Z. A. Shah. 2013. Equity valuation models and target price accuracy in Europe: Evidence from equity reports. *International Review of Financial Analysis* 28, 9-19.
Joos, P., J. D. Piotroski, and S. Srinivasan. 2016. Can analysts assess fundamental risk and valuation uncertainty? An empirical analysis of scenario-based value estimates. *Journal of Financial Economics* 121(3), 645-663.
Joos, P. R., and J. D. Piotroski. 2017. The best of all possible worlds: Unraveling target price optimism using analysts' scenario-based valuations. *Review of Accounting Studies* 22, 1492-1540.
Lawrence, A., J. P. Ryans, and E. Y. Sun. 2017. Investor demand for sell-side research. *The Accounting Review* 92(2), 123-149.
Li, X., H. Feng, S. Yan, and H. Wang. 2021. Dispersion in analysts' target prices and stock returns. *North American Journal of Economics and Finance* 56, 1-18.
Malkiel, B. G. 1982. Risk and return: A new look. In Friedman, B. (Ed.), *The Changing Roles of Debt and Equity in Financing U.S. Capital Formation*. Chicago: University of Chicago Press.
Malmendier, U., and D. Shanthikumar. 2007. Are small investors naïve about incentives? *Journal of Financial Economics* 85(2), 457-489.
McNichols, M., and P. C. O'Brien. 1997. Self-selection and analyst coverage. *Journal of Accounting Research* 35, 167-199.
Miller, E. M. 1977. Risk, uncertainty, and divergence of opinion. *Journal of Finance* 32(4), 1151-1168.
Morgan, J., and P. C. Stocken. 2008. Information aggregation in polls. *American Economic Review* 98(3), 864-896.
Raedy, J. S., P. Shane, and Y. Yang. 2006. Horizon-dependent underreaction in financial analysts' earnings forecasts. *Contemporary Accounting Research* 23(1), 291-322.
Schipper, K. 1991. Analysts' forecasts. *Accounting Horizons* 5(4), 105-121.
Surowiecki, J. 2005. *The Wisdom of Crowds*. Anchor Books, New York.
Trueman, B. 1994. Analyst forecasts and herding behavior. *The Review of Financial Studies* 7(1), 97-124.

Appendix
Variable Definitions

Variable	Definition
Main dependent variable	
$RET_{t+1,t+12}$	12-month future realized stock return from months *t*+1 to *t*+12, where month *t* is the month of calculation for the corresponding consensus analyst target price. Calculated using returns from the CRSP monthly stock file.
Main independent variables	
PRET	Predicted 12-month stock return based on the consensus analyst target price issued by IBES in month *t*. Calculated as (average target price – stock price)/stock price in month *t*. Monthly stock price is taken from the IBES Summary History Actuals + Pricing and Ancillary File. The value of the stock price is the closing price on the day before the monthly IBES Statistical Period Date (the day when consensus information is calculated).
DISP	Standard deviation of the predicted 12-month stock return (PRET), calculated as the IBES-reported standard deviation of individual analysts' target prices contributing to the consensus in month *t*, scaled by the stock price in month *t* (the same stock price used to calculate PRET). As part of our sample selection criteria, we only retain firm-months in IBES with at least four analysts contributing to the consensus calculation.
Other variables	
ACC	Accruals based on Compustat data, measured as the change in (non-cash current assets (ACT−CHE) minus non-debt current liabilities (LCT−DLC)) minus depreciation expense (DP), with the result scaled by average total assets. Similar to BM, ACC data are from the prior fiscal year end with at least a four-month lag.
AN	The number of analysts contributing to the IBES consensus target price calculation in month *t*.
BM	The book-to-market ratio from the prior fiscal year end, with at least a four-month lag between fiscal year end and month *t*. Calculated as Compustat CEQ scaled by (CSHO×PRCC_F).
CDISP	Current-month dispersion, calculated as the standard deviation of the predicted 12-month stock return using target prices issued in month *t* only, scaled by the stock price in month *t*. We require at least four analysts when calculating the variable.
CMA	Conservative minus aggressive investment factor from Fama and French (2015)
CPRET	Current-month predicted 12-month stock return using target prices issued in month *t* only, calculated as (average target price – stock price)/stock price in month *t*.
EARET	Average earnings announcement return over all earnings announcements occurring from months *t*+1 to *t*+12, where month *t* is the month of calculation for the corresponding consensus analyst target price. Each earnings announcement return is the three-day raw return centered on the earnings announcement date.
EDISP	Standard deviation of analysts' FY1 earnings forecasts (i.e., the first annual earnings announced after month *t*) from the monthly I/B/E/S summary file scaled by stock price in month *t*.
HiDISP	An indicator variable with the value of 1 for the top DISP quartile in a given month and 0 otherwise.
HML	High minus low value factor from Fama and French (1996).
INST	Institutional ownership from the most recent quarterly filing, calculated as the sum of shares owned by all institutional investors in the 13F database scaled by

	outstanding shares. We also calculated residual institutional ownership as the residual from regressing INST on firm size each month.
LowDISP	An indicator variable with the value of 1 for the bottom DISP quartile in a given month and 0 otherwise.
MOM	Momentum factor from Carhart (1997).
MV	Market value of equity at the end of month *t*, where month *t* is the month of calculation for the corresponding consensus analyst target price.
PRET−CPRET	The difference between PRET and CPRET.
$R_{it} - R_{ft}$	The average monthly excess return for each portfolio from month *t*+1 where month *t* is the month when consensus target prices and dispersion are measured.
$R_{Mt} - R_{ft}$	Excess market return as defined in Fama and French (1996).
RANGE	The range of analyst target prices underlying the consensus. Calculated as the highest target price in month *t* minus the lowest target price in month *t*, scaled by the stock price in month *t*.
$RET_{t-11,t}$	The 12-month realized return from months *t*-11 to *t*, where month *t* is the month of calculation for the corresponding consensus analyst target price. Calculated using returns from the CRSP monthly stock file.
$RET_{t-6,t-1}$	The six-month realized return from months *t*-6 to *t*-1, where month *t* is the month of calculation for the corresponding consensus analyst target price. Calculated using returns from the CRSP monthly stock file.
RET_{t+1}	One-month realized return for month *t*+1, used for the factor models in Table 3. Month *t* is the month of calculation for the corresponding consensus analyst target price. Calculated using returns from the CRSP monthly stock file.
RMW	Robust minus weak operating profitability factor from Fama and French (2015).
SIZE	Natural logarithm of MV.
SMB	Small minus big size factor from Fama and French (1996).
$SURPRISE_{FY1}$	Earnings surprise for FY1 earnings (i.e., the first annual earnings announced after month *t*), measured as actual earnings minus the median forecasted earnings in month *t*, scaled by stock price on the forecast date. Month *t* is the month of calculation for the corresponding consensus analyst target price.
$SURPRISE_{FY2}$	Same as $SURPRISE_{FY1}$ except that actual and forecasted earnings for the *next* fiscal year (FY2) are used.
$TPREV_{t-3,t}$	Change in the mean analyst target price from month *t*-3 to month *t*, scaled by stock price in month *t*. Monthly stock price is taken from the IBES Summary History Actuals + Pricing and Ancillary File. The value of the stock price is the closing price on the day before the monthly IBES Statistical Period Date (the day when consensus information is calculated).
TPREVTIME	Average of the number of days since the last time analysts updated their target prices. For each firm-month, we calculate the number of days since each analyst last updated her target price, and then calculate the average of the number of days across all analysts covering the firm in that month.

Table 1
Descriptive Statistics

Panel A: Univariate statistics

Variable	N	Mean	StDev	Min	Q1	Median	Q3	Max
$RET_{t+1,t+12}$	523,247	0.100	0.471	-0.998	-0.157	0.075	0.303	20.58
PRET	523,247	0.225	0.317	-0.421	0.056	0.146	0.290	6.643
DISP	523,247	0.181	0.177	0.021	0.088	0.133	0.210	4.181
AN	523,247	9.61	5.75	4	5	8	12	50
MV	523,247	8,995	29,752	1	762	2,027	6,068	1,562,781
BM	504,492	0.47	0.35	-0.60	0.23	0.40	0.64	4.24
$RET_{t-6,t-1}$	522,327	0.08	0.36	-0.99	-0.10	0.05	0.21	27.83
ACC	407,195	-0.040	0.061	-0.359	-0.070	-0.038	-0.011	0.257
$SURPRISEE_{FY1}$	447,464	-0.004	0.033	-1.188	-0.005	0.000	0.004	0.269
EARET	520,882	0.002	0.047	-0.856	-0.018	0.003	0.024	1.170

Panel B: Correlation matrix (Pearson above and Spearman below the diagonal)

	$RET_{t+1,t+12}$	PRET	DISP	MV	BM	$RET_{t-6,t-1}$	ACC
$RET_{t+1,t+12}$	1	-0.003	-0.004	-0.009	0.011	-0.007	-0.005
PRET	-0.046	1	0.726	-0.072	-0.084	-0.312	0.012
DISP	-0.048	0.446	1	-0.088	-0.044	-0.216	-0.020
MV	0.031	-0.260	-0.267	1	-0.090	0.008	-0.018
BM	0.028	-0.081	-0.079	-0.170	1	0.064	-0.002
$RET_{t-6,t-1}$	0.018	-0.440	-0.267	0.113	0.049	1	-0.029
ACC	-0.003	0.008	-0.050	-0.022	0.010	-0.031	1

Panel C: The revision frequency of annual earnings forecasts, target prices, and stock recommendations

Variable	N	Mean	StDev	Min	Q1	Median	Q3	Max
Annual earnings forecasts	42,772	3.85	1.32	1.00	3.00	3.68	4.50	26.00
Target prices	43,505	2.82	1.03	1.00	2.08	2.70	3.42	17.14
Stock recommendations	42,987	1.33	0.39	1.00	1.00	1.25	1.50	14.67

Table 1, continued

Panel D: Future realized returns across ten PRET deciles

	$RET_{t+1,t+12}$	PRET
PRET1	10.51%	-5.57%
PRET2	11.11%	3.14%
PRET3	11.32%	7.62%
PRET4	11.40%	11.48%
PRET5	11.51%	15.33%
PRET6	11.31%	19.59%
PRET7	10.82%	24.82%
PRET8	10.59%	32.06%
PRET9	9.16%	44.39%
PRET10	6.27%	84.71%
PRET10 – PRET1	-4.24% (-2.91)	

This table provides descriptive statistics and correlations among key variables. $RET_{t+1,t+12}$ is the 12-month future realized stock return. PRET is the predicted 12-month stock return based on the consensus analyst target price issued by IBES in month *t*. DISP is the standard deviation of the predicted 12-month stock return (PRET). MV is the market value of equity at the end of month *t*; BM is the book-to-market ratio from the end of the previous fiscal year. $RET_{t-6,t-1}$ is the 6-month past realized stock return. ACC is accruals from the end of the previous fiscal year. AN is the number of analysts contributing to the IBES consensus target price calculation in month *t*. $SURPRISE_{FY1}$ is the earnings surprise for FY1 earnings (i.e., the first annual earnings announced after month *t*). EARET is the average earnings announcement return over all earnings announcements occurring from months *t*+1 to *t*+12. Please see the appendix for detailed variable definitions. Our final sample includes 523,247 firm-month observations from July 1999 to June 2020 with non-missing $RET_{t+1,t+12}$, PRET, and DISP. Each month, all variables except returns are winsorized at 1% and 99%. Panel C reports average revision frequencies of annual earnings (FY1) forecasts, target prices, and stock recommendations made by each analyst. We first calculate average revision frequencies by analyst in each firm's fiscal year. Then we calculate average revision frequencies over more than 42,000 firm-year observations. Panel D reports the time-series average of mean future realized stock returns ($RET_{t+1,t+12}$) and predicted stock returns (PRET) across ten PRET deciles. Each month, we sort stocks into deciles based on PRET. Then we calculate average $RET_{t+1,t+12}$ and PRET for each decile. Finally, we calculate the time-series average of mean $RET_{t+1,t+12}$ and PRET for each decile. Panel D also reports the hedge return, with the Fama-MacBeth *t*-statistic in parentheses.

Table 2
Future Returns based on Two-way Sort by Dispersion and Predicted Return

	PRET1	PRET2	PRET3	PRET4	PRET5	PRET6	PRET7	PRET8	PRET9	PRET10	PRET10 -PRET1
DISP1	9.14%	10.16%	9.96%	10.72%	10.56%	11.47%	11.59%	11.06%	12.31%	11.78%	2.64%
											(2.35)
DISP2	9.29%	10.60%	10.37%	11.51%	10.33%	11.47%	10.73%	10.81%	11.72%	11.22%	1.93%
											(1.59)
DISP3	10.85%	10.34%	11.08%	11.07%	11.31%	11.05%	11.78%	10.44%	9.76%	10.92%	0.07%
											(0.05)
DISP4	9.42%	10.65%	11.00%	11.10%	10.94%	12.13%	11.53%	11.01%	10.46%	9.83%	0.41%
											(0.35)
DISP5	10.89%	11.71%	11.24%	11.44%	11.26%	12.29%	10.95%	11.66%	9.62%	7.98%	-2.91%
											(-2.18)
DISP6	11.01%	11.72%	11.89%	11.45%	10.67%	11.55%	11.12%	11.81%	9.38%	8.00%	-3.00%
											(-2.21)
DISP7	11.54%	14.77%	12.41%	12.71%	11.96%	11.68%	10.57%	10.22%	9.49%	7.73%	-3.81%
											(-2.28)
DISP8	12.14%	13.06%	12.64%	13.24%	11.41%	11.44%	10.48%	10.05%	10.01%	7.22%	-4.92%
											(-3.26)
DISP9	11.25%	10.78%	12.44%	10.22%	10.21%	9.38%	8.84%	9.27%	8.31%	4.42%	-6.84%
											(-3.83)
DISP10	10.94%	8.68%	5.59%	8.60%	6.65%	6.95%	6.29%	7.49%	5.60%	1.52%	-9.42%
											(-4.68)
RET(DISP1, PRET10) – RET(DISP10, PRET10)										10.27%	
										(4.86)	

This table reports time series portfolio means for 12-month future realized stock returns ($RET_{t+1,t+12}$) based on two-way sorts by the standard deviation of predicted returns (DISP) and predicted stock returns based on consensus target prices (PRET). Each month, we first sort stocks into ten deciles by DISP. Then for each resulting DISP decile, we further sort stocks into ten groups by PRET. This process leaves us with 100 (10×10) portfolios each month. PRET10–PRET1 is a hedge portfolio with a long position on PRET10 stocks and a short position on PRET1 stocks. Please see the appendix for detailed variable definitions. Our final sample includes 523,247 firm-month observations from July 1999 to June 2020 with non-missing $RET_{t+1,t+12}$, PRET, and DISP. The tabulated portfolio returns are the average of $RET_{t+1,t+12}$ for each portfolio over time; Fama-MacBeth *t*-statistics are in parentheses.

Table 3
Factor Models on Hedge Portfolio Returns across Dispersion Deciles

Panel A: Fama-French 4-factor model

	Intercept	$R_{Mt} - R_{ft}$	SMB	HML	MOM	Adj. R^2
Long	0.342	1.012	0.271	0.370	-0.013	0.724
(DISP1, PRET10)	(1.74)	(20.95)	(4.28)	(5.99)	(-0.31)	
Short	-1.659	1.732	1.127	-0.643	-0.639	0.716
(DISP10, PRET10)	(-3.72)	(15.80)	(7.84)	(-4.59)	(-6.96)	
Hedge	2.000	-0.720	-0.856	1.103	0.626	0.504
(Long – Short)	(4.46)	(-6.52)	(-5.92)	(7.18)	(6.78)	

Panel B: Fama-French 5-factor model

	Intercept	$R_{Mt} - R_{ft}$	SMB	HML	RMW	CMA	Adj. R^2
Long	0.154	1.079	0.417	0.202	0.338	-0.039	0.740
(DISP1, PRET10)	(0.77)	(21.50)	(5.88)	(2.47)	(3.73)	(-0.32)	
Short	-1.238	1.684	0.759	0.141	-0.929	-1.126	0.698
(DISP10, PRET10)	(-2.58)	(13.91)	(4.44)	(0.72)	(-4.24)	(-3.78)	
Hedge	1.391	-0.605	-0.343	0.061	1.267	1.087	0.503
(Long – Short)	(2.96)	(-5.11)	(-2.05)	(0.32)	(5.92)	(3.73)	

This table reports coefficient estimates of four-factor (Panel A) and five-factor (Panel B) models for monthly returns for the long, short, and hedge portfolios. The hedge portfolios are from the two-way sorts by the standard deviation of predicted returns (DISP) and predicted stock returns based on consensus target prices (PRET). Each month, we first sort stocks into ten deciles by DISP. Then, for each resulting DISP decile, we further sort stocks into ten groups by PRET. The long position is for stocks in the low-DISP and high-PRET group, whereas the short position is for stocks in the high-DISP and high-PRET group. We rebalance our portfolio and calculate one-month-ahead returns (RET_{t+1}) each month. Please see the appendix for detailed variable definitions. The four- and five-factor models estimated are:

$$R_{it} - R_{ft} = a + b_{iM}\left(R_{Mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + m_i MOM_t + \varepsilon_{it},$$
$$R_{it} - R_{ft} = a + b_{iM}(R_{Mt} - R_{ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{it},$$

where R_{Mt} -R_{ft}, SMB, and HML are as defined in Fama and French (1996), MOM is the momentum factor as defined in Carhart (1997), and RMW and CMA are profitability and investment factors as defined in Fama and French (2015). Factor data comes from Kenneth French's website. The time-series data of one-month-ahead returns used in the multi-factor models are from August 1999 to July 2020, corresponding to the target price data from July 1999 to June 2020.

Table 4
Regressions of Future Returns on Predicted Returns and Dispersion

Column:	1		2
Intercept	0.142 (9.98)	Intercept	0.160 (9.79)
PRET	0.016 (1.72)	PRET	-0.039 (-4.58)
DISP	0.038 (3.19)	LowDISP	-0.016 (-3.23)
PRET×DISP	-0.108 (-8.41)	HiDISP	0.021 (2.70)
		PRET×LowDISP	0.046 (6.08)
		PRET×HiDISP	-0.051 (-5.61)
SIZE	-0.035 (-4.25)	SIZE	-0.034 (-4.14)
BM	-0.033 (-2.77)	BM	-0.033 (-2.72)
$RET_{t-6,t-1}$	0.001 (0.05)	$RET_{t-6,t-1}$	0.001 (0.05)
ACC	0.003 (0.88)	ACC	0.004 (1.09)
Adj. R^2	0.059	Adj. R^2	0.058

This table describes regressions of 12-month future realized stock returns ($RET_{t+1,t+12}$) on predicted stock returns based on consensus target prices (PRET), the standard deviation of predicted returns (DISP), and control variables. DISP is the standard deviation of the predicted 12-month stock return (PRET). LowDISP is an indicator variable with the value of 1 for the bottom DISP quartile in a given month and 0 otherwise. HiDISP is an indicator variable with the value of 1 for the top DISP quartile in a given month and 0 otherwise. Controls are SIZE (natural logarithm of the market value of equity), BM (the book-to-market ratio), $RET_{t-6,t-1}$ (the 6-month past realized stock return), and ACC (accruals). Please see the appendix for detailed variable definitions. Our main sample includes 523,247 firm-month observations from July 1999 to June 2020 with non-missing $RET_{t+1,t+12}$, PRET, and DISP, but these regressions also require non-missing control variables. Each month, all independent variables except dummy variables are decile ranks converted to a [0,1] scale. The coefficient estimates are the average of monthly estimates over time; Fama-MacBeth *t*-statistics are in parentheses.

Table 5
Regressions of Future Returns on Current-month Predicted Returns and Dispersion

Column:	1	2	3
Intercept	0.161	0.145	0.155
	(8.10)	(7.54)	(7.94)
PRET	0.016		-0.001
	(0.93)		(-0.06)
DISP	0.041		0.033
	(2.17)		(1.68)
PRET×DISP	-0.133		-0.106
	(-5.14)		(-3.50)
CPRET		0.006	0.029
		(0.39)	(1.57)
CDISP		0.019	0.011
		(1.24)	(0.77)
CPRET×CDISP		-0.080	-0.039
		(-3.66)	(-1.61)
SIZE	-0.061	-0.053	-0.060
	(-4.91)	(-4.30)	(-4.84)
BM	-0.050	-0.047	-0.050
	(-3.58)	(-3.38)	(-3.62)
$RET_{t-6,t-1}$	0.022	0.037	0.020
	(1.37)	(2.28)	(1.29)
ACC	0.003	0.004	0.004
	(0.43)	(0.58)	(0.51)
Adj. R^2	0.091	0.084	0.097

This table describes regressions of 12-month future realized stock returns ($RET_{t+1,t+12}$) on predicted stock returns based on consensus target prices (PRET), the standard deviation of predicted returns (DISP), and control variables. DISP is the standard deviation of the predicted 12-month stock return (PRET). In columns (2) and (3), we construct our own consensus target prices (CPRET) and their standard deviation (CDISP) based on individual target prices issued in month *t* to consider only recently issued target prices, but we still require at least four individual target prices to calculate the standard deviation. Controls are SIZE (natural logarithm of the market value of equity), BM (the book-to-market ratio), $RET_{t-6,t-1}$ (the 6-month past realized stock return from month), and ACC (accruals). Please see the appendix for detailed variable definitions. Each month, all independent variables except dummy variables are decile ranks converted to a [0,1] scale. The coefficient estimates are the average of monthly estimates over time; *t*-statistics in parentheses are Fama-MacBeth *t*-statistics. The sample includes 127,512 firm-month observations with non-missing CPRET and CDISP from July 1999 to June 2020.

Table 6
Past Returns, Target Price Revisions, and Staleness in Target Prices for Portfolios Sorted by Dispersion and Predicted Returns

	PRET Decile:	1	2	3	4	5	6	7	8	9	10
DISP1	$RET_{t\text{-}11,t}$	0.334	0.255	0.242	0.233	0.215	0.215	0.207	0.207	0.192	0.173
	$TPREV_{t\text{-}3,t}$	0.024	0.033	0.032	0.031	0.030	0.035	0.031	0.031	0.031	0.022
	TPREVTIME	133	133	134	134	133	131	133	132	130	129
	PRET−CPRET	-4.8%	-3.7%	-2.5%	-2.3%	-1.6%	-1.2%	-0.5%	0.1%	1.1%	3.6%
DISP6	$RET_{t\text{-}11,t}$	0.461	0.343	0.290	0.243	0.178	0.167	0.124	0.100	0.085	0.049
	$TPREV_{t\text{-}3,t}$	0.041	0.034	0.025	0.015	0.007	-0.003	-0.013	-0.020	-0.024	-0.029
	TPREVTIME	122	128	129	128	131	130	130	131	132	133
	PRET−CPRET	-8.8%	-5.9%	-3.3%	-2.0%	-0.6%	0.7%	2.2%	3.8%	5.4%	9.8%
DISP10	$RET_{t\text{-}11,t}$	0.411	0.143	0.039	-0.033	-0.066	-0.089	-0.089	-0.129	-0.155	-0.222
	$TPREV_{t\text{-}3,t}$	-0.078	-0.143	-0.181	-0.197	-0.217	-0.237	-0.248	-0.270	-0.283	-0.317
	TPREVTIME	133	131	130	131	131	129	133	138	143	156
	PRET−CPRET	-5.9%	4.5%	10.6%	13.6%	19.1%	22.8%	26.7%	34.5%	47.6%	53.0%

This table describes the relation between our variables of interest (PRET and DISP) and the following variables: past 12-month returns from months t-11 to t ($RET_{t\text{-}11,t}$), past three-month analyst target price revision ($TPREV_{t\text{-}3,t}$), the average time lag since analysts last updated their target prices (TPREVTIME), and the difference between PRET and CPRET (PRET−CPRET). CPRET is the current-month predicted returns based on individual target prices issued in month t (also used in Table 5). Please see the appendix for detailed variable definitions. We present portfolio averages of these variables for each PRET decile within the first, sixth, and tenth DISP deciles (for parsimony not all DISP deciles are shown).

Table 7
Regressions of Future Returns on Predicted Returns and Dispersion with Partitions by Institutional Ownership

Sample:	Low INST	High INST	Low residual INST	High residual INST
Column:	1	2	3	4
Intercept	0.164	0.149	0.167	0.149
	(9.61)	(9.28)	(9.73)	(9.35)
PRET	-0.044	-0.033	-0.049	-0.030
	(-4.11)	(-3.90)	(-4.58)	(-3.47)
LowDISP	-0.017	-0.016	-0.017	-0.013
	(-2.33)	(-3.23)	(-2.62)	(-2.63)
HiDISP	0.034	-0.000	0.029	0.003
	(3.07)	(-0.05)	(2.87)	(0.40)
PRET×LowDISP	0.048	0.046	0.046	0.041
	(3.32)	(4.99)	(4.10)	(4.25)
PRET×HiDISP	-0.082	-0.004	-0.070	-0.012
	(-5.82)	(-0.37)	(-5.49)	(-1.18)
SIZE	-0.041	-0.019	-0.039	-0.020
	(-4.37)	(-2.43)	(-4.26)	(-2.73)
BM	-0.016	-0.040	-0.018	-0.039
	(-1.21)	(-3.56)	(-1.37)	(-3.50)
$RET_{t-6,t-1}$	0.001	-0.001	0.000	-0.001
	(0.04)	(-0.09)	(0.03)	(-0.09)
ACC	-0.005	0.009	-0.007	0.011
	(-0.96)	(2.12)	(-1.47)	(2.24)
Adj. R^2	0.063	0.055	0.067	0.052

This table describes regressions of 12-month future realized stock returns ($RET_{t+1,t+12}$) on predicted stock returns based on consensus target prices (PRET), the standard deviation of predicted returns (DISP), and control variables for subsamples partitioned by raw and residual institutional ownership (INST). DISP is the standard deviation of the predicted 12-month stock return (PRET). LowDISP is an indicator variable with the value of 1 for the bottom DISP quartile in a given month and 0 otherwise. HiDISP is an indicator variable with the value of 1 for the top DISP quartile in a given month and 0 otherwise. Controls are SIZE (natural logarithm of the market value of equity), BM (the book-to-market ratio), $RET_{t-6,t-1}$ (the 6-month past realized stock return), and ACC (accruals). For the sample partitions, residual institutional ownership is the residual of regressing raw INST on firm size each month. The low and high residual institutional ownership subsamples include observations with residual ownership below and above the median each month, respectively. The split on raw INST is also median-based. Please see the appendix for detailed variable definitions. Each month, all independent variables except dummy variables are decile ranks converted to a [0,1] scale. The coefficient estimates are the average of monthly estimates over time; Fama-MacBeth t-statistics are in parentheses. The sample includes 510,159 firm-month observations with non-missing institutional ownership data from July 1999 to June 2020. The sample is slightly smaller than that from the main analysis because we require non-missing institutional ownership data.

Table 8
Regressions of Future Fundamental Performance on Predicted Returns and Dispersion

Dependent variable:	EARET	$SURPRISE_{FY1}$	$SURPRISE_{FY2}$
Column:	1	2	3
Intercept	0.004	-0.003	-0.010
	(7.02)	(-9.82)	(-11.89)
PRET	-0.002	-0.004	-0.016
	(-4.42)	(-9.63)	(-17.49)
LowDISP	-0.002	-0.000	-0.001
	(-6.23)	(-0.84)	(-3.24)
HiDISP	-0.000	0.000	0.001
	(-0.60)	(0.79)	(0.64)
PRET×LowDISP	0.006	0.001	0.008
	(7.21)	(3.66)	(11.89)
PRET×HiDISP	-0.004	-0.006	-0.013
	(-4.84)	(-5.42)	(-5.41)
SIZE	0.000	0.003	0.012
	(0.44)	(18.29)	(18.68)
BM	-0.000	-0.006	-0.016
	(-0.92)	(-11.57)	(-14.08)
$RET_{t-6,t-1}$	0.001	0.007	0.015
	(1.61)	(18.29)	(22.64)
ACC	0.001	-0.000	-0.000
	(2.23)	(-0.55)	(-0.55)
Adj. R^2	0.007	0.055	0.099

This table describes regressions of future earnings announcement returns (EARET), earnings surprises for FY1 earnings ($SURPRISE_{FY1}$), and earnings surprises for FY2 earnings ($SURPRISE_{FY2}$) on predicted stock returns based on consensus target prices (PRET), the standard deviation of predicted returns (DISP), and control variables. DISP is the standard deviation of the predicted 12-month stock return (PRET). LowDISP is an indicator variable with the value of 1 for the bottom DISP quartile in a given month and 0 otherwise. HiDISP is an indicator variable with the value of 1 for the top DISP quartile in a given month and 0 otherwise. Controls are SIZE (natural logarithm of the market value of equity), BM (the book-to-market ratio), $RET_{t-6,t-1}$ (the 6-month past realized stock return), and ACC (accruals). Please see the appendix for detailed variable definitions. Each month, all independent variables except dummy variables are decile ranks converted to a [0,1] scale. The coefficient estimates are the average of monthly estimates over time; Fama-MacBeth *t*-statistics are in parentheses.

Table 9
Regressions of Future Returns on Predicted Returns and Dispersion Controlling for Earnings Forecast Dispersion

Column:	1	2
Intercept	0.164	0.156
	(7.18)	(7.19)
PRET	-0.014	0.019
	(-0.78)	(0.97)
DISP		0.035
		(1.90)
PRET×DISP		-0.086
		(-2.94)
EDISP	0.004	-0.021
	(0.23)	(-1.22)
PRET×EDISP	-0.080	-0.031
	(-3.03)	(-1.09)
SIZE	-0.054	-0.056
	(-4.16)	(-4.44)
BM	-0.031	-0.032
	(-2.36)	(-2.57)
$RET_{t\text{-}6,t\text{-}1}$	0.022	0.024
	(1.37)	(1.46)
ACC	-0.001	-0.001
	(-0.18)	(-0.09)
Adj. R^2	0.095	0.103

This table describes regressions of 12-month future realized stock returns ($RET_{t+1,t+12}$) on predicted stock returns based on consensus target prices (PRET), the standard deviation of predicted returns (DISP), and control variables. DISP is the standard deviation of the predicted 12-month stock return (PRET). EDISP is the dispersion in analysts' FY1 earnings forecasts scaled by stock price. Controls are SIZE (natural logarithm of the market value of equity), BM (the book-to-market ratio), $RET_{t\text{-}6,t\text{-}1}$ (the 6-month past realized stock return from month), and ACC (accruals). Please see the appendix for detailed variable definitions. Each month, all independent variables except dummy variables are decile ranks converted to a [0,1] scale. The sample includes 443,151 firm-month observations with non-missing EDISP data from July 1999 to June 2020. The coefficient estimates are the average of monthly estimates over time; Fama-MacBeth t-statistics are in parentheses.