Consensus Analyst Target Prices:
Information Content and Implications for Investors

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ABSTRACT: Consensus analyst target prices are widely available online at no cost to investors. In this paper we consider whether these consensus target prices are informative for predicting future returns. We find that when considered in isolation, consensus target prices are not generally informative about future returns. However, we also show that the *dispersion* of individual analysts' target prices that comprise the consensus is an important moderating factor. More specifically, when dispersion is low (high), there is a strong positive (negative) correlation between predicted returns based on the consensus target price and future realized returns. Additional analyses suggest that this phenomenon is due to consensus target prices being slow to reflect bad news. Finally, we show that the negative correlation between consensus-based predicted returns and future realized returns for high-dispersion stocks exists only for high short interest and low institutional ownership, suggesting that limits to arbitrage play a role in the observed mispricing and that unsophisticated investors are negatively impacted by high consensus target prices.

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

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1. Introduction

The purposes of this study are to better understand the information content of consensus analyst target prices and to provide evidence about the implications of having consensus target prices widely available to investors. We view this as an important topic of research for several reasons. First, as has been noted in prior literature (e.g., Bradshaw 2002; Dechow and You 2018), consensus target prices are freely available to individual investors on many financial websites.[1] This suggests that either investors find these measures useful, or the purveyors of financial information believe they should be useful to investors. Second, target prices are among the primary components of analysts' research reports (Bradshaw et al. 2016), and they are straightforward for investors to understand (Bilinski et al. 2013; Ho et al. 2018). While investors may also observe more detailed data about earnings, growth, or sales forecasts, they need to decide how to map this information into a stock price. On the other hand, it is simple for any investor (even a less sophisticated one) to compare today's stock price with a future price target in order to estimate the future return.[2] Third, compared to the large literatures on analysts' earnings forecasts and stock recommendations, relatively little research has focused on target prices (Bradshaw et al. 2016; Ho et al. 2018), particularly the *consensus* target price. Online financial platforms report the consensus rather than individual target prices, and consensus measures reduce the noise that is inherent in individual judgments (Dimson and Marsh; Larrick and Soll 2006) and represent the collective opinion of analysts who cover the firm (e.g., Galton 1907; Surowiecki 2005). In light of

[1] For example, the following websites provide consensus analyst target prices for free online: Yahoo! Finance, MarketWatch, MSN Money, and CNBC.
[2] Analysts' stock recommendations (e.g., sell/hold/buy) are also available and straightforward. However, like Francis and Soffer (1997), we argue that while recommendations capture "discrete rather than continuous assessments of security mispricing,…the *degree of mispricin*g is important to investors" (p. 194, emphasis added).

these motivating reasons, our study contributes to the literature that examines the central questions of whether and how analysts' outputs are useful to capital markets.[3]

As with most analyst-based research, target price data used by most researchers comes from Thomson Reuters' IBES database. We begin our analysis by providing a brief overview of the consensus target price provided monthly by IBES. This is a necessary first step because the few prior studies that consider consensus target prices (e.g., Gleason et al. 2013; Dechow and You 2018) do not use the consensus provided by IBES but instead construct their own consensus measures after screening individual analyst target prices available to researchers. These custom consensus measures may not correspond to the consensus information widely available to investors on the internet. Given that many financial websites obtain their underlying target price data from Thomson Reuters/Refinitiv, we believe that examining the characteristics of the IBES consensus (a Refinitiv product) will shed light on the consensus information that is freely available to investors.[4]

We construct a sample of 465,797 firm-month observations with available consensus target price data from July 1999 to June 2018. Comparing the consensus target price to current stock price, we find that the mean (median) predicted return in our sample is 21.7% (14.4%), while the realized return averages 9.3%. This finding is consistent with prior research suggesting that analysts' target prices are overly optimistic (e.g., Brav and Lehavy 2003; Asquith et al. 2005; Bradshaw et al. 2013). On average, these consensus target prices are based on the targets of 9.5 individual analysts, and the standard deviation of the predicted return averages 18%, indicating considerable disagreement among analysts contributing to the consensus target price. Turning to our main analyses, we first consider the

[3] See Bradshaw et al. (2016) for a recent review of the literature on analysts and their roles in capital markets.

[4] While financial websites provide the consensus target price information freely, they do not provide access to historical data. As a result, our main analyses rely on IBES data. However, as explained in Section 2.1, we manually collected consensus target price data each day during the month of April 2019 for a random sample of 30 firms in order to provide more information about how online consensus information differs across websites and compares to the consensus target prices reported by IBES. Our analyses suggest the IBES consensus is very similar to the consensus measures reported on the financial websites.

information content of the consensus target price by forming deciles each month based on the consensus predicted return and examining over-time average portfolio returns for each decile. If the predicted returns based on the consensus target price are an informative signal, we would expect these predicted returns to be positively correlated with future realized returns. However, we find that while the realized portfolio returns are quite similar from decile 1 (lowest predicted returns) to decile 8, the realized returns are *worst* for deciles 9 and 10 (highest predicted returns). In other words, stocks with the highest predicted returns based on the consensus target price tend to perform the worst, a pattern opposite to what is suggested by predicted returns based on consensus target prices. Overall, this result suggests that consensus target prices are not generally informative about relative stock performance.

To shed light on this counterintuitive result, we next perform a double-sort each month using the consensus predicted return and its standard deviation based on the individual target prices that comprise the consensus. We focus on the standard deviation because the degree of dispersion in individual estimates can provide an important signal about the amount of uncertainty associated with the consensus (e.g., Malkiel 1982; Barron and Stuerke 1998; Barron et al. 2009), and greater disagreement among the analysts may predict lower accuracy of the average estimate (Fisher and Raman 1994, Guar et al. 2007; Gaba et al. 2019). In addition, if some analysts are slow in updating their target prices, the information in the consensus measure will be distorted, and the standard deviation will tend to increase. This issue could be particularly important for retail investors because individual target prices (and the corresponding standard deviation) are *not* freely available online and must be acquired by subscribing to a data provider such as Bloomberg or Thomson Reuters/Refinitiv.

Interestingly, we find a positive relation between the consensus predicted return and future realized returns when the dispersion in predicted returns is low. These results suggest that when analysts agree in their target prices, the cross-sectional variation in predicted returns is informative about future realized returns. However, the relation becomes strongly negative when the dispersion is high, suggesting that predicted returns based on these high-dispersion consensus target prices correlate with future returns in the opposite direction. Utilizing the predictable mispricing patterns from both low- and high-dispersion cases, a hedge portfolio that takes a long (short) position in the stocks with the highest decile of predicted returns within the lowest (highest) standard deviation decile earns nearly 12% annually. This result is robust to 4-factor model, 5-factor model, and regression frameworks.

To further unpack this result, we next show that the standard deviation of the predicted return also moderates the relation between the predicted return and the following measures of future fundamental performance: realized returns at future earnings announcements and future analyst forecast errors. Specifically, the predicted return based on target prices is positively (negatively) correlated with future earnings announcement returns and future analyst forecast errors for stocks with low (high) standard deviation of predicted returns. Put differently, the double-sort return results described above reflect future fundamental performance.

We next consider the question of *why* the information content of consensus predicted returns differs between low- and high-standard-deviation stocks. We find that past realized returns and past earnings forecast revisions are positively correlated with the predicted return for stocks with a low standard deviation of predicted returns, indicating that the consensus target price reflects past performance-related news. However, for the stocks with a high standard deviation of predicted return, the association between the consensus predicted return and past performance is highly negative. To confirm this result, we also examine past target price revisions and find that for low-dispersion stocks, there is a much more positive association between the consensus predicted return and past target price revisions; however, there is no such association for high-dispersion stocks, suggesting that target prices are not being revised downward after the arrival of bad news. This result is consistent with Brav and Lehavy's (2003) conclusion that target prices are more likely to accompany stock recommendation upgrades (i.e., good news) than recommendation downgrades (i.e., bad news).

In light of our findings, we consider two possible channels for why consensus-target-price-based predicted returns are negatively correlated with future realized returns when target price dispersion is high. First, some analysts are slow to revise their target price downward when firm fundamentals deteriorate, which simultaneously increases the standard deviation of the predicted return and pushes the consensus target price too high. Second, the dispersion in predicted returns may simply be capturing fundamental uncertainty and investor disagreement. Given limits to arbitrage, Miller (1977) suggests that stocks with higher uncertainty and investor disagreement tend to be overvalued. To explore these two possible channels, we perform several empirical tests.

First, we consider earnings forecast dispersion as a proxy for fundamental uncertainty by using it in place of, and in addition to, our main dispersion measure (dispersion in consensus-target-price-based predicted returns) in our regression framework. To the extent that both channels are responsible for our results, we expect a smaller effect of earnings forecast dispersion as it only captures the fundamental uncertainty channel. By the same token, controlling for earnings forecast dispersion should weaken the effect of our main dispersion measure. Observed empirical results confirm these expectations. Turning to the issue of forecast staleness, we construct two alternative versions of the consensus-target-price-based predicted return (and its dispersion) using only individual target prices issued in month *t* and issued in months *t-1* and *t*. As these two versions do not include any stale target prices, they tend to capture the channel of fundamental uncertainty and investor disagreement only. As expected, while the coefficient of interest in the regressions is reduced somewhat, it remains negative and highly significant. Taken together, these findings are consistent with the view that both channels contribute to the relation between predicted returns and future performance.

Finally, we consider our findings more explicitly in the context of Miller's (1977) argument that when there is more opinion divergence about future performance among investors, stock prices will be higher because the price will reflect the opinions of those with the highest expectations. As some investors (i.e., retail/unsophisticated investors) rely on the inaccurate consensus target price while other investors (i.e., institutional/sophisticated investors) rely on more complete information, the price will be too high when there are limits to arbitrage, resulting in lower future returns. Consistent with these arguments, we confirm that the observed mispricing for high-dispersion stocks with inflated consensus target prices is concentrated in stocks with higher limits to arbitrage as proxied by high short interest (i.e., stocks with high costs of shorting). Next, we show that the negative correlation between consensus predicted returns and future realized returns for high-dispersion stocks exists only for those stocks with low institutional ownership. This suggests that retail/unsophisticated investors are more likely to be fooled by relying on high consensus target prices than institutional investors who may have access to more underlying data (i.e., dispersion in individual analysts' target prices) and more information about the firm. These results are consistent with the Miller (1977) story and also have implications for the type of financial information that is provided freely online. Because this information is likely to be used by retail investors and appears "official" and "valid," providers must exercise caution in deciding what information to supply to investors.

This paper makes several contributions to the literature. Our evidence that the dispersion of individual analysts' target prices plays an important moderating role and flips the informativeness of target prices between low- and high-dispersion stocks could be of interest to academics, practitioners, and regulators. These findings extend the academic literature on target prices by providing a more complete understanding of the information content of consensus target prices and their implications for future returns. Practitioners will be interested in our findings as they provide a road map for portfolio management based on consensus target prices. Finally, regulators could be concerned that retail investors appear to be fooled by optimistic target prices when the dispersion is high and may want to regulate the disclosure practice of target prices, and perhaps even analyst behavior, to level the playing field for all investors.

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

2. Background and research questions

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 (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.[5] 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). 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). 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 point of view that target prices are important to investors.

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 too much about forecast accuracy (e.g., 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). Moreover, many potential conflicts of interest relating to analysts have been identified in the literature. For

[5] Of the 5.2 million observations in the IBES Target Price Detail History file, over 90% have a 12-month horizon, and according to WRDS, all target price summary statistics calculated by IBES are based on the 12-month horizon.

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 may also play a role in analysts' target prices.

While the majority of prior target price research focuses on individual analysts' target prices (and their revisions), we focus specifically on the *consensus* target price for several reasons. First, financial websites commonly provide consensus target price information to the investing public at no cost.[6] Moreover, retail/unsophisticated investors are more likely to use these websites than institutional/sophisticated investors because the latter typically pay for access to more detailed data from providers such as Bloomberg or Thomson Reuters/Refinitiv. As a result, it is important to understand the informativeness of a particular signal that is more likely to be seen and relied upon by certain types of investors, particularly those who are less sophisticated. Second, while the consensus target price is not the only analyst-based information available online, it is perhaps the easiest to interpret, particularly for unsophisticated investors. 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 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 (Bilinski et al. 2013). Finally, because the reported target price is a consensus (usually the average is reported) and the "wisdom of crowds" is typically more accurate than an individual estimate (e.g., Galton 1907; Surowiecki 2005), the credibility of the information in the minds of investors may increase. The

[6] As Dechow and You (2018) note, Investopedia also provides a summary article and video presentation explaining target prices: https://www.investopedia.com/terms/p/pricetarget.asp

consensus target price also represents the equilibrium view of analysts who cover the firm and thus speaks to the usefulness of one of the analyst industry's primary outputs.

Our research uses analyst target price information accessed through the IBES database, which provides consensus target price information every month (usually on the third Thursday). The few prior papers that consider the consensus target price create their own consensus by screening and aggregating particular analysts' target prices from the IBES detail files (e.g., Gleason et al. 2013; Feng and Yan 2016; Dechow and You 2018); however, we focus on the consensus target price provided by IBES because we believe this more closely matches the consensus target pråice information available online to investors.[7] To better understand the consensus target price data available online and investigate its correspondence with the IBES database, we tracked a representative sample of stocks each day in the month of April 2019. We constructed this sample from stocks with (1) non-missing consensus target price data in IBES for all 14 months from January 2018 through February 2019, and (2) at least four analysts contributing target prices in each of those months. Based on the average market capitalization over this period, we split the stocks into quintiles and randomly picked six stocks in each quintile, resulting in 30 stocks. We then collected target price data for all 30 stocks every day during the month of April 2019 from the following financial websites: 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.

Appendix A provides example screenshots of consensus target price information for one of the firms in our random sample (FedEx Corporation) taken on May 9, 2019, alongside IBES consensus target price data from April and May 2019. We note that while Yahoo! Finance and CNBC agree on the consensus target price ($208.48), the other estimates are different, with MarketWatch reporting a

[7] Antonio et al. (2017) also consider consensus target prices for Latin American firms, but it is unclear how the consensus is calculated. They find that dispersion is positively associated with predicted returns, consistent with our evidence in Panel B of Table 1.

consensus of $210.08 and MSN Money reporting $201.00. Given that the current stock price on May 9, 2019 was $178.78, the range in estimates corresponds to a range in consensus-based predicted returns of 5.1%. The mean (median) IBES consensus target price in May 2019 is $208.28 ($201.00), suggesting that the information reported online is very similar to the consensus information in IBES.

Appendix A also provides summary statistics for the four websites examined during our manual data collection. While all four platforms had consensus target prices available for more than 90% of the 900 firm-days considered (30 firms over 30 days), Yahoo! Finance and CNBC had the best coverage while MarketWatch and MSN Money had slightly less complete coverage. These differences are interesting given that Yahoo! Finance, MSN Money, and CNBC all source their data from Thomson Reuters/Refinitiv (MarketWatch uses SIX Financial for their data which may explain the slightly different consensus target price for FedEx shown in Appendix A). In other words, even though platforms gain access to data from the same provider, they appear to exercise some discretion in what is reported online. To shed light on the updating frequency of each platform, we checked how many different target prices appeared for each firm on each platform. On the MarketWatch platform, firms had an average of 4.0 different target prices during April 2019, suggesting approximately weekly updating of the consensus price. CNBC and Yahoo! Finance had averages of 3.6 and 3.2, respectively, followed by MSN Money with 2.6. However, all platforms had firms with only one unique target price observed during the entire month (i.e., no updating of the consensus target price) and other stocks with 7, 8, or 12 unique consensus target prices observed (i.e., more frequent updating of the consensus target price).

Finally, we present summary statistics on the difference between the consensus target prices observed online during April 2019 and calculated by IBES.[8] For completeness, we present signed and

[8] Because the IBES consensus calculation date for the month is April 18, we compare online data from April 1 through April 18 (April 19 to 30) to the consensus from March (April) in order to benchmark it against the most recent IBES consensus calculation.

absolute differences in both raw and percentage form, and we also perform comparisons to the IBES mean and median. The overall takeaway from these differences is that the online consensus target prices tend to be very similar to the IBES consensus. For example, the online numbers are less than 1% different from the IBES numbers across all platforms whether we consider means or medians (looking at signed percentage differences). Eyeballing the raw data suggests two more patterns. First, Yahoo! Finance, CNBC, and MarketWatch often have the same target price, whereas MSN Money seems to report the median rather than the mean target price as the consensus (the FedEx example in Appendix A is consistent with this conclusion). Second, these four financial websites update their consensus target price on different dates, with CNBC often updating a day or two earlier than other websites. Taken together, the information provided in Appendix A suggests that, while there is some degree of heterogeneity in the consensus target price information available to investors online, target prices are close to each other across the various financial websites, and these also tend to be close to the IBES consensus. These findings validate our use of historical IBES data in our efforts to shed light on the information content of consensus analyst target prices that are freely available online for all investors.

2.2. Prior literature and research questions

As mentioned previously, the majority of research about target price informativeness focuses on individual analysts issuing target prices.[9] These papers generally support the view that target price levels and revisions are informative, even though target prices tend to be positively biased and the majority 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; Bradshaw et al. 2013). Analysts' target prices and recommendations are related to their forecasts of earnings and long-term growth (e.g., Bandyopadhyay

[9] Another stream of research considers target prices in the context of the implied cost of capital. We do not review this literature here, but Dechow and You (2018) provide a useful summary of this research (see their Appendix 2).

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 accuracy is associated with analyst characteristics, valuation techniques, firm-specific factors, and aspects of country culture (Bilinksi et al. 2013; Gleason et al. 2013). However, it does not appear that the market responds 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) and relative rankings within industries (Da and Schaumburg 2011; Da et al. 2016).

While prior research generally supports the view that target prices contain information, these papers also suggest "that target prices are highly inaccurate and biased. Analysts appear to have little skill in forecasting future value, and when they are accurate, it appears to be more by luck than by skill" (Dechow and You 2018, citing Bradshaw et al. 2013; also see 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 financial platform (wallmine.com) is an apt summary: "While the average or median recommendation may be predictive and reflect the actual future value, the results are usually not extremely successful."[10]

Given these potential conflicting views and general lack of evidence about consensus target prices, our first research question in this paper is: Do consensus target prices contain information predictive of future returns? Our second research question is: Does the dispersion of the individual target prices that comprise the consensus affect the relationship between the consensus price target and future realized stock price? We believe that the dispersion is an important aspect to consider for at least two reasons. First, both analytical (Gaba et al. 2019) and empirical (Malkiel 1982; Barron and Stuerke

[10] 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).

1998; Barron et al. 2009) analyses of the relationship between sets of individual estimates and their target variable suggests that the dispersion of the estimates is positively related to the amount of uncertainty in the consensus estimate. Second, the dispersion in target prices tends to increase if some analysts are slow in updating their target prices, resulting in distorted information in the consensus measure. This issue could be particularly important for retail investors because while any investor can freely observe the consensus target price (see examples in Appendix A), only relatively sophisticated investors have access to information about the dispersion and the timeliness of individual target prices (i.e., those who pay to access underlying data from sources like Bloomberg or Thomson Reuters/Refinitiv). As a result, considering this characteristic of target prices will help shed light on the implications of providing (incomplete) consensus target price information to all investors.

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, are only widely available on IBES starting in 1999, so our sample covers the period from July 1999 to June 2018. Because IBES releases consensus target price statistics once per month, our observations occur at the firm-month level.

Our main dependent variable is $\text{RET}_{t+1,t+12}$, the 12-month future realized return from months t+1 to t+12, where t refers to the month in which IBES calculates the consensus target price. Our primary explanatory variable is the 12-month predicted stock return based on the IBES consensus analyst target price (PRET), measured as the average target price in month t minus stock price in month

t, scaled by stock price in month t.[11] Another key variable of interest is the standard deviation of the predicted stock return across analysts for a given firm-month (PRSTD). We calculate PRSTD by taking the standard deviation from the IBES summary target price data for month t and scaling by stock price in month t.[12] Because PRSTD is an important variable throughout our analyses, we limit our sample to firm-month observations with at least four analysts in the consensus target price calculations. In our analysis of the data, we observe that IBES has some issues with stock split adjustments in target prices. As a precaution, we also drop firm-month observations where 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 price below \$5. Our main sample includes 465,797 firm-month observations with non-missing $\mathrm{RET}_{t+1,t+12}$, PRET, and PRSTD.

Table 1 presents descriptive statistics and correlations for $\mathrm{RET}_{t+1,t+12}$, PRET, and PRSTD, our three primary variables of interest, along with several other control variables used throughout the analyses. COV captures 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 ($\mathrm{RET}_{t-6,t-1}$), and accruals from the fiscal year prior to month t (ACC) are commonly-used factors that potentially explain stock returns.[13] Panel A presents summary statistics, with all variables except returns winsorized each month at their 1st and 99th percentiles. Comparing $\mathrm{RET}_{t+1,t+12}$ with PRET at both the mean (9.3% vs. 21.7%) and median (7.3% vs. 14.4%), it is clear that analysts' target prices tend to be optimistic, consistent with findings from prior literature (e.g., Bradshaw et al. 2013). It is

[11] 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.

[12] We acknowledge that our approach for calculating PRET and PRSTD does not account for analysts' individual target prices being issued at different times. In other words, we do not calculate the mean and standard deviation based on the set of individual predicted returns using each individual analyst's target price and the current stock price at the time of issuance. We make this choice because (1) we are motivated by the availability of consensus information available online, which closely mirrors IBES' consensus calculations (see Appendix A); and (2) it is unclear which individual target prices are included in IBES' consensus calculations.

[13] See Appendix B for detailed variable definitions.

also important to note that there is significant variation in the individual analysts' target prices contributing to each consensus calculation, as shown by the mean (median) PRSTD of 18.0% (13.3%). On average there are 9.49 individual analysts contributing (COV variable), with a median of 8 analysts considered per consensus calculation. As explained previously, the minimum number of analysts is 4 in order to ensure meaningful variation captured by PRSTD.

Panel B of Table 1 presents Pearson (above the diagonal) and Spearman (below the diagonal) correlations among the variables in Panel A. Given our interest in the potential information content of consensus target prices, we first note the negative correlation between consensus-based predicted returns (PRET) and future realized returns ($RET_{t+1,t+12}$). This surprising result suggests that as the consensus-based predicted return increases, actual stock performance is worse. We also observe that $RET_{t+1,t+12}$ is negatively correlated with PRSTD, indicating 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 PRSTD, which demonstrates that stocks with higher predicted returns also tend to have higher disagreement among the individual analysts contributing to the consensus prediction.

Panel C of Table 1 provides evidence about the revision frequency of analysts' target prices compared to revisions in their annual earnings forecasts and stock recommendations. We first calculate average revision frequencies by analyst in each firm's fiscal year; we then calculate summary statistics for approximately 38,000 firm-year observations. The results show that on average, annual earnings forecasts are updated 3.82 times per year, consistent with updates happening around quarterly earnings announcements. Target prices are updated less frequently at 2.78 times per year (on average), and

[14] Feng and Yan (2016) 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. 6), which contradicts the (untabulated) strong positive correlation between PRSTD and earnings forecast dispersion in our sample (Pearson and Spearman correlation coefficients are above 0.33 and 0.37, respectively). As a result, it appears that their measures of dispersion capture something quite different from our PRSTD measure.

recommendations are updated only 1.34 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 monthly consensus calculations may rely on stale target prices. We consider the impact of staleness in our main analyses, discussed below.

4. Main results

We use decile portfolio analyses and regression models to further examine the relations among $RET_{t+1,t+12}$, PRET, and PRSTD in order to shed light on the information content of consensus target prices.

4.1 One-way sort by the predicted return based on consensus target price

We begin with a simple portfolio analysis by sorting stocks into deciles each month based on PRET. For the stocks in each decile-month, we take the average value of future realized returns ($RET_{t+1,t+12}$) and report the over-time averages for each decile in Table 2. As expected based on the sorting process, the average PRET increases monotonically from -5.66% for PRET1 to 81.55% 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 11% before dropping to 8.43% for PRET9 and 4.57% for PRET10.

These results are consistent with the negative correlation between PRET and $RET_{t+1,t+12}$ observed in Table 1 Panel B and suggest that stocks with the highest predicted returns based on consensus target prices perform the worst. This inference is corroborated by a significantly *negative* hedge portfolio return of -5.06% (t = -3.34) to a strategy that takes a long (short) position in PRET10 (PRET1) stocks. Overall, the results from Table 2 suggest that consensus target prices are generally

[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 numbers indicating smaller values of the sorting variable X.

not informative about future stock returns due to the inability to meaningfully distinguish future performance among the majority of stocks (PRET1 to PRET8) and the unexpected finding that stocks with the highest predicted returns based on the consensus target price have the worst future realized returns.

4.2 Two-way sort by the predicted return and its dispersion.

Our next analysis considers how dispersion among analysts' target prices impacts the informativeness of the consensus and the patterns from Table 2 previously discussed. Table 3 presents results of an additional portfolio analysis based on a double sort performed monthly. Each month, we first sort stocks into deciles based on PRSTD. Then, within each PRSTD decile, we further sort stocks into deciles based on PRET. The reason we first sort by PRSTD is the reasoning that irrespective of the value of PRET, smaller (larger) values of PRSTD may indicate more (less) certainty in the consensus-based predicted return (e.g., Malkiel 1982; Barron and Stuerke 1998; Barron et al. 2009). This procedure results in 100 portfolios each month, and similar to the approach in Table 2, we take the average realized future stock return ($RET_{t+1,t+12}$) for each of the 100 portfolios each month and then present the over-time average for each portfolio in Table 3.

The most striking result in Table 3 comes from comparing the stocks with the lowest dispersion (PRSTD1) to those with the highest dispersion (PRSTD10). Within the PRSTD1 decile, realized future returns clearly tend to increase when moving from PRET1 (9.12%) to PRET10 (11.53%). As shown in the far right column of Table 3, a hedge portfolio that goes long (short) in PRET10 (PRET1) stocks within the PRSTD1 decile earns a return of 2.41% (t = 2.05). This is in stark contrast to the pattern observed in Table 2 and suggests that when analysts agree in their target prices (i.e., when PRSTD is low), there is a positive correlation between PRET and $RET_{t+1,t+12}$, indicating that consensus target prices can be useful for predicting future stock returns if analysts are in agreement.

On the other hand, within the PRSTD10 decile, we observe a pattern consistent with, but even more drastic than, the results shown in Table 2. Within this decile, realized future returns decrease from PRET1 (9.36%) to PRET10 (-0.15%). In other words, among stocks with high dispersion in target prices, those with the highest predicted returns based on the consensus target price perform far worse than those stocks with the lowest predicted returns. Further supporting this point is the -9.51% return (t = -4.86) for a hedge portfolio that goes long (short) in PRET10 (PRET1) stocks within the PRSTD10 decile.[16] Thus, it appears that the negative correlation between PRET and $RET_{t+1,t+12}$ observed in Tables 1 and 2 is driven by stocks with greater dispersion among individual analysts' target prices (i.e., those with higher values of PRSTD). Further supporting this inference is the near monotonic decrease in realized future returns moving across deciles from PRSTD1 to PRSTD10 within the PRET10 column. Indeed, the bottom row indicates a 11.68% return (t = 5.73) to a hedge portfolio going long (short) in the stocks from PRET10 in PRSTD1 (PRSTD10).

To provide additional evidence that the results from Table 3 are robust after considering the potential impact of known risk factors, we estimate four-factor and five-factor models for monthly returns on the hedge portfolio of (PRET10 – PRET1). For parsimony, we focus on the hedge returns from PRSTD1 and PRSTD10, as well as the hedge portfolio going long (short) in the stocks from PRET10 in PRSTD1 (PRSTD10):

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

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

In equations (1a) and (1b), R_{it} -R_{ft} is average monthly excess returns from target price strategies from months t-11 to t, 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

[16] Similarly, significantly negative hedge portfolio returns are observed for deciles 6, 7, 8, and 9 of PRSTD.

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 the other risk factors. Results of estimating the models are presented in Table 4. Focusing on the intercept column, we observe a pattern similar to Table 3 where the PRSTD1 decile has a positive abnormal return (only significant in Panel A for the four-factor model) while the PRST10 decile has negative abnormal returns of -1.761% (t = -3.75) for the four-factor model and -1.253% (t = -2.53) for the five-factor model. As in Table 3, the most striking result comes from the hedge portfolio going long (short) in the stocks from PRET10 in PRSTD1 (PRSTD10), which shows a strong positive abnormal monthly return of 2.132% (t = 4.48) for the four-factor model and 1.389% (t = 2.89) for the five-factor model. These findings indicate an economically significant annual hedge return between 18.0% and 28.8% to the trading strategy that utilizes consensus predicted returns and their dispersion.

4.3 Regression analyses

As an additional test of our main result from Table 3, we estimate the following regression models for each month in the sample period:

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

$$\begin{aligned} RET_{t+1,t+12,it} = {} & \alpha_0 + \alpha_1 PRET_{it} + \alpha_2 LOWPRSTD_{it} + \alpha_3 HIPRSTD + \alpha_4 PRET_{it} \times LOWPRSTD_{it} \\ & + \alpha_5 PRET_{it} \times HIPRSTD_{it} + \sum_{1}^{k} \alpha_{5+k}\, CTRL_k + \varepsilon_{it} \qquad (3) \end{aligned}$$

In equation (2), we directly regress the future 12-month realized return ($RET_{t+1,t+12}$) for firm *i* on the predicted return based on the consensus target price (PRET) and the standard deviation of the predicted return (PRSTD) for firm *i* in month *t*, along with their interaction given the nature of the pattern observed in Table 3. In equation (3), the approach is similar except that we replace the continuous

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

measure of PRET with two indicator variables: LOWPRSTD (HIPRSTD) is an indicator equal to one for observations falling in the bottom (top) quartile of the PRSTD distribution in month *t*. We take this approach to compare stocks with both low and high dispersion in target-price-based predicted returns against stocks with middle levels of dispersion given that Table 3 shows the most differences occur in the smallest and largest deciles of PRSTD. 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 independent variables except dummy variables are decile rankings converted to a [0,1] scale. The main variables of interest are the interaction terms in equations (2) and (3).

Table 5 presents the average coefficient estimates after running the models each month, and Fama-MacBeth *t*-statistics are presented in parentheses. In column (1), we do not observe a significant coefficient estimate for PRET (0.010, t = 1.06), but PRSTD loads positively (0.021, t = 2.01). Most importantly, the interaction of PRET×PRSTD is highly significant and negative (-0.104, t = -8.21). This result is consistent with our prior findings that stocks with high predicted returns *and* high dispersion among individual analysts' target prices have the worst performance. Turning to column (2) of Table 5, we continue to observe strong results for the interaction terms, and the indicator variable approach yields results even more consistent with the patterns observed in Table 3. More specifically, PRET×LOWPRSTD loads significantly positive (0.043, t = 5.78), showing that for stocks with low dispersion among individual analysts' target prices, PRET is much more positively associated with future stock returns (relative to stocks with middle levels of dispersion). On the other side, PRET×HIPRSTD loads significantly negative (-0.045, t = -5.06), consistent with the result in column (1) and previous tables that stocks with the highest dispersion show a strong negative association between predicted returns based on the consensus target price and future stock performance.

Taken together, the results from Tables 3, 4, and 5 suggest that the informativeness of consensus analyst target prices critically depends on the dispersion of the individual target prices aggregated in the consensus. When the dispersion is small (i.e., lower PRSTD), predicted stock returns generated from the consensus target price are positively correlated with future stock returns. On the other hand, when dispersion is large (i.e., higher PRSTD), predicted stock returns from the consensus target price are negatively correlated with future stock returns.

5. Why does target price dispersion influence the association between predicted returns and future stock returns?

5.1. Future fundamental performance

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. Our first 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 the test is to check whether the usefulness of consensus-target-price-based predicted returns for predicting future fundamental performance differs depending on the degree of dispersion among individual analysts' target prices. We expect this to be the case given that future returns (examined in Tables 3, 4, and 5) should be correlated with future performance, but we view this analysis as a necessary step to ensure that the return patterns observed previously are not due to some unobserved factor(s).

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) FE_{FY1} is analysts' forecast error for annual earnings for the current fiscal year, measured as actual earnings minus the median analyst forecast in month t

(scaled by stock price on the forecast date); and (3) FE_{FY2} is the same as FE_{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 FE measures capture the difference between firms' announced future accounting performance and analysts' expectations in month *t*.

Similar to column (2) of Table 5, in Table 6 we observe significantly positive estimates of PRET×LOWPRSTD for all three future performance measures (*t*-statistics range from 3.79 to 8.86), while PRET×HIPRSTD loads significantly negative for all three specifications (*t*-statistics range from -5.40 to -9.40). These results support the conclusion that the patterns in future stock returns observed in Tables 3, 4, and 5 are strongly correlated with future fundamental performance. In other words, when analysts' target price dispersion is high (low), predicted returns based on the consensus target price are negatively (positively) associated with future fundamental accounting performance, which helps explain the pattern for future returns documented in Tables 3, 4, and 5.

5.2. Past fundamental performance and analyst revision activity

Our next test considers how PRET and PRSTD in month *t* are associated with *past* performance and analysts' tendency to update their earnings forecasts and target prices. The purpose of this analysis is to examine whether predicted returns based on the consensus target price and the dispersion of predicted returns observed in month *t* differentially reflect past performance-related news and/or analysts' earnings forecast revisions. For these tests, we keep the same general framework from equation (3) and use the following four measures as dependent variables: (1) $RET_{t-11,t}$ is the stock return from the prior 12 months; (2) $EREV_{t-2,t}$ is the three-month analyst revision of forecasted earnings for the current fiscal year, FY1 earnings, from month *t*-2 to *t*, scaled by stock price in month *t*; (3) $TPREV_{t-2,t}$ is the three-month analyst revision of target prices from month *t*-2 to *t*, scaled by stock price in month *t*; and (4) TPREVTIME is the natural log of the average number of days since analysts last updated their target prices (i.e., averaged across individual analysts for each firm-month).[18]

Column (1) of Table 7 presents results with $RET_{t\text{-}11,t}$ as the dependent variable. As with previous tables, we focus primarily on the interaction terms of PRET×LOWPRSTD and PRET×HIPRSTD. PRET×LOWPRSTD loads significantly positive (0.188, t = 12.38), indicating that for stocks with low dispersion among analysts' target prices in month *t*, stock returns over the previous 12 months are strongly positively associated with predicted returns based on the consensus target price. In other words, past performance (whether positive or negative) appears to have a strong influence on the consensus target price when PRSTD is low. On the other hand, PRET×HIPRSTD loads significantly negative (-0.259, t = -11.88), suggesting that for stocks with high dispersion among analysts' individual target prices in month *t*, past stock returns are *negatively* associated with predicted returns. The negative relation between past stock returns and implied returns from target prices suggests that analysts do not update their target prices in a timely manner after observing poor performance. This finding is consistent with Brav and Lehavy's (2003) evidence that target prices are more likely to accompany recommendation upgrades than downgrades, and it is also in line with prior research suggesting analysts may not update forecasts after receiving bad news due to their incentives and/or conflicts of interest (e.g., McNichols and O'Brien 1997; Hayes 1998).[19] In the context of our research questions, this finding also suggests that predicted returns from consensus target prices will be too high if target prices are not updated after stock prices drop.

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[18] Given that we are not attempting to explain future returns or performance, we drop the control variables from these regressions. In essence we are using the regression models to identify patterns in past performance and analyst revisions that relate to the interaction of PRET and PRSTD.

[19] 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. However, as Bradshaw et al. (2016) argue, "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 slow to update target prices after bad news, which is consistent with Ho et al. (2018) in that when they do decide to issue a negative target price revision, it is likely to be after observing significant bad news.

To further understand this result, we turn to columns (2) and (3) of Table 7 with $EREV_{t-2,t}$ and $TPREV_{t-2,t}$ as dependent variables, respectively. The $EREV_{t-2,t}$ results in column (2) show a pattern similar to column (1) in terms of sign and significance on the two interaction terms, but the $TPREV_{t-2,t}$ model in column (3) only finds a significant (positive) result for PRET×LOWPRSTD (0.074, t = 18.18) while the PRET×HIPRSTD coefficient is not negative or significant (0.052, t = 0.24). These contrasting results are important for better understanding why dispersion in analysts' target prices impacts the association between consensus-based predicted returns and future stock performance.

Similar results for the $EREV_{t-2,t}$ and $RET_{t-11,t}$ models suggest that the predicted return based on consensus target prices increases with past performance for low-dispersion stocks relative to medium-dispersion stocks. This result is consistent with a momentum story in the sense that when firm performance improves, analysts expect higher future returns. In contrast, for high-dispersion stocks, the predicted return is negatively correlated with past performance, suggesting that higher predicted returns are not supported by firm fundamentals. In addition, the lack of a significant coefficient on PRET×HIPRSTD in the $TPREV_{t-2,t}$ model shows that predicted returns from consensus target prices in month t are not associated with recent target price revisions for stocks with high target price dispersion observed in month t. In other words, it appears that the lack of timely updates to target prices is one key potential reason for high dispersion to exist in the first place (i.e., if not all analysts update their target prices, the 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 high. If high dispersion is a signal of stale information, particularly when more recent performance has been poor, it suggests the consensus target price is too high, which will lead to lower future returns being observed for high-dispersion stocks with high predicted returns.

The final column of Table 7 presents results with TPREVTIME as the dependent variable. The significant negative coefficient on PRET×LOWPRSTD (-0.071, t = -7.24) indicates that stocks with higher predicted returns and lower target price dispersion in month *t* tend to have more recently updated target prices than stocks with higher predicted returns and middle or high levels of dispersion, which further supports the inferences from columns (1) through (3).

5.3. Two potential channels underlying target price dispersion

Our main results indicate that dispersion in analysts' target prices is a critical moderating factor for the informativeness of consensus target prices. In this section we consider two potential channels for our result that consensus-based predicted returns are negatively correlated with future realized returns when dispersion is high. First, we test whether the dispersion is simply capturing fundamental uncertainty and/or investor disagreement (e.g., Diether et al. 2002; Feng and Yan 2016). With limits to arbitrage, Miller (1977) suggests stocks with higher uncertainty and investor disagreement will be overvalued. Second, given the results in Table 7, we consider whether staleness in target prices after bad performance is primarily responsible for the negative association between predicted and realized returns for high-dispersion stocks.

To test the first potential channel, we first replace target price dispersion (PRSTD) in our regression models with EFSTD: the standard deviation of earnings forecasts. We also include EFSTD (and its interaction with PRET) in addition to PRSTD. In these models, EFSTD is meant to capture fundamental uncertainty. To the extent that both fundamental uncertainty and staleness are important channels, we expect the EFSTD coefficients to be smaller than the PRSTD coefficients. Column (1) of Table 8 presents results when replacing PRSTD with EFSTD. Similar to our main results, the PRET×EFSTD interaction term is significantly negative (-0.061, t = -3.79), but the magnitude is much smaller compared to the PRET×PRSTD coefficient reported in Table 5 (-0.104, t = -8.21). Moreover, when EFSTD and PRSTD are included simultaneously (column (2) of Table 8), PRET×PRSTD continues to load strongly negative (-0.084, t = -5.80) while PRET×EFSTD loads only marginally (-

0.028, t = -1.76). These results are consistent with expectations and suggest that fundamental uncertainty is part of the underlying mechanisms responsible for our main results.

To consider staleness as a potential mechanism, we construct two alternative versions of the consensus target price using only individual target prices from month t and those issued in months $t-1$ and t. We then use these alternative consensus measures to construct corresponding versions of PRET and PRSTD, and we re-estimate the model from column (1) of Table 5. Results are presented in columns (3) and (4) of Table 8, and in both models PRET×PRSTD continues to load significantly negative. However, the coefficient magnitudes (-0.072 and -0.078, respectively) are smaller than the -0.104 observed in column (1) of Table 5, suggesting that staleness is partially driving the overall result using our main PRSTD measure.[20]

5.4. Using Miller (1977) to interpret the results

We believe it is useful to consider our findings in the context of Miller (1977), who argues that when there is more dispersion in investors' expectations about future returns, stock prices will be higher because the price will reflect the opinions of those with the highest expectations. One of the interesting takeaways from Table 7 is that analysts don't appear to be unaware of information that pertains to future performance. For example, their earnings forecast revisions prior to month t exhibit patterns similar to prior stock returns, suggesting that analysts are updating their earnings expectations based on the arrival of relevant information. In other words, the dispersion observed for the consensus target price in month t does not accurately reflect dispersion in analysts' true opinion but rather dispersion due to not all analysts incorporating relevant information in their target prices. We argue that one potential reason for this dispersion being associated with inflated prices (i.e., lower future

[20] Because the alternative consensus measures result in fewer available firm-month observations, we also estimate the Table 5 column (1) model on the subsamples used in columns (3) and (4) of Table 8. The PRET×PRSTD coefficient is -0.104 (t = -4.26) for the column (3) subsample, and it is -0.115 (t = -6.56) for the column (4) subsample. These coefficients are very similar to the -0.104 (t = -8.21) reported in Table 5.

returns) for stocks with high predicted returns is because as some investors consume the (inflated) consensus target price information for these stocks, the price will reflect these inaccurately high expectations. As Miller (1977) explains, as opinion divergence decreases (i.e., as investors observe future fundamental performance and realize the consensus price was too high), the price will decrease, resulting in lower future returns. To provide support for the Miller (1977) explanation for our results, we perform two additional analyses.

First, we consider limits to arbitrage because mispricing related to Miller's (1977) explanation exists in the presence of these limits.[21]Under this story, we expect mispriced stocks (i.e., those with high PRET and high PRSTD) to exhibit greater limits to arbitrage. As a proxy for limits to arbitrage, we consider short interest. However, because short interest is strongly associated with firm size and institutional ownership, we first regress short interest (the percentage of outstanding shares shorted) on firm size and institutional ownership each month. We take the residual from these monthly regressions as our measure of short interest to ensure that we capture limits to arbitrage rather than effects related to firm size and/or institutional ownership. Table 9 presents results of estimating the model from column (2) of Table 5 after splitting the sample based on median residual short interest. Because stocks with high short interest are more costly to short, these stocks exhibit greater limits to arbitrage, and we expect our main result to be stronger in the high residual short interest subsample. The results in Table 9 confirm these expectations. While the PRET×LOWPRSTD coefficient is similarly positive and significant in both subsamples, the mispriced stocks are concentrated in the high residual short interest subsample: PRET×HIPRSTD is insignificant in the low subsample (-0.007, t = -0.50) but strongly significant in the high subsample (-0.048, t = -3.75).

[21] Other than limits to arbitrage, another potential reason is that the market is unaware of this mispricing as our paper is the first one to document it.

Finally, Miller's (1977) theory also requires some investors to rely on the inflated consensus target prices (i.e., those with high dispersion). Because institutional investors base their trading decisions on more comprehensive information and are likely able to observe dispersion in analysts' target prices (by paying for access to underlying target price data from), we argue that retail/individual investors are more likely to be influenced by high consensus target prices available freely online. Our final test is similar to Table 9 except that instead of partitioning the sample on residual short interest, we split the sample based on residual institutional ownership. Because institutional ownership is strongly correlated with firm size, we regress institutional ownership on firm size each month. We use the residuals as our measure of institutional ownership to ensure that we are not capturing effects related to firm size. Table 10 reports results of repeating the model from column (2) of Table 5 after partitioning the sample based on median residual institutional ownership. If retail investors are those whose opinions are impacted by inflated consensus target prices, we expect the mispricing to be concentrated in the low subsample. Results reported in Table 10 are consistent with these expectations. Similar to Table 9, PRET×LOWPRSTD loads significantly positive in both subsamples. However, PRET×HIPRSTD is significantly negative only in the low residual institutional ownership subsample (-0.070, t = -5.48 vs. -0.003, t = -0.27).

Taken together, the results in Tables 9 and 10 suggest that when dispersion in analysts' target prices is low, all classes of investors benefit from the information contained in predicted returns based on the consensus target price. However, the negative association between predicted returns and future performance for high-dispersion stocks is concentrated in those stocks with higher residual short interest and higher retail ownership. In our view, these results support our reliance on Miller's (1977) theory and have important implications for retail investors consuming target price information online while remaining unaware of the dispersion in the point estimates and the implications for future returns.

6. Conclusion

We investigate whether predicted returns based on consensus target prices are informative about future stock returns. In general, consensus-based predicted returns are not informative, and in fact, stocks with the highest predicted returns tend to have the lowest future realized returns. However, we also show that the *dispersion* in individual analyst target prices that comprise the consensus is an important moderating factor. More specifically, when dispersion is low, we observe a positive association between consensus-based predicted returns and future realized returns. This shows that when individual analysts are more in agreement about the target price, consensus-based predicted returns are informative about future stock price. On the other hand, when dispersion is high, we observe a strong negative association between consensus-based predicted returns and future realized returns. Our additional analyses suggest that for high-dispersion and high-predicted-return stocks, the consensus target price is slow to reflect bad news.

Our final analyses show that the strong negative correlation between consensus-based predicted returns and future realized returns only appears for stocks with high short interest and low institutional ownership, suggesting that limits to arbitrage are an important factor in the observed mispricing and that retail/unsophisticated investors are misled by high consensus target prices. Given that consensus target prices are readily available online at no cost, but the dispersion is *not* freely available, we believe our results suggest caution when deciding which (incomplete) financial information should be made widely available to investors online. From the regulator's perspective, one potential remedy is to require financial websites to disclose the dispersion in target prices along with the consensus.

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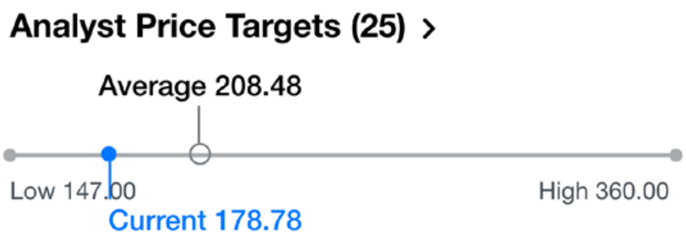
Appendix A
IBES Consensus Target Prices and Screenshots of Consensus Target Price Information from Financial Websites for FedEx Corporation (FDX) on May 9, 2019

<u>IBES Consensus Target Price Information for FDX in April and May 2019</u>

Consensus Date	# Analysts	Mean	Median	Std. Dev
April 18, 2019	25	208.88	201.00	40.47
May 16, 2019	25	208.28	201.00	40.99

<u>Yahoo! Finance: May 9, 2019</u>



<u>MarketWatch: May 9, 2019</u>

Average Target Price:	**210.08**

<u>MSN Money: May 9, 2019</u>

1 Year Price Target	201.00
Analysts	29

<u>CNBC: May 9, 2019</u>

The current Price Target for FDX is **$208.48.**

Appendix A, continued
Summary of Consensus Target Price Information
Manually Collected during April 2019

Target price coverage

	Valid observations	*Missing observations*	*Missing %*
Yahoo! Finance	900	0	0.0%
MarketWatch	816	84	9.3%
MSN Money	812	88	9.8%
CNBC	872	28	3.1%

Number of unique target prices per firm

	Firms	*Mean*	*Std. Dev.*	*Min*	*25%*	*Median*	*75%*	*Max*
Yahoo! Finance	30	3.2	1.8	1.0	2.0	3.0	5.0	7.0
MarketWatch	28	4.0	2.8	1.0	2.0	3.0	5.5	12.0
MSN Money	28	2.6	2.2	1.0	1.0	2.0	3.0	12.0
CNBC	30	3.6	2.3	1.0	2.0	3.5	5.0	8.0

Online consensus target prices compared to IBES consensus target prices

		Online consensus – IBES mean				(Online consensus – IBES mean) / IBES mean			
		Signed		Absolute Value		Signed		Absolute Value	
	N	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*
Yahoo! Finance	888	0.0599	0	0.6330	0	0.0039	0	0.0091	0
MarketWatch	816	-0.1649	0	0.8133	0.2510	0.0003	0	0.0128	0.0069
MSN Money	812	0.2308	0	2.0866	0.6000	0.0023	0	0.0296	0.0213
CNBC	872	0.0997	0	0.7366	0.0050	0.0046	0	0.0105	0.0004

		Online consensus – IBES median				(Online consensus – IBES median) / IBES median			
		Signed		Absolute Value		Signed		Absolute Value	
	N	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*	*Mean*	*Median*
Yahoo! Finance	888	-0.0688	0.1400	1.4977	0.5000	0.0080	0.0056	0.0254	0.0170
MarketWatch	816	-0.2895	0.0200	1.5081	0.6500	0.0055	0.0014	0.0252	0.0193
MSN Money	812	0.0861	0	1.0375	0	0.0061	0	0.0138	0
CNBC	872	-0.0319	0.2900	1.5555	0.5650	0.0087	0.0063	0.0259	0.0170

Appendix B
Variable Definitions

Variable	**Definition**
Dependent variables	
$RET_{t+1,t+12}$	12-month future stock returns from months t+1 to t+12, where month t is the month of analysts' target prices.
EARET	Average three-day [-1, 1] earnings announcement returns during the 12-month window from months t+1 to t+12, where month t is the month of analysts' target prices.
FE_{FY1}	Analysts' forecast error on FY1 earnings, measured as actual earnings minus median forecast in month t, scaled by stock price on the forecast date.
FE_{FY2}	Analysts' forecast error on FY2 earnings, measured as actual earnings minus median forecast in month t, scaled by stock price on the forecast date.
Main independent variables	
PRET	Average predicted 12-month stock returns from target prices across analysts, calculated as (target price – stock price)/stock price in month t.
PRSTD	The standard deviation of predicted 12-month stock returns across analysts, calculated as the standard deviation of (target price – stock price)/stock price in month t. We require at least four analysts' data to calculate the standard deviation.
Other variables	
MV	The market value of equity at the end of month t.
SIZE	The logarithm of MV
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.
$RET_{t-6,t-1}$	Price momentum measured as six-month returns from months t-6 to t-1.
ACC	Accruals measured as changes in non-cash current assets (ACT-CHE) minus non-debt current liabilities (LCT-DLC) minus depreciation expense (DP), scaled by average total assets. ACC data are matched with PRET in month t with at least a four-month lag.
COV	The number of analysts that provide target prices in month t.
$EREV_{t-2,t}$	Three-month analyst revision of FY1 earnings forecasts from month t-2 to t, scaled by stock price in month t.
$TPREV_{t-2,t}$	Three-month analyst revision of target price from month t-2 to t, scaled by stock price in month t.
TPREVTIME	The logarithm of the number of days since the last time the analyst updates her target price.
COV	The number of analysts that provide target prices in month t.
INST	Institutional ownership from the most recent quarterly filings.
EFSTD	The dispersion in analysts' FY1 earnings forecasts scaled by stock price.

Table 1
Descriptive Statistics

Panel A: Univariate statistics

Variable	N	Mean	Stdev	Min	Q1	Median	Q3	Max
$RET_{t+1,t+12}$	465,797	0.093	0.450	-0.998	-0.157	0.073	0.298	13.81
PRET	465,797	0.217	0.302	-0.421	0.055	0.144	0.284	6.64
PRSTD	465,797	0.180	0.174	0.021	0.088	0.133	0.208	4.18
COV	465,797	9.49	5.63	4	5	8	12	50
MV	465,797	8,485	26,393	1	743	1,951	5,808	918,492
BM	449,476	0.473	0.352	-0.598	0.234	0.405	0.635	4.24
$RET_{t-6,t-1}$	464,986	0.084	0.356	-0.987	-0.093	0.057	0.212	27.83
ACC	364,416	-0.040	0.061	-0.359	-0.071	-0.039	-0.011	0.257
FE_{FY1}	399,665	-0.004	0.029	-0.667	-0.005	0.000	0.004	0.189
EARET	463,674	0.002	0.046	-0.856	-0.018	0.002	0.024	1.170

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

	$RET_{t+1,t+12}$	PRET	PRSTD	MV	BM	$RET_{t-6,t-1}$	ACC
$RET_{t+1,t+12}$	1	-0.04	-0.03	-0.02	0.04	-0.01	-0.01
PRET	-0.06	1	0.72	-0.07	-0.10	-0.33	0.01
PRSTD	-0.06	0.43	1	-0.09	-0.05	-0.22	-0.02
MV	0.02	-0.25	-0.26	1	-0.09	0.01	-0.02
BM	0.06	-0.09	-0.08	-0.16	1	0.08	0.00
$RET_{t-6,t-1}$	0.02	-0.44	-0.25	0.11	0.06	1	-0.03
ACC	-0.01	0.01	-0.05	-0.02	0.01	-0.03	1

Table 1, continued

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	38,193	3.82	1.31	1.00	3.00	3.64	4.43	24.00
Target prices	38,735	2.78	0.99	1.00	2.05	2.67	3.33	15.38
Stock recommendations	38,424	1.34	0.37	1.00	1.08	1.27	1.50	11.75

This table provides descriptive statistics and correlation matrix. $RET_{t+1,t+12}$ is the 12-month future stock return. PRET is the average predicted 12-month stock returns from analysts' target prices. PRSTD is the standard deviation of predicted 12-month stock prices from target prices across analysts. MV is the market value of equity, BM is the book-to-market ratio. $RET_{t-6,t-1}$ is the 6-month stock returns from month *t*-6 to *t*-1. ACC is accruals. COV is the number of analysts providing target prices in month *t*. FE_{FY1} is analyst forecast error on FY1 earnings. ARET is the average three-day [-1,1] earnings announcement returns during the 12-month period from *t*+1 to *t*+12. Please see Appendix B for detailed variable definitions. Our final sample includes 465,797 firm-month observations from July 1999 to June 2018 with non-missing $RET_{t+1,t+12}$, PRET, and PRSTD. 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 analysts in each firm's fiscal year. Then we calculate average revision frequencies across over 38,000 firm-year observations.

Table 2
Future Returns based on Deciles of Predicted Stock Returns from Consensus Target Prices

	$RET_{t+1,t+12}$	PRET	MV
PRET1	9.64%	-5.66%	6,077
PRET2	10.76%	3.06%	9,620
PRET3	10.98%	7.52%	10,936
PRET4	10.99%	11.35%	11,369
PRET5	11.27%	15.15%	11,474
PRET6	11.04%	19.35%	10,548
PRET7	10.48%	24.50%	9,665
PRET8	9.91%	31.58%	7,446
PRET9	8.43%	43.51%	4,893
PRET10	4.57%	81.55%	2,116
PRET10 – PRET1	-5.06% (-3.34)		

The table reports mean future 12-month stock returns ($RET_{t+1,t+12}$) and predicted stock returns based on target prices (PRET) across ten PRET deciles. Please see Appendix B for detailed variable definitions. Our final sample includes 465,797 firm-month observations from July 1999 to June 2018 with non-missing $RET_{t+1,t+12}$, PRET, and PRSTD. Each month, all variables except returns are winsorized at 1% and 99%. The portfolio returns are the average of monthly $RET_{t+1,t+12}$ over time; *t*-statistics in parentheses are Fama-MacBeth t-statistics.

Table 3
Future Returns based on Double Sorts by Standard Deviation of Predicted Stock Returns and Predicted Stock Returns from Consensus Target Prices

	PRET1	PRET2	PRET3	PRET4	PRET5	PRET6	PRET7	PRET8	PRET9	PRET10	PRET10 -PRET1
PRSTD1	9.12%	10.34%	10.39%	11.26%	10.86%	12.26%	12.19%	11.55%	12.62%	11.53%	2.41% (2.05)
PRSTD2	9.08%	10.26%	10.06%	11.44%	10.14%	11.60%	10.77%	10.93%	11.61%	10.50%	1.42% (1.16)
PRSTD3	10.41%	9.93%	10.74%	10.52%	10.85%	10.85%	11.63%	10.26%	9.75%	10.13%	-0.28% (-0.21)
PRSTD4	9.10%	10.34%	10.52%	10.55%	10.64%	11.76%	11.30%	10.90%	10.10%	9.09%	-0.02% (-0.01)
PRSTD5	9.43%	11.41%	10.54%	10.69%	10.60%	12.23%	10.00%	11.41%	9.59%	6.96%	-2.47% (-1.75)
PRSTD6	9.87%	10.72%	11.08%	10.78%	10.47%	11.33%	10.50%	11.33%	8.90%	7.13%	-2.73% (-1.90)
PRSTD7	10.11%	14.39%	11.64%	11.93%	11.41%	11.38%	9.81%	9.37%	8.67%	6.47%	-3.64% (-2.08)
PRSTD8	10.47%	12.46%	11.78%	12.82%	11.48%	10.73%	10.14%	9.95%	8.53%	5.52%	-4.95% (-3.18)
PRSTD9	8.93%	9.26%	11.82%	9.78%	9.36%	8.84%	8.06%	8.52%	6.57%	1.82%	-7.11% (-3.76)
PRSTD10	9.36%	8.50%	4.91%	7.60%	5.77%	5.53%	4.83%	5.92%	2.91%	-0.15%	-9.51% (-4.86)
RET(PRSTD1, PRET10) – RET(PRSTD10, PRET10)										11.68% (5.73)	

The table reports mean future 12-month stock returns ($RET_{t+1,t+12}$) based on two-way sorts by the standard deviation of predicted returns (PRSTD) and predicted stock returns based on consensus target prices (PRET) and. Each month, we first sort stocks into ten deciles by PRSTD. Then for each resulting PRSTD decile, we further sort stocks into ten groups by PRET. In this way, we have 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 Appendix B for detailed variable definitions. Our final sample includes 465,797 firm-month observations from July 1999 to June 2018 with non-missing $RET_{t+1,t+12}$, PRET, and PRSTD. The portfolio returns are the average of monthly $RET_{t+1,t+12}$ over time; *t*-statistics in parentheses are Fama-MacBeth *t*-statistics.

Table 4
The 4-Factor Model on Hedge Portfolio Returns across PRSTD Deciles

Panel A: Fama-French 4-factor model

	Intercept	$R_{Mt} - R_{ft}$	*SMB*	*HML*	*MOM*	Adj. R^2
Long (PRSTD1, PRET10)	0.371 (1.82)	0.979 (18.92)	0.230 (3.58)	0.303 (4.59)	-0.013 (-0.33)	0.687
Short (PRSTD10, PRET10)	-1.761 (-3.75)	1.735 (14.56)	1.101 (7.44)	-0.591 (-3.88)	-0.623 (-6.62)	0.704
Hedge (Long-Short)	2.132 (4.48)	-0.756 (-6.26)	-0.871 (-5.81)	0.894 (5.79)	0.610 (6.39)	0.499

Panel B: Fama-French 5-factor model

	Intercept	$R_{Mt} - R_{ft}$	*SMB*	*HML*	*RMW*	*CMA*	Adj. R^2
Long (PRSTD1, PRET10)	0.137 (0.66)	1.089 (19.60)	0.370 (5.01)	0.103 (1.18)	0.357 (3.63)	0.085 (0.68)	0.705
Short (PRSTD10, PRET10)	-1.253 (-2.53)	1.596 (11.96)	0.651 (3.67)	0.270 (1.29)	-1.168 (-4.94)	-1.071 (-3.55)	0.697
Hedge (Long-Short)	1.389 (2.89)	-0.507 (-3.92)	-0.282 (-1.64)	-0.167 (-0.82)	1.525 (6.65)	1.156 (3.96)	0.530

The table reports the coefficient estimates of the four-factor or five-factor model for monthly returns for the long, short, and hedge portfolios. The hedge portfolios are from the two-way sorts by predicted stock returns based on target prices (PRET) and the standard deviation of predicted returns (PRSTD) in Table 3. Each month, we first sort stocks into ten deciles by PRSTD. Then for each resulting PRSTD decile, we further sort stocks into ten groups by PRET. The long position is stocks in low-PRSTD and high-PRET group, whereas the short position is stocks in the high-PRSTD and high-PRET group. We rebalance our portfolio and calculate one-month-ahead returns (RET_{t+1}) each month. Please see Appendix B for detailed variable definitions. The four- and five-factor models estimated are:

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

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

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), RMW and CMA are profitability and investment factors as defined in Fama and French (2015). These factor data are from Kenneth French's website.

Table 5
Regressions of Future Returns on Standard Deviation of Predicted Stock Returns and Predicted Stock Returns from Consensus Target Prices

	Coefficient (t-stat)		Coefficient (t-stat)
Intercept	0.141 (9.31)	Intercept	0.152 (9.01)
PRET	0.010 (1.06)	PRET	-0.045 (-5.06)
PRSTD	0.021 (2.01)	LOWPRSTD	-0.012 (-2.50)
PRET×PRSTD	-0.104 (-8.21)	HIPRSTD	0.011 (1.43)
		PRET×LOWPRSTD	0.043 (5.78)
		PRET×HIPRSTD	-0.045 (-5.06)
SIZE	-0.035 (-4.12)	SIZE	-0.034 (-3.95)
BM	-0.001 (-0.08)	BM	-0.000 (-0.01)
$RET_{t\text{-}6,t\text{-}1}$	-0.012 (-0.94)	$RET_{t\text{-}6,t\text{-}1}$	-0.012 (-0.89)
ACC	-0.006 (-1.46)	ACC	-0.005 (-1.24)
Adj. R^2	0.058	Adj. R^2	0.057

This table describes regressions of future 12-month stock returns ($RET_{t+1,t+12}$) on predicted stock returns based on target prices (PRET), the standard deviation of predicted returns (PRSTD), and control variables. PRSTD is the standard deviation of predicted 12-month stock prices from target prices across analysts. LOWPRSTD is a dummy variable with the value of 1 for the bottom PRSTD quartile in a given month and 0 otherwise. HIPRSTD is a dummy variable with the value of 1 for the top PRSTD quartile in a given month and 0 otherwise. Controls are SIZE (the logarithm of the market value of equity), BM (the book-to-market ratio), $RET_{t\text{-}6,t\text{-}1}$ (the 6-month stock return from month *t*-6 to *t*-1), and ACC (accruals). Please see Appendix B for detailed variable definitions. The final sample includes 465,797 firm-month observations from July 1999 to June 2018 with non-missing $RET_{t+1,t+12}$, PRET, and PRSTD. Each month, all independent variables except dummy variables are decile rankings converted into the [0,1] scale. The coefficient estimates are the average of monthly estimates over time; *t*-statistics in parentheses are Fama-MacBeth *t*-statistics.

Table 6
Regressions of Future Earnings Announcement Returns and Analysts' Earnings Forecast Errors on Standard Deviation of Predicted Stock Returns and Predicted Stock Returns from Consensus Target Prices

	Dep Var = ARET	Dep Var = FE_{FY1}	Dep Var = FE_{FY2}
Intercept	0.003 (6.44)	-0.003 (-10.25)	-0.010 (-12.48)
PRET	-0.002 (-5.14)	-0.004 (-9.75)	-0.015 (-16.24)
LOWPRSTD	-0.002 (-5.76)	-0.000 (-0.35)	-0.001 (-2.87)
HIPRSTD	0.000 (0.14)	0.000 (0.34)	0.001 (0.91)
PRET×LOWPRSTD	0.006 (6.99)	0.001 (3.79)	0.007 (8.86)
PRET×HIPRSTD	-0.005 (-5.40)	-0.005 (-7.47)	-0.013 (-9.40)
SIZE	0.000 (0.67)	0.004 (18.34)	0.014 (23.80)
BM	0.001 (1.46)	-0.005 (-11.31)	-0.013 (-13.11)
$RET_{t-6,t-1}$	0.001 (1.44)	0.007 (21.53)	0.014 (21.00)
ACC	0.001 (1.32)	-0.001 (-4.26)	-0.002 (-4.68)
Adj. R^2	0.007	0.056	0.100

This table describes regressions of future earnings announcement returns (EARET), analyst forecast error on FYE1 earnings (FE_{FY1}), and analyst forecast error on FYE2 earnings (FE_{FY2}) on predicted stock returns based on target prices (PRET), the standard deviation of predicted returns (PRSTD), and control variables. PRSTD is the standard deviation of predicted 12-month stock prices from target prices across analysts. LOWPRSTD is a dummy variable with the value of 1 for the bottom PRSTD quartile in a given month and 0 otherwise. HIPRSTD is a dummy variable with the value of 1 for the top PRSTD quartile in a given month and 0 otherwise. Controls are SIZE (the logarithm of the market value of equity), BM (the book-to-market ratio), $RET_{t-6,t-1}$ (the 6-month stock return from month *t*-6 to *t*-1), and ACC (accruals). Please see Appendix B for detailed variable definitions. The final sample includes 465,797 firm-month observations from July 1999 to June 2018 with non-missing $RET_{t+1,t+12}$, PRET, and PRSTD. Each month, all independent variables except dummy variables are decile rankings converted into the [0,1] scale. The coefficient estimates are the average of monthly estimates over time; *t*-statistics in parentheses are Fama-MacBeth *t*-statistics.

Table 7
Regressions of Past Performance on Standard Deviation of Predicted Stock Returns and Predicted Stock Returns from Consensus Target Prices

Dependent Var:	$RET_{t-11,t}$	$EREV_{t-2,t}$	$TPREV_{t-2,t}$	TPREVTIME
Intercept	0.403 (16.82)	-0.000 (-0.53)	0.049 (10.05)	4.661 (434.9)
PRET	-0.402 (-13.36)	-0.002 (-10.35)	-0.092 (-16.05)	0.052 (6.96)
LOWPRSTD	-0.095 (-8.16)	0.000 (2.28)	-0.013 (-4.52)	0.051 (10.29)
HIPRSTD	0.154 (6.50)	-0.001 (-3.01)	-0.255 (-1.14)	-0.022 (-2.89)
PRET ×LOWPRSTD	0.188 (12.38)	0.001 (3.80)	0.074 (18.18)	-0.071 (-7.24)
PRET ×HIPRSTD	-0.259 (-11.88)	-0.005 (-9.31)	0.052 (0.24)	0.003 (0.38)
Adj. R^2	0.129	0.059	0.111	0.008

This table describes regressions of past 12-month returns from months *t*-11 to *t* ($RET_{t-11,t}$), past three-month analyst earnings revision from months *t*-2 to *t* ($EREV_{t-2,t}$), past three-month analyst target price revision ($TPREV_{t-2,t}$), and the average time lag since the last time analysts update their target prices (TPREVTIME) on predicted stock returns based on target prices (PRET) and the standard deviation of predicted 12-month stock prices from target prices across analysts (PRSTD). LOWPRSTD is a dummy variable with the value of 1 for the bottom PRSTD quartile in a given month and 0 otherwise. HIPRSTD is a dummy variable with the value of 1 for the top PRSTD quartile in a given month and 0 otherwise. Please see Appendix B for detailed variable definitions. The final sample includes 465,797 firm-month observations from July 1999 to June 2018 with non-missing $RET_{t+1,t+12}$, PRET, and PRSTD. Each month, all independent variables except dummy variables are decile rankings converted into the [0,1] scale. The coefficient estimates are the average of monthly estimates over time; *t*-statistics in parentheses are Fama-MacBeth *t*-statistics.

Table 8
Controlling for Earnings Forecast Dispersion and Staleness in Target Prices

	EFSTD instead of PRSTD	Controlling for EFSTD	Using target prices from month *t*	Using target prices from months *t-1* and *t*
Intercept	0.147 (8.18)	0.143 (8.86)	0.138 (7.05)	0.143 (8.29)
PRET	-0.017 (-1.29)	0.021 (1.71)	-0.000 (-0.03)	-0.001 (-0.09)
PRSTD		0.020 (1.93)	0.005 (0.39)	0.011 (0.94)
PRET×PRSTD		-0.084 (-5.80)	-0.072 (-3.55)	-0.078 (-5.58)
EFSTD	-0.003 (-0.22)	-0.014 (-1.32)		
PRET×EFSTD	-0.061 (-3.79)	-0.028 (-1.76)		
SIZE	-0.033 (-3.59)	-0.036 (-4.05)	-0.053 (-4.44)	-0.047 (-4.71)
BM	0.007 (0.65)	0.005 (0.43)	-0.011 (-0.84)	-0.010 (-0.82)
$RET_{t-6,t-1}$	-0.009 (-0.67)	-0.011 (-0.84)	0.028 (1.53)	0.015 (0.91)
ACC	-0.008 (-2.05)	-0.008 (-2.25)	-0.003 (-0.52)	-0.007 (-1.33)
Adj. R^2	0.062	0.067	0.077	0.071
N	395,737	395,737	120,431	240,832

This table describes regressions of future 12-month stock returns ($RET_{t+1,t+12}$) on predicted stock returns based on target prices (PRET), the standard deviation of predicted returns (PRSTD), and control variables. PRSTD is the standard deviation of predicted 12-month stock prices from target prices across analysts. EFSTD is the dispersion in analysts' FY1 earnings forecasts scaled by stock price. In columns 3 (4), we construct consensus target prices and its standard deviation based on individual target prices issued in month t (months t-1 and t) to address the staleness problem, where we require at least individual target prices to calculate the standard deviation. Controls are SIZE (the logarithm of the market value of equity), BM (the book-to-market ratio), $RET_{t-6,t-1}$ (the 6-month stock return from month *t*-6 to *t*-1), and ACC (accruals). Please see Appendix B for detailed variable definitions. The final sample includes 465,797 firm-month observations from July 1999 to June 2018 with non-missing $RET_{t+1,t+12}$, PRET, and PRSTD. Each month, all independent variables except dummy variables are decile rankings converted into the [0,1] scale. The coefficient estimates are the average of monthly estimates over time; *t*-statistics in parentheses are Fama-MacBeth *t*-statistics.

Table 9
Partitions of Table 5 Analyses by Residual Short Interest

	Low residual short interest	High residual short interest
Intercept	0.178 (11.43)	0.135 (7.89)
PRET	-0.027 (-2.58)	-0.028 (-3.02)
LOWPRSTD	-0.018 (-4.01)	-0.011 (-1.83)
HIPRSTD	0.011 (1.07)	0.008 (0.77)
PRET×LOWPRSTD	0.039 (4.24)	0.032 (2.82)
PRET×HIPRSTD	-0.007 (-0.50)	-0.048 (-3.75)
SIZE	-0.047 (-5.46)	-0.016 (-1.72)
BM	-0.025 (-3.46)	-0.006 (-0.63)
$RET_{t-6,t-1}$	-0.009 (-0.76)	-0.002 (-0.19)
ACC	0.005 (1.04)	-0.011 (-2.47)
Adj. R^2	0.045	0.050

This table describes regressions of future 12-month stock returns ($RET_{t+1,t+12}$) on predicted stock returns based on target prices (PRET), the standard deviation of predicted 12-month stock prices from target prices across analysts (PRSTD), and control variables for subsamples partitioned by residual short interest. PRSTD is the standard deviation of predicted 12-month stock prices from target prices across analysts. LOWPRSTD is a dummy variable with the value of 1 for the bottom PRSTD quartile in a given month and 0 otherwise. HIPRSTD is a dummy variable with the value of 1 for the top PRSTD quartile in a given month and 0 otherwise. Controls are SIZE (the logarithm of the market value of equity), BM (the book-to-market ratio), $RET_{t-6,t-1}$ (the 6-month stock return from month *t*-6 to *t*-1), and ACC (accruals). For the sample partitions, residual short interest is the residual of regressing short interest (the percentage of outstanding shares shorted), on SIZE and INST each month. The low and high residual short interest subsamples correspond to observations below and above the median each month, respectively. Please see Appendix B for detailed variable definitions. The final sample includes 465,797 firm-month observations from July 1999 to June 2018 with non-missing $RET_{t+1,t+12}$, PRET, and PRSTD. Each month, all independent variables except dummy variables are decile rankings converted into the [0,1] scale. The coefficient estimates are the average of monthly estimates over time; *t*-statistics in parentheses are Fama-MacBeth *t*-statistics.

Table 10
Partitions of Table 5 Analyses by Residual Institutional Ownership

	Low residual institutional ownership	High residual institutional ownership
Intercept	0.161 (8.86)	0.145 (8.81)
PRET	-0.057 (-5.23)	-0.035 (-3.80)
LOWPRSTD	-0.013 (-1.95)	-0.010 (-2.06)
HIPRSTD	0.018 (1.87)	-0.005 (-0.55)
PRET×LOWPRSTD	0.044 (3.82)	0.037 (3.80)
PRET×HIPRSTD	-0.070 (-5.48)	-0.003 (-0.27)
SIZE	-0.040 (-4.00)	-0.026 (-3.36)
BM	0.018 (1.51)	-0.010 (-0.97)
$RET_{t\text{-}6,t\text{-}1}$	-0.017 (-1.29)	-0.009 (-0.65)
ACC	-0.013 (-2.74)	-0.001 (-0.26)
Adj. R^2	0.068	0.050

This table describes regressions of future 12-month stock returns ($RET_{t+1,t+12}$) on predicted stock returns based on target prices (PRET), the standard deviation of predicted 12-month stock prices from target prices across analysts (PRSTD), and control variables for subsamples partitioned by institutional ownership. PRSTD is the standard deviation of predicted 12-month stock prices from target prices across analysts. LOWPRSTD is a dummy variable with the value of 1 for the bottom PRSTD quartile in a given month and 0 otherwise. HIPRSTD is a dummy variable with the value of 1 for the top PRSTD quartile in a given month and 0 otherwise. Controls are SIZE (the logarithm of the market value of equity), BM (the book-to-market ratio), $RET_{t\text{-}6,t\text{-}1}$ (the 6-month stock return from month *t*-6 to *t*-1), and ACC (accruals). For the sample partitions, residual institutional ownership is the residual of regressing institutional ownership on firms size each month. The low and high residual institutional ownership subsamples include observations with residual ownership below and above the median each month, respectively. Please see Appendix B for detailed variable definitions. The final sample includes 465,797 firm-month observations from July 1999 to June 2018 with non-missing $RET_{t+1,t+12}$, PRET, and PRSTD. Each month, all independent variables except dummy variables are decile rankings converted into the [0,1] scale. The coefficient estimates are the average of monthly estimates over time; *t*-statistics in parentheses are Fama-MacBeth *t*-statistics.