

**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 find that the *dispersion* of individual analysts' target prices that comprise the consensus is an important moderating factor. 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. Further analyses suggest that this phenomenon is partially due to consensus target prices being slow to reflect bad news. In addition, we show that the negative correlation between consensus-based predicted returns and future realized returns for high-dispersion stocks exists only for stocks with high short interest or 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

Many publicly traded stocks are covered by a number of dedicated financial analysts who provide periodic research reports and valuation estimates after studying information and interpreting news about the firm. 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). Although investors can also observe more detailed data about earnings, growth, and revenue forecasts, they need to decide how to map this information into a stock price to make it useful for trading decisions. 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 its return.¹

While detailed research reports and individual analyst target prices for a given stock may be accessed through paid subscription services, consensus analyst target prices are freely available to retail investors on many financial websites.² These consensus target prices may be useful to investors because consensus measures reduce the noise that is inherent in individual judgments (Dimson and Marsh 1984; Larrick and Soll 2006) and represent the collective opinion of analysts who cover the firm (e.g., Galton 1907; Surowiecki 2005). The widespread availability of consensus target prices suggests that either investors find these measures useful, or the purveyors of financial information believe that they should be useful to investors. Despite their prevalence and potential influence on investor behavior, consensus target prices have received relatively little attention in the existing literature. The

¹ 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 mispricing* is important to investors" (p. 194, emphasis added; also see Asquith et al. 2005 and Bradshaw et al. 2013). Prior literature also argues that target prices and recommendations are not identical sources of information (Brav and Lehavy 2003; Bradshaw et al. 2013; Gleason et al. 2013; Engelberg et al. 2019).

² For example, the following websites provide consensus analyst target prices for free online: Yahoo! Finance, MarketWatch, MSN Money, and CNBC.

purposes of this study are to better understand the information content of consensus analyst target prices and to consider the implications of making these price targets widely available to investors. In doing so, our paper 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 the Thomson Reuters/Refinitiv 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., Feng and Yan 2016; Dechow and You 2018; Engelberg et al. 2019) 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 mean (median) realized return is 9.3% (7.3%). 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; Dechow and You 2018). On average, these consensus target prices are based on the targets

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.

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 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 1996, Guar et al. 2007; Gaba et al. 2019; Engelberg 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-dispersion stocks. We find that relative to low-dispersion stocks, high-dispersion stocks' predicted returns are more negatively associated with prior stock returns and prior forecast revisions. We also find that analysts are slower in updating their target prices for stocks with high dispersion and high predicted returns. 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, and our main dispersion measure remains strongly significant. 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 (Asquith et al. 2005; Bradshaw et al. 2013; Bradshaw et al. 2016). In practice, the vast majority of target prices have a 12-month horizon and represent the analyst's opinion about the stock price 12 months in the future.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; Gleason et al. 2013). Schipper (1991, p. 106) calls stock recommendations "the ultimate analyst judgment," and target prices are critical because they form the basis of these recommendations (Bradshaw 2004; Gleason et al. 2013). The fact that target price disclosure is explicitly regulated in FINRA Rule 2241 (and its predecessors NASD Rule 2711 and NYSE Rule 472) provides additional support for the 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., Francis and Philbrick 1993; Groyberg et al. 2011; Bradshaw 2011; Brown et al. 2015). For example, consider the bank research director quoted in Groyberg 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

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.

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).⁶ Moreover, many potential conflicts of interest relating to analysts have been identified in the literature. For example, Bradshaw (2011) lists incentives related to investment banking fees, currying favor with management, trade generation, institutional investor relationships, research for hire, and analysts’ own behavioral biases as potential concerns when considering analysts’ research, forecasts, and recommendations. These types of conflicts have been discussed as potential drivers of the positively skewed distribution of stock recommendations (e.g., Bradshaw 2002), which suggests they 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. 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 consensus target price represents the aggregate opinion of multiple analysts, the

⁶ Supporting the view that analysts may not focus on forecast accuracy, Engelberg et al. (2019) and Drake et al. (2011) show that analysts’ target prices and recommendations do not fully reflect public information related to documented stock return anomalies.

“wisdom of crowds” (Surowiecki 2005) suggests that it will generally be more accurate than an individual target price, which may increase the credibility of the consensus information in the minds of investors.⁷ The 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., Feng and Yan 2016; Dechow and You 2018; Engelberg et al. 2019); however, we focus on the consensus target price provided by IBES because we believe this more closely matches the consensus target price information available online to investors. 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.

⁷ Given our interest in unsophisticated investors’ use of consensus target price information, we appeal to these arguments of perceived credibility of the consensus. However, we also acknowledge prior research that documents bias in measures aggregated from poll-type settings (such as analysts submitting forecasts) when respondents may behave strategically (e.g., Trueman 1994; Morgan and Stocken 2008). These findings provide additional motivation for understanding the information content of consensus target prices and the resulting implications for investors.

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 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 consensus target prices corresponds to a range in consensus-based predicted returns of 5.1%. The mean (median) IBES consensus target price for 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, on all platforms there were both firms with only one unique target price observed during the entire 30-day period (i.e., no updating of the consensus target price) and firms 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 those calculated by IBES.⁸ For completeness, we present signed and 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, looking at average signed differences, the IBES consensus differs from the online consensus by less than 1% on each of the platforms for both mean and median prices. 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, consensus target prices are similar across the various financial websites, and 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 a large

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.

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).

proportion of stocks do not reach their target prices (e.g., Dimson and Marsh 1984; Brown et al. 1991; Brav and Lehavy 2003; Asquith et al. 2005; Bradshaw et al. 2013). Analysts' target prices and recommendations are related to their forecasts of earnings and long-term growth (e.g., Bandyopadhyay et al. 1995; Bradshaw 2004), and analysts' target price revisions are influenced by recent market performance, stock returns, and other analysts' revisions (Ho et al. 2018). Target price accuracy is associated with analyst characteristics, valuation techniques, earnings forecast accuracy, firm-specific factors, and aspects of country culture (Bilinski et al. 2013; Gleason et al. 2013; Imam 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 (e.g., Asquith et al. 2005), 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, Bradshaw et al. 2013; 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...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

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).

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; Fisher and Raman 1996; Barron and Stuerke 1998; Guar et al. 2007; Barron et al. 2009; Engelberg et al. 2019) analyses suggest that the dispersion of a set of individual estimates is negatively related to the accuracy of 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, have only been 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 $RET_{t+1,t+12}$, the 12-month future realized return from month $t+1$ to month $t+12$, where t refers to the month in which IBES calculates the consensus target price. Our 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 $RET_{t+1,t+12}$, PRET, and PRSTD.

Table 1 presents descriptive statistics and correlations for $RET_{t+1,t+12}$, PRET, and PRSTD, our three primary variables of interest, along with several other control variables used throughout the analyses. The variable COV records the number of analysts contributing to the consensus target price calculation. Market value of equity (MV), the book-to-market ratio (BM), past realized returns from months $t-6$ to $t-1$ ($RET_{t-6,t-1}$), and accruals from the fiscal year prior to month t (ACC) are commonly-used factors that potentially explain stock returns.¹³ Panel A presents summary statistics, with all variables except returns winsorized each month at their 1st and 99th percentiles. Comparing $RET_{t+1,t+12}$ with PRET at both the mean (9.3% vs. 21.7%) and median (7.3% vs. 14.4%), it is clear that analysts'

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 based on each individual analyst's target price and the current stock price at the time of each 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.

target prices tend to be optimistic, consistent with findings from prior literature (e.g., Bradshaw et al. 2013; Dechow and You 2018). It is 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, 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 tends to be 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 is consistent with Engelberg et al. (2019) and 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

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 (un-tabulated) 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.

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 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

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

We use decile portfolios and regression models to further examine the relations among $RET_{t+1,t+12}$, $PRET$, and $PRSTD$ to shed light on the information content of consensus target prices. 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 indicate that stocks with the highest predicted returns based on consensus target prices in fact perform the worst on average. 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

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 lower values of the sorting variable X .

prices are generally 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% ($t = 2.05$). In stark contrast to the overall pattern observed in Table 2, there is a positive correlation between PRET and $RET_{t+1,t+12}$ when analysts agree in their target prices (i.e., when PRSTD is low), 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 dramatic 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. A corresponding hedge portfolio that goes long (short) in PRET10 (PRET1) stocks within the PRSTD10 decile yields a -9.51% return ($t = -4.86$).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 an 11.68% return ($t = 5.73$) to a hedge portfolio going long (short) in the stocks from PRET10 in PRSTD1 (PRSTD10).

4.3 Four-factor and five-factor models

To provide additional evidence that the results from Table 3 are robust after considering the potential impact of commonly-used factors, we estimate four-factor and five-factor models for monthly returns on the long (PRSTD1, PRET10), short (PRSTD10, PRET10), and the hedge portfolio:

$$R_{it} - R_{ft} = a + b_{iM}(R_{Mt} - R_{ft}) + s_iSMB_t + h_iHML_t + m_iMOM_t + \varepsilon_{it} \quad (1a)$$

$$R_{it} - R_{ft} = a + b_{iM}(R_{Mt} - R_{ft}) + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + \varepsilon_{it} \quad (1b)$$

In equations (1a) and (1b), $R_{it} - R_{ft}$ is the average monthly excess return for each portfolio from month $t+1$, $R_{Mt} - R_{ft}$, SMB , and HML are as defined in Fama and French (1996); MOM is the momentum factor as defined in Carhart (1997); and RMW and CMA are profitability and investment factors as defined in Fama and French (2015).¹⁷ In equations (1a) and (1b), the intercept a captures the monthly abnormal return for each hedge portfolio after controlling for commonly-used factors. Results of estimating the models are presented in Table 4. Focusing on the intercept column, we observe a pattern similar to

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

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

Table 3 where the PRSTD1 decile has a positive abnormal return (only significant in Panel A for the four-factor model) while the PRSTD10 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. Converting these average monthly returns to an annual basis indicates an economically significant annual hedge return between 18.0% and 28.8% to the trading strategy that utilizes consensus predicted returns and their dispersion.

4.4 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:

$$RET_{t+1,t+12,it} = \beta_0 + \beta_1 PRET_{it} + \beta_2 PRSTD_{it} + \beta_3 PRET_{it} \times PRSTD_{it} + \sum_1^k \beta_{3+k} CTRL_k + \varepsilon_{it} \quad (2)$$

$$RET_{t+1,t+12,it} = \alpha_0 + \alpha_1 PRET_{it} + \alpha_2 LOWPRSTD_{it} + \alpha_3 HIPRSTD + \alpha_4 PRET_{it} \times LOWPRSTD_{it} + \alpha_5 PRET_{it} \times HIPRSTD_{it} + \sum_1^k \alpha_{5+k} CTRL_k + \varepsilon_{it} \quad (3)$$

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 measure of PRSTD 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), the interaction of $PRET \times PRSTD$ 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 future stock performance.¹⁸ 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, $PRET \times LOWPRSTD$ 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, $PRET \times HIPRSTD$ 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 depends crucially 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

¹⁸ In untabulated analysis, we also interact $PRSTD$ with $SIZE$ and $RET_{t-6,t-1}$ and find that both interactions are statistically insignificant whereas the coefficient on the main variable of interest, $PRET \times PRSTD$, is largely unchanged at -0.099 ($t = -7.68$).

other hand, when dispersion is large (i.e., higher PRSTD), the relation flips with predicted stock returns from the consensus target price becoming 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 because future returns (examined in Tables 3, 4, and 5) should reflect future fundamental performance, but we view this analysis as necessary to ensure that the observed stock return patterns 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 $\text{PRET} \times \text{LOWPRSTD}$ for all three future performance measures (t -statistics range from 3.79 to 8.86), while $\text{PRET} \times \text{HIPRSTD}$ 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 reflect 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 tests consider 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' forecast revisions. Intuitively, this analysis sheds light on what kinds of firms fall into the two-way sort portfolios shown in Table 3. For these analyses, we consider the following measures: (1) $\text{RET}_{t-11,t}$ is the stock return from the prior 12 months; (2) $\text{EREV}_{t-3,t}$ is the three-month analyst revision of forecasted earnings for the current fiscal year (FY1), from month $t-3$ to t , scaled by stock price in month t ; (3) $\text{TPREV}_{t-3,t}$ is the three-month analyst revision of target prices from month $t-3$ to t , scaled by stock price in month t ; and (4) TPREVTIME is the average natural log of the number of days since each analyst last updated their target price (i.e., averaged across all analysts for each firm-month).

Using a structure similar to Table 3, Table 7 presents means for each of these four variables for each PRET decile in the first, sixth, and tenth PRSTD deciles (for parsimony we do not show all PRSTD deciles). We observe a general negative trend for $\text{RET}_{t-11,t}$ moving from $\text{PRET}1$ to $\text{PRET}10$ in all PRSTD deciles, indicating that stocks with higher predicted returns have experienced worse recent

realized returns than stocks with lower predicted returns. However, the magnitude of this negative trend increases dramatically from PRSTD1 to PRSTD10, suggesting that the high-PRSTD, high-PRET stocks tend to be those with particularly poor past performance.¹⁹ The observed patterns of $EREV_{t-3,t}$ and $TPREV_{t-3,t}$ also suggest that high-PRSTD, high-PRET stocks are those with the most negative recent performance (as captured by analyst revision activity).²⁰ More importantly, average target price revision time (TPREVTIME) declines from 131 days in PRET1 to 127 days in PRET10 for low-PRSTD stocks, yet it increases from 128 days in PRET1 to 149 days in PRET10 for high-PRSTD stocks. The high-PRSTD, high-PRET stocks are those with the longest revision times, implying that these stocks have more stale consensus target prices. 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, and these stocks also tend to have the worst recent performance, it suggests the consensus target price is too high, as analysts do not update their target prices in a timely fashion. To the extent that investors buy stocks based on consensus target prices, limits to arbitrage will prevent these high-PRSTD, high-PRET stocks from converging towards their fundamental values, which leads to lower future returns.

Overall, the evidence in Table 7 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 (1) incorporate all public information into their price targets, particularly when the information is negative (Engelberg et al. 2019), and (2) update

¹⁹ To illustrate the magnitude of the difference in the negative trend for PRSTD1 vs. PRSTD10, consider the difference between the PRET10 and PRET1 values of $RET_{t-11,t}$ for stocks in PRSTD1 ($-0.166 = 0.181 - 0.347$) vs. PRSTD10 ($-0.654 = -0.213 - 0.441$).

²⁰ The only notable difference in the patterns for $EREV_{t-3,t}$ and $TPREV_{t-3,t}$ vs. the pattern for $RET_{t-11,t}$ is that there isn't a clear negative trend in $EREV_{t-3,t}$ and $TPREV_{t-3,t}$ moving from PRET1 to PRET10 for the PRSTD1 stocks.

earnings forecasts after receiving bad news due to their incentives and/or conflicts of interest (e.g., McNichols and O'Brien 1997; Hayes 1998; Raedy et al. 2006).²¹ 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.

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 key 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; Dechow and You 2018). With limits to arbitrage, Miller (1977) suggests stocks with higher uncertainty and investor disagreement will be overvalued, resulting in lower subsequent returns. Second, given the results in Table 7, we consider whether staleness in target prices after bad performance is partially responsible for the negative association between predicted and realized returns for high-dispersion stocks.²²

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 use a model with both EFSTD and PRSTD (and their interactions with PRET). 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

²¹ Ho et al. (2018) find that target price revisions are more sensitive to bad news than good news for UK firms, but their analyses are conditional upon observing a target price revision. Bradshaw et al. (2016) argue that "self-censoring is likely to contaminate studies that draw inferences based on revisions, for example, because some downward revisions may be missing" (p. 142). Our findings suggest that analysts are slower to update target prices after recent poor performance, which is consistent with Ho et al. (2018) in that when analysts do decide to issue a negative target price revision, it is likely to be after observing very significant bad news.

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

results, the $\text{PRET} \times \text{EFSTD}$ interaction term is significantly negative ($-0.061, t = -3.79$), but the magnitude is much smaller compared to the $\text{PRET} \times \text{PRSTD}$ coefficient reported in Table 5 ($-0.104, t = -8.21$). Moreover, when EFSTD and PRSTD are included simultaneously (column (2) of Table 8), $\text{PRET} \times \text{PRSTD}$ continues to load strongly negative ($-0.084, t = -5.80$) while $\text{PRET} \times \text{EFSTD}$ loads only marginally ($-0.028, t = -1.76$). These results are consistent with our expectations and suggest that while fundamental uncertainty is one mechanism responsible for our main results, PRSTD itself captures more than that.

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 $\text{PRET} \times \text{PRSTD}$ 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.²³

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 not all analysts appear to be unaware of information that pertains to future performance. For example, we observe that earnings forecast and target price

²³ 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 $\text{PRET} \times \text{PRSTD}$ 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.

revisions prior to month t exhibit patterns similar to prior stock returns, suggesting that at least some analysts are updating their expectations based on the arrival of relevant information. In other words, the dispersion observed for the consensus target price in month t seems to not accurately reflect dispersion in analysts' true opinions 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 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.²⁴ Limits to arbitrage prevent mispriced stocks (i.e., those with high PRSTD and high PRET) from converging towards their fundamental values. We use residual short interest as a proxy for limits to arbitrage. Specifically, we regress short interest (the percentage of outstanding shares shorted) on firm size and institutional ownership each month because short interest is strongly associated with firm size and institutional ownership. 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 $PRET \times LOWPRSTD$

²⁴ 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.

coefficient is similarly positive and significant in both subsamples, the mispriced stocks are concentrated in the high residual short interest subsample: $\text{PRET} \times \text{HIPRSTD}$ is insignificant in the low subsample ($-0.007, t = -0.50$) but strongly significant in the high subsample ($-0.048, t = -3.75$).

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 use 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, $\text{PRET} \times \text{LOWPRSTD}$ loads significantly positive in both subsamples. However, $\text{PRET} \times \text{HIPRSTD}$ 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 the Miller (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. More importantly, we show that the *dispersion* in individual analyst target prices that comprise the consensus is a critical moderating factor. 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 recent poor performance.

Finally, we find that the strong negative correlation between consensus-based predicted returns and future realized returns appears only for stocks with high short interest or 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 a regulatory perspective, one potential remedy would be to require financial websites to disclose the dispersion or other information about the variation in target prices along with the consensus.

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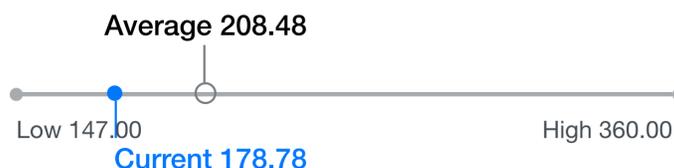
Appendix A
IBES Consensus Target Prices and Screenshots of Consensus Target Price Information
from Financial Websites for FedEx Corporation (FDX) on May 9, 2019

IBES Consensus Target Price Information for FDX in April and May 2019

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

Yahoo! Finance: May 9, 2019

Analyst Price Targets (25) >



MarketWatch: May 9, 2019

Average Target Price: **210.08**

MSN Money: May 9, 2019

1 Year Price Target	201.00
Analysts	29

CNBC: May 9, 2019

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

	<i>Valid observations</i>	<i>Missing observations</i>	<i>Missing %</i>
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

	<i>Firms</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>Min</i>	<i>25%</i>	<i>Median</i>	<i>75%</i>	<i>Max</i>
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

	<i>N</i>	Online consensus – IBES mean				Online consensus – IBES mean IBES mean			
		Signed		Absolute Value		Signed		Absolute Value	
		<i>Mean</i>	<i>Median</i>	<i>Mean</i>	<i>Median</i>	<i>Mean</i>	<i>Median</i>	<i>Mean</i>	<i>Median</i>
Yahoo! Finance	888	\$0.06	\$0	\$0.63	\$0	0.39%	0%	0.91%	0%
MarketWatch	816	-\$0.16	\$0	\$0.81	\$0.25	0.03%	0%	1.28%	0.69%
MSN Money	812	\$0.23	\$0	\$2.09	\$0.60	0.23%	0%	2.96%	2.13%
CNBC	872	\$0.10	\$0	\$0.74	\$0.01	0.46%	0%	1.05%	0.04%

	<i>N</i>	Online consensus – IBES median				Online consensus – IBES median IBES median			
		Signed		Absolute Value		Signed		Absolute Value	
		<i>Mean</i>	<i>Median</i>	<i>Mean</i>	<i>Median</i>	<i>Mean</i>	<i>Median</i>	<i>Mean</i>	<i>Median</i>
Yahoo! Finance	888	-\$0.07	\$0.14	\$1.50	\$0.50	0.80%	0.56%	2.54%	1.70%
MarketWatch	816	-\$0.29	\$0.02	\$1.51	\$0.65	0.55%	0.14%	2.52%	1.93%
MSN Money	812	\$0.09	\$0	\$1.04	\$0	0.61%	0%	1.38%	0%
CNBC	872	-\$0.03	\$0.29	\$1.56	\$0.57	0.87%	0.63%	2.59%	1.70%

Appendix B Variable Definitions

Variable	Definition
<i>Main dependent variable</i>	
RET _{t+1,t+12}	12-month future realized stock return from months $t+1$ to $t+12$, where month t is the month of calculation for the corresponding consensus analyst target price. Calculated using returns from the CRSP monthly stock file.
<i>Main independent variables</i>	
PRET	Predicted 12-month stock return based on the consensus analyst target price issued by IBES in month t . Calculated as (average target price – stock price)/stock price in month t . Monthly stock price is taken from the IBES Summary History Actuals + Pricing and Ancillary File. The value of the stock price is the closing price on the day before the monthly IBES Statistical Period Date (the day when consensus information is calculated).
PRSTD	Standard deviation of the predicted 12-month stock return (PRET), calculated as the IBES-reported standard deviation of individual analysts' target prices contributing to the consensus in month t , scaled by the stock price in month t (the same stock price used to calculate PRET). As part of our sample selection criteria, we only retain firm-months in IBES with at least four analysts contributing to the consensus calculation.
<i>Other variables</i>	
EARET	Average earnings announcement return over all earnings announcements occurring from months $t+1$ to $t+12$, where month t is the month of calculation for the corresponding consensus analyst target price. Each earnings announcement return is the three-day raw return centered on the earnings announcement date.
FE _{FY1}	Consensus analyst forecast error on FY1 earnings (i.e., the first annual earnings announced after month t), measured as actual earnings minus the median forecasted earnings in month t , scaled by stock price on the forecast date. Month t is the month of calculation for the corresponding consensus analyst target price.
FE _{FY2}	Same as FE _{FY1} except that actual and forecasted earnings for the <i>next</i> fiscal year (FY2) are used.
MV	Market value of equity at the end of month t , where month t is the month of calculation for the corresponding consensus analyst target price.
SIZE	Natural 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 . Calculated as Compustat CEQ / (CSHO×PRCC_F).
RET _{t-6,t-1}	Price momentum measured as the six-month realized return from months $t-6$ to $t-1$, where month t is the month of calculation for the corresponding consensus analyst target price. Calculated using returns from the CRSP monthly stock file.
RET _{t+1}	One-month realized return for month $t+1$, used for the factor models in Table 4. Month t is the month of calculation for the corresponding consensus analyst target price. Calculated using returns from the CRSP monthly stock file.
ACC	Accruals based on Compustat data, measured as the change in (non-cash current assets (ACT-CHE) minus non-debt current liabilities (LCT-DLC)) minus depreciation expense (DP), with the result scaled by average total assets. Similar to BM, ACC data are from the prior fiscal year end with at least a four-month lag.

COV	The number of analysts contributing to the IBES consensus target price calculation in month t .
EREV _{$t-3,t$}	Change in the median analyst forecast of FY1 earnings from month $t-3$ to t , scaled by stock price in month t . Monthly stock price is taken from the IBES Summary History Actuals + Pricing and Ancillary File. The value of the stock price is the closing price on the day before the monthly IBES Statistical Period Date (the day when consensus information is calculated).
TPREV _{$t-3,t$}	Change in the mean analyst target price from month $t-3$ to month t , scaled by stock price in month t . Monthly stock price is taken from the IBES Summary History Actuals + Pricing and Ancillary File. The value of the stock price is the closing price on the day before the monthly IBES Statistical Period Date (the day when consensus information is calculated).
TPREVTIME	Average natural logarithm of the number of days since the last time analysts update their target prices. For each firm-month, we calculate the number of days since each analyst last updated her target price, and then calculate the average logarithm of the number of days across all analysts covering the firm.
EFSTD	Standard deviation of analysts' FY1 earnings forecasts from the monthly I/B/E/S summary file scaled by stock price in month t .
SHORT	The percentage of outstanding shares shorted in month t , calculated as short interest scaled by outstanding shares from monthly Compustat file.
INST	Institutional ownership from the most recent quarterly filings, calculated as the sum of shares owned by all institutional investors in the 13F database scaled by outstanding shares.

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 correlations among key variables. $RET_{t+1,t+12}$ is the 12-month future realized stock return. $PRET$ is the predicted 12-month stock return based on the consensus analyst target price issued by IBES in month t . $PRSTD$ is the standard deviation of the predicted 12-month stock return ($PRET$). MV is the market value of equity at the end of month t , BM is the book-to-market ratio from the end of the previous fiscal year. $RET_{t-6,t-1}$ is the 6-month past realized stock return. ACC is accruals from the end of the previous fiscal year. COV is the number of analysts contributing to the IBES consensus target price calculation in month t . FE_{FY1} is the consensus analyst forecast error on FY1 earnings (i.e., the first annual earnings announced after month t). $EARET$ is the average earnings announcement return over all earnings announcements occurring from months $t+1$ to $t+12$. Please see 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 analyst in each firm's fiscal year. Then we calculate average revision frequencies over more than 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 12-month future realized stock returns (RET_{t+1,t+12}) and predicted stock returns based on consensus target prices (PRET) across ten PRET deciles. Each month, we sort stocks into deciles based on PRET. 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 RET_{t+1,t+12} for each decile 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 12-month future realized 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). 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 $RET_{t+1,t+12}$ for each portfolio over time; t -statistics in parentheses are Fama-MacBeth t -statistics.

Table 4
Factor Models 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 (Panel A) or five-factor (Panel B) model for monthly returns for the long, short, and hedge portfolios. The hedge portfolios are from the two-way sorts by the standard deviation of predicted returns (PRSTD) and predicted stock returns based on consensus target prices (PRET). 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), and 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 _{<i>t-6,t-1</i>}	-0.012 (-0.94)	RET _{<i>t-6,t-1</i>}	-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 12-month future realized stock returns ($RET_{t+1,t+12}$) on predicted stock returns based on consensus target prices (PRET), the standard deviation of predicted returns (PRSTD), and control variables. PRSTD is the standard deviation of the predicted 12-month stock return (PRET). 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 (natural logarithm of the market value of equity), BM (the book-to-market ratio), $RET_{t-6,t-1}$ (the 6-month past realized stock return), and ACC (accruals). Please see Appendix B for detailed variable definitions. Our main sample includes 465,797 firm-month observations from July 1999 to June 2018 with non-missing $RET_{t+1,t+12}$, PRET, and PRSTD, but these regressions also require non-missing control variables. 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' Future Earnings Forecast Errors on Standard Deviation of Predicted Stock
Returns and Predicted Stock Returns from Consensus Target Prices

	Dep Var = EARET	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 _{<i>t-6,t-1</i>}	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), consensus analyst forecast errors on FY1 earnings (FE_{FY1}), and consensus analyst forecast errors on FY2 earnings (FE_{FY2}) on predicted stock returns based on consensus target prices (PRET), the standard deviation of predicted returns (PRSTD), and control variables. PRSTD is the standard deviation of the predicted 12-month stock return (PRET). 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 (natural logarithm of the market value of equity), BM (the book-to-market ratio), RET_{*t-6,t-1*} (the 6-month past realized stock return), and ACC (accruals). Please see Appendix B for detailed variable definitions. 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
Past Performance and Analyst Revisions based on Double Sorts by Standard Deviation of Predicted Stock Returns and Predicted Stock Returns from Consensus Target Prices

PRET Decile:		1	2	3	4	5	6	7	8	9	10
PRSTD1	RET _{<i>t-11,t</i>}	0.347	0.261	0.248	0.239	0.223	0.223	0.216	0.222	0.199	0.181
	EREV _{<i>t-3,t</i>}	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.001
	TPREV _{<i>t-3,t</i>}	0.025	0.034	0.033	0.032	0.032	0.037	0.034	0.034	0.034	0.025
	TPREVTIME	131	131	132	131	132	130	132	129	127	127
PRSTD6	RET _{<i>t-11,t</i>}	0.473	0.362	0.303	0.256	0.190	0.179	0.138	0.106	0.092	0.055
	EREV _{<i>t-3,t</i>}	-0.001	0.000	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002	-0.003
	TPREV _{<i>t-3,t</i>}	0.042	0.038	0.030	0.020	0.011	0.002	-0.007	-0.018	-0.021	-0.026
	TPREVTIME	119	123	125	123	127	126	126	128	128	130
PRSTD10	RET _{<i>t-11,t</i>}	0.441	0.161	0.046	-0.019	-0.059	-0.084	-0.085	-0.119	-0.147	-0.213
	EREV _{<i>t-3,t</i>}	-0.006	-0.008	-0.009	-0.011	-0.012	-0.013	-0.011	-0.011	-0.012	-0.014
	TPREV _{<i>t-3,t</i>}	-0.062	-0.132	-0.175	-0.190	-0.214	-0.240	-0.248	-0.270	-0.290	-0.324
	TPREVTIME	128	126	124	127	127	125	129	133	137	149

This table describes the relation between our variables of interest (PRET and PRSTD) and the following variables: 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-3,t*}), past three-month analyst target price revision (TPREV_{*t-3,t*}), and the average time lag since the last time analysts update their target prices (TPREVTIME). Please see Appendix B for detailed variable definitions. We present portfolio averages of these variables for each PRET decile within the first, sixth, and tenth PRSTD deciles (for parsimony not all PRSTD deciles are shown).

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 12-month future realized stock returns ($RET_{t+1,t+12}$) on predicted stock returns based on consensus target prices (PRET), the standard deviation of predicted returns (PRSTD), and control variables. PRSTD is the standard deviation of the predicted 12-month stock return (PRET). EFSTD is the dispersion in analysts' FY1 earnings forecasts scaled by stock price. In column 3 (4), we construct our own consensus target prices and their 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 four individual target prices to calculate the standard deviation. Controls are SIZE (natural logarithm of the market value of equity), BM (the book-to-market ratio), $RET_{t-6,t-1}$ (the 6-month past realized stock return from month), and ACC (accruals). Please see Appendix B for detailed variable definitions. 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 _{<i>t-6,t-1</i>}	-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 12-month future realized stock returns ($RET_{t+1,t+12}$) on predicted stock returns based on consensus target prices (PRET), the standard deviation of predicted returns (PRSTD), and control variables for subsamples partitioned by residual short interest. PRSTD is the standard deviation of the predicted 12-month stock return (PRET). 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 (natural logarithm of the market value of equity), BM (the book-to-market ratio), $RET_{t-6,t-1}$ (the 6-month past realized stock return), and ACC (accruals). For the sample partitions, residual short interest is the residual of regressing SHORT (the percentage of outstanding shares shorted), on SIZE and INST (percentage of institutional ownership from the most recent quarterly filings) 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. 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 _{<i>t-6,t-1</i>}	-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 12-month future realized stock returns ($RET_{t+1,t+12}$) on predicted stock returns based on consensus target prices (PRET), the standard deviation of predicted returns (PRSTD), and control variables for subsamples partitioned by residual institutional ownership. PRSTD is the standard deviation of the predicted 12-month stock return (PRET). 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 (natural logarithm of the market value of equity), BM (the book-to-market ratio), $RET_{t-6,t-1}$ (the 6-month past realized stock return), and ACC (accruals). For the sample partitions, residual institutional ownership is the residual of regressing INST on firm size each month. The low and high residual institutional ownership subsamples include observations with residual ownership below and above the median each month, respectively. Please see Appendix B for detailed variable definitions. 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.