The predictive power of analyst price target and its dispersion

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ABSTRACT

We document that the consensus target price and the target price dispersion do provide investors valuable information in stock returns. Using a large database for target price announcements from 2000 to 2017, the monthly profitability of the combination investment strategy can achieve over 3%. The results are both economically and statistically significant and not easily explained by stock characteristics and risk factors. Moreover, the target price implied expected return and the target price dispersion contain independent information in the presence of the other.

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I. Introduction

Financial economists over the last decade have become increasingly interested in examining whether investors could construct profitable investment strategies based on the analyst's forecasts and advices. Reporting decisions by analysts (i.e. analysts employed by brokerage houses, independent research institutes, or investment-banking firms) provide valuable information for both managers and investors. It is not surprising that the earning forecast is the first analyst measure that is widely considered powerful enough to predict stock returns in early studies. Prior literature found the importance of earnings forecasts(e.g., Lander, Orphanides, and Douvogiannis (1997)) and earning forecast horizon(e.g., Bandyopadhyay, Brown, and Richardson (1995)) for stock returns forecasts. In addition, Diether, Malloy, and Scherbina (2002) established a negative relationship between stock returns and the dispersion of analysts' earning forecast, while Johnson (2005) offer an alternative explanation based on the interpretation of dispersion as a proxy for unpriced information risk arising when asset value are unobservable.

Following the track of analysts' earnings forecasts , the price target comes into sight. A target price reflects the analyst's estimate of the firms stock price level at the end of a specific, usually 12-month, forecast horizon, providing easy-to-interpret, direct investment advice (Bilinski, Lyssimachou, and Walker (2013)). Although analysts' target prices are arguably noisy and potentially biased measures, they do provide additional information that fundamentals cannot capture. An increasing number of articles found the predictive and informational power of consensus target prices (e.g. Da and Schaumburg (2011); Huang, Mian, and Sankaraguruswamy (2009); Da, Hong, and Lee (2016)); while Feng and Yan (2016) consider the target price dispersion as a proxy for risk and show that the target price dispersion also positively predicts stock returns.

The results in these studies raise the possibility that investment strategies that combine the information content of both consensus target prices and target price dispersions could outperform those that rely solely on any one of them. This possibility is explored in this paper. We double sort stocks according to consensus target prices and target price dispersions to assess the profitability of the strategies that combine the information content of both consensus target prices and target price dispersions. We then compare the profitability of these strategies with similar strategies that rely solely on either consensus target price or target price dispersions. Possible profitable reasons, such as firms' performances and analysts' recommendations, are also examined. The results supports the superiority of the combination investment strategies.

There are several reasons to expect that the target price expected return and the target price dispersion of a stock would contain useful independent information in the presence of the other. First, the target price dispersion contains the information about the forecast errors (forecast accuracy), not only the consensus price. Bradshaw, Brown, and Huang (2013) found that analyst target price accuracy is largely related to overall market performance. It is not surprising that analyst are less ex-post optimistic in rising market, and their target price forecasts are more accurate in up rather than down markets. In addition, target price dispersion is likely associated with categories of stocks[1]. Therefore, we expect to see that the target price dispersion reflects different information from the target price expected returns in terms of the stock return prediction.

Our sample is extended to all the stocks in NYSE, AMEX, and NASDAQ, not constrained in S&P 500 companies as in Da and Schaumburg (2011). The longer period of our analyses ranges from January 2000 through December 2017. The measure of the consensus target price (TPER) is computed by subtracting one from the ratio of target price and the current stock price. The measure of the target price dispersion (TPD) is the standard deviation of all non-duplicate forecasts from months $t-11$ to t scaled by the current consensus target price. We examine the first month post-formation returns from long-short strategies, including sub-samples and sub-periods.

We document that a combination strategy that buys (sells short) the stocks with the highest (lowest) value in both TPERs and TPDs outperforms the comparable strategies that rely solely on TPERs or TPDs. The profitability of the combination strategy can achieve 4.03%. The profitability is still over 3.4% after controlling for the systematic risks (i.e. Fama-French three factors, a momentum factor and a reversal factor). Although the first four factors are statistically significant across 25 portfolios, this five-factor model is only able to explain part of the stock excess returns. A large amount of the profits remain unexplained. Thus, the profits by sorting stocks based on TPERs and TPDs cannot be fully explained by the five risk factors. The traditional theory that more risk and more equity returns cannot explain this anomaly.

Possible profitable reasons are examined. Similar long-short strategies are implemented accord-

[1] Da and Schaumburg (2011) define the target price dispersion measure as the standard deviation of target prices received from different analysts divided by the consensus target price, and found that the target prices for technology stocks has larger dispersions.

ing to different performance measures (i.e. 1/P, EP, BP, Ret1M, DTP, ΔRec, ΔRec$\times$Ret1M). Neither of those long-short strategies obtain a risk-adjusted alphas greater than 2%. No single strategy is able to produce a higher excess return or risk-adjusted premium than the TPER-TPD combination strategy. Cross-sectional regressions are further examined on the possible drivers of the profitability in our TPER-TPD combination strategy. After controlling for lagged one-month return, book-to-price ratio, firm size, the most recent revision in recommendations and average recommendation changes, the TPER and the TPD are still powerful enough to predict stock returns. Since most prior researchers analyse the investment strategy on target price specifically before 2004 and some focus on S& P 500 companies. Therefore, we establish the TPER-TPD combination strategy in the sub-sample of S&P 500 companies and in the sub-period of 2000-2004. The results of the profitability are relatively consistent across sub-samples and sub-periods.

We expect our results to be of interest to both finance academics and practitioners. The extant analyst literature primarily focuses on either target price expected returns or target price dispersions in isolation. From an academic perspective, our paper contributes to the literature about the predictive power of target price dispersions and underlines the importance of studying the multiple analyst outputs jointly. From the perspective of practitioners, our paper helps identify superior investment strategies that could be constructed from the analyst forecasts. We document that the strategies that rely on both target price expected returns and target price dispersions perform significantly better than those that rely on only one analyst output.

The remainder of the paper is structured as follows: Section 2 summarizes the literature review. Section 3 discusses data sources and the key TPER and TPD variables. The portfolio construction and the main results are given in Section 4. Section 5 analyzes potential sources to the profit of our TPER-TPD strategy and Section 6 concludes.

II. Literature Review

Compared to earning forecast studies, the literature on target price forecasts is much more recent and limited. It is discussed in several articles that the target price presents relevant predictive and informational power. Brav and Lehavy (2003) find a significant market reaction to the information contained in analysts' target prices, both unconditionally and conditional on contemporaneously issued stock recommendation and earnings forecast revisions. They provide a starting point for further research on various related questions. Da and Schaumburg (2011) document a within-industry abnormal return up to 1.77% between the top and the bottom portfolios sorted by the target price implied one-year ahead expected return (TPER). They emphasize that their findings are not merely a small stock phenomenon but apply to the sample of S&P 500 stocks. Da et al. (2016) further decompose target price forecasts and find that abnormal returns are associated with both earnings and price-to-earnings forecasts. The empirical results support that the informativeness of target price forecasts comes from analysts' ability to forecast both short-term earnings and long-term growth. The target-price strategy is further applied it to options (Bali, Hu, and Murray (2014)). The price target-based expected return is showed to be associated with both systematic risk such as market beta and non-systematic risk such as idiosyncratic volatility and a simple price target-based measure does a good job at capturing cross-sectional variation in the market's required rate of return. A recently published article analyzing the asset pricing power of analyst's forecasts, Wu (2018), uses analysts price targets to generate ex-ante risk premium estimates and conducts asset pricing tests.

Analysts' target prices are arguably noisy and affected by many factors such as analyst skills, institutional and regulatory environment and macro economies. Furthermore, analysts are not bound to fully and truthfully report their private information. Thus, many researchers and investors express concern about the accuracy of target prices. Bilinski et al. (2013) observed that analysts who produced better past forecasts for target prices, who have more experience in forecasting, who follow a greater number of companies, who are experts in a country's market, and who are employed by large brokerage firms, tend to produce target prices with greater accuracy. Some articles claim the relationship between accuracy and consensus (Clement and Tse (2005); Huang, Liu, and Yin (2017)). They argue that the economic and reputation incentives lead analysts to be inclined toward consensus. Antnio, Ambrozini, Gatsios, and Magnani (2017) expand the discussion of the consequences of the effect of consensus in the market, discussing specifically the effects on target prices in Latin America, and concluded that the consensus has a negative correlation with forecast errors. In other words, the greater the consensus (smaller standard deviation/dispersion), the smaller the forecast errors. In this sense, the standard deviation/dispersion of target-price estimates also presents an informative tool to investors about forecast accuracy. A major contribution of this paper evidences that both target prices and its dispersion (consensus degree) have predictive and informational power for excess stock returns.

While target price is generally found to have a short-term impact on stock prices (Brav and Lehavy (2003), Huang et al. (2009), Da and Schaumburg (2011), etc.), the medium to long run accuracy is limited. Bradshaw, Richardson, and Sloan (2006) connect corporate financing activities to analysts' forecast and stock returns. A strong positive relation was found between net external financing and overoptimism in analysts' forecasts, including target prices. In other words, analysts set significantly higher target prices for firms raising new financing. Gerritsen (2015) uses mergers and acquisitions (M&A) to evaluate the relevance of analysts' target prices and shows that the expected returns by analysts are significantly related to the takeover premium paid. Moreover, recent target prices are more relevant than relative old ones. In addition, the analysts' target price study is not constrained in domestic market and is extended to international studies. Imam, Chan, and Shah (2013) examine asset pricing models that are better to improve the target price accuracy in Europe. The results support the use of accrual models, within which book value based models provide lower forecast error than other models. Ishigami and Takeda (2018) provide an analysis of the effects of stock rating and target prices in Japan and find that market responses are affected by the information quality of securities companies issuing analyst reports and the number of reports issued on the same day.

Some earlier studies in the literature focus solely on the analysts stock recommendations and find the relationship between changes in recommendations and investment signals (e.g. Womack (1996); Barber, Lehavy, McNichols, and Trueman (2001); Jegadeesh, Kim, Krische, and Lee (2004); Green (2006)). However, a stock recommendation provides only a coarse measure of the analysts view of the stock. A target price, in contrast, is revised far more often than stock recommendations (Brav and Lehavy (2003)) and allows analysts more flexibility in expressing their refined views about the investment potential of the stock (Asquith, Mikhail, and Au (2002)). Huang et al. (2009) propose a combination strategy based on both stock recommendations and TPERs, that is, buying (selling) stocks with the most favorable (unfavorable) revisions in both consensus recommendation and TPER. It turns out the combination strategy outperforms the comparable strategies that rely solely on recommendations or TPERs.

Despite the evidence of profitability from trading on TPER portfolios, most studies found little evidence of investors being able to earn abnormal returns based on the level of analysts buy/sell recommendations or price targets unless trading takes place at the time of announcement (e.g., Barber et al. (2001);Brav and Lehavy (2003)). Thus, a certain number of articles analyze the accuracy of target prices or the analysts' ability to forecast target prices. Previous research shows that analysts' target prices are consistently biased and tries to use analysts' incentives to deliver biased target price to explain the target price accuracy. In addition to ad hoc departures from traditional valuation methods and inaccurate forecasts of other analysts measures (i.e. earnings, cash flows, or other firm fundamentals) that serve as valuation model inputs, Gleason, Bruce, and Li (2013) point out a third potential contributor to low quality price targets, inefficient heuristics[2]. Even analyst adept at formulating accurate earnings forecasts may favor the use of simple valuation heuristics rather than more rigorous and proven techniques. Chen, Chang, Cheng, and Tu (2016) explain the analyst target price bias through the framework of catering theory. Their results show that analysts do cater to investors via overshooting actual end-of-forecast-period prices and that foreign analysts produced more biased target prices compared to domestic peers.

So far, only a few articles discussed the question of the target price dispersion. Da and Schaumburg (2011) follow the calculation method of earning forecast dispersion from Diether et al. (2002) to obtain the measure of target price dispersion. However, the target price dispersion is only used for sub-sample robustness test as a control variable of characteristics. Gerritsen and Weitzel (2017) consider target price dispersion as a reference point for investors and find a negative relation between target price dispersion and takeover completion. Feng and Yan (2016) is the only article focusing on the asset pricing power of target price dispersion. They use three target dispersion measures to exploit the dispersion in analyst target price and document a significant positive relation between the target price dispersion and future stock returns for horizons up to 24 months. We propose that both target price implied expected return and target price dispersion provide valuable information for the prediction of stock returns. In the next section, we describe the proxy formation of target price implied expected return (TPER) and target price dispersion (STP) and the corresponding data descriptions.

[2]Gleason et al. (2013) propose that some analysts favor the use of simple valuation heuristics rather than more rigorous and proven techniques. The popularity of simple valuation heuristics can be traced to their ease of implementation and to the absence of unambiguous feedback about their actual success or failure in use. Feedback can be ambiguous because, under certain circumstances, the investment signals generated by a simple valuation heuristic can be consistent with those derived from more rigorous valuation techniques.

III. Data description

We obtain data on target prices, deviation of target prices, consensus recommendations from I/B/E/S, stock prices from CRSP, and fundamental data from Compustat. For each month from 2000 to 2017, we include the stocks in NYSE, AMEX, and NASDAQ, and require at least one target price and one FY1 earning forecast during the month. We consider stocks that trade above a price of $5, which can help to alleviate any possible impact from the bid-ask bounce and other market microstructure related noise. We finally obtain 371,311 observations from 2000 to 2017. The target price implied expected return (TPER) is computed as the consensus target price divided by the end of month stock price: $TPER_T = \bar{TP}_t/P_t - 1$. The consensus target price is the simple average of all target prices received during the first 25 calendar days of month t. We do not make use of analyst identities in constructing the consensus forecast since several studies, including Bradshaw et al. (2013) and Bonini, Zanetti, Bianchini, and Salvi (2010), have found no systematic difference in analyst target price forecasting abilities. Since more than 90% of the target prices in the database are coded as one-year ahead prices, this ratio can be interpreted as the analysts' stated estimate of the firm's annual expected return. The proxy of target price dispersion is the standard deviation of all non-duplicate forecasts during the previous one year scaled by the consensus target price, TPD. The reason why we use the dispersion traced back to one year is that a number of companies only have one target price, leading to zero dispersion. To get rid of this sample-selection bias, we do not use the monthly target price dispersion. We acknowledge that there are still some existing companies who have the zero value of TPD, but the sample bias issue is significantly relieved by using the TPD proxy. Different from Feng and Yan (2016), we scaled the standard deviation of all non-duplicate forecasts by consensus target price rather than the average value of all non-duplicate forecasts. It helps us to avoid the variation issue when a company has limited analyst forecasts during the previous one year. Scaling by the consensus target price is also consistent with the target price expected returns(TPER). After removing the missing observations of TPD, we finally got 327,391 observations.

Table I provides the descriptive statistics of analysts target prices and its dispersions. There are on average 2235 number of stocks each year. The number of stocks increase gradually from 2000, drops in 2009, and rebound thereafter. For each stock, there are on average 3.15 number of target price forecasts. The target price implied expected return is 23.17% on average and tilt to the left since TPER medians are less than TPER means across years. The average value of TPDs is 16.60% and also tilt to the left. The sample on average covers 79% of the CRSP stock universe in terms of market capitalization, increasing from 64.25% in 2000 to 89.76% in 2017. Consistent with the NASDAQ bubble in 2000, the mean TPER is as high as 39.03% (Median 32.68%) and drops dramatically to 17.70% (Median 10.88%) in 2003.

[**Insert Table I here**]

Different from the conclusion of Da and Schaumburg (2011) that analysts on average are unable to forecast the market risk-premium, Fig 1 visually shows that TPERs and TPDs closely follow the same trend to actual one-year returns. During the recent financial crisis, the actual stock returns climb up since 2008, reach a peak in 2009 and collapse to a trough in 2010. TPERs and TPDs follow the actual stock returns in the same direction, but it shows that TPERs react faster than TPDs during the financial crisis. Focusing on the period from 2008 to 2011, the target price expected return dropped deeper when the actual stock return decreased, while the target price expected return climbed higher when the actual stock return increased. This is consistent with previous findings that analyst target price accuracy is largely related to overall market performance. Overall, Fig1 gives us a visual sense that TPERs and TPDs are able to predict stock returns. Next, we construct a strategy based on TPERs and TPDs, which are described in Section IV.

[**Insert Figure 1 here**]

IV. A value strategy based on analyst target price forecasts and its dispersion

In this section, we describe the construction and performance of long-short portfolio of the sample based on 12 month ahead target price implied expected return (TPER) and target price dispersion (TPD). As Da and Schaumburg (2011) illustrated, the TPER is an imperfect predictor of future returns, and the TPER can be decomposed into three components.

$$TPER = E^A[\alpha] + \beta_M E^A[Mkt] + \sum_{i=1}^{n-1} \beta_i' E^A[\lambda_i]$$

The first component is the analyst's estimated alpha that measures the current deviation between price and fundamentals as perceived by the analysts. The second and third terms reflect the forward-looking systematic risk components consisting of market risk and "other" risk factors. $E^A[\cdot]$ denotes analysts' expectations, which are contaminated by noise due to different opinions, modeling error, and behavioral biases. The target price dispersion provides additional information not contained in the target price expected return. We set up portfolios according to TPERs and TPDs and use the factor model to obtain the risk-adjusted stock premium. After controlling for the market and other systematic risks, we come up with a question that whether the TPER and the TPD have the predictive power of stock returns.

A. Description of TPER and TPD-sorted portfolios

We first sort stocks into five portfolios according to TPERs and TPDs separately. Table II shows the difference between the portfolios sorted by TPER and the portfolios sorted by TPD. Based on TPERs, the average TPER-value of the top portfolio is 53.23% and the value of the bottom portfolio is -0.67% (Table II). There are no monotonic changes across five portfolios in terms of the fundamentals (i.e., firm size, book-to-price ratio, and earning-to-price ratio). For the TPER-sorted portfolios, the average TPD-value of the top portfolio is 18.72% and the value of the bottom portfolio is 17.37%. The value of TPDs does not decrease monotonically with the value of TPERs, showing that the portfolios sorted by TPERs are not the same as the portfolios sorted by TPDs. The one-month returns (RET1M) of TPER-sorted portfolios during the formation period increase with quintiles, while the one-month returns(RET1M) of TPD-sorted portfolios decrease with quintiles. The quintiles sorted by TPERs and the quintiles sorted by TPDs have different stock characteristics and different one-month stock returns. The inconsistency of TPER, TPD, and RET1M across quintiles further supports our argument that the target price expected return and the target price dispersion contains independent information in the presence of the other.

[Insert Table II here]

We further divide the sample into 25 (5×5) TPER and TPD-sorted portfolios. Similar results are shown in Table III. Portfolio 1 has an average TPER-value of 56.79% and an average TPD-value of 33.67%; while Portfolio 25 has an average TPER-value of 0.19% and an average TPD-value of 6.12%. Portfolio 1 has the lowest one-month stock return (RE1M), -4.72%. The highest one-month stock returns are located in the last five portfolios. It is not surprising that the highest RET1M is not located in the bottom portfolio since TPER quintiles and TPD quintiles possess an opposite direction of RET1M values. No obvious characteristics are found across these 25 portfolios.

[**Insert Table III here**]

In order to figure out whether TPER and TPD have the ability to predict stock returns, the excess returns of 25 portfolios are compared. The factor model is also used to compute the risk-adjusted stock premium.

B. *Empirical results*

Table IV shows that the first post-formation month excess returns (in excess of the risk-free rate) in general are increasing in TPER and TPD. Portfolio 1, which has the stocks with the highest TPER and the highest TPD, earns the highest first-month excess return (3.75%/month) and Portfolio 25, which has the stocks with the lowest TPER and TPD, earns the lowest first-month excess return (-0.28%/month). The return on the spread Portfolio 1-25, 4.03%, is the return to a portfolio of long-short strategies or the value strategies (long stocks with the highest TPERs and TPDs and short stocks with the lowest TPERs and TPDs). It also shows that all of the first-month excess returns are highly significant. Portfolio 1 earns 1.95%(3.75%-1.80%) higher first-month excess returns than Portfolio 2. In addition, Portfolio 6, 11, 16, and 21 have relatively higher first-month excess returns since they belong to the highest TPD-portfolio. This finding confirms that TPERs and TPDs both have a positive relation with excess stock returns.

To account for the fact that the significant first-month excess returns on the spread Portfolio 1-25 may be the result of systematic risk exposures, we risk adjust the returns using a five-factor model that includes the Fama-French three factors by Fama and French (1993), Fama and French (1995) and Fama and French (1996), the momentum factor by Carhart (1997), and the short-run reversal factor by Jegadeesh (1990) and Lehmann (1990) and. To investigate whether the excess return is related to but different from the standard short-run reversal effect in small stocks, we also include the short-run reversal factor as a fifth factor.

Table IV shows that the five-factor risk-adjusted returns are still highly significant over 25 portfolios. Although part of the high excess return is explained by these five systematic risk factors, the spread Portfolio 1-25 still yields a high five-factor alpha of 3.48% per month. These 25 portfolios loads significantly on Fama-French three factors and the momentum factor and the majority of short-run reversal factor loadings are not significant. It is not surprising that the MKT factor is significantly positive since, ceteris paribus, high beta stocks will receive higher target price relative to their current market price (higher TPER) and more diversified price forecasts (higher TPD). Consistent with the results of Fama-French three factor model, all the SMB coefficients are significantly positive, and the same to SMB loadings except for the first portfolio. Fourteen out of twenty-five portfolios load significantly and negatively on the UMD factor, while the loadings are positive and significant for the last eight portfolios. In other words, the portfolios with lower TPERs follows a standard momentum strategy, but the portfolios with higher TPERs do not. Although some of loadings on the short-run reversal factor (DMU) are positive, most of them are not significant. Overall, this five factor model does not explain the high yield earned by the long-short strategy. Da and Schaumburg (2011) stress the crucial role played by sector control since the first month post-formation portfolio excess returns lose their significance without sector control, and we got similar result during the sample period from 2000 to 2004. However, the excess returns become significant after including more recent samples (until Dec. 2017) and further sort the sample by TPDs.

[**Insert Table IV here**]

V. Potential sources of the profit

In this section, we examine possible drivers of the risk-adjusted return to our combination strategy sorted by TPERs and TPDs.

A. *Different long-short strategies*

The profitability appears in the TPER-TPD combination strategy. It raises the question of whether our results are simply driven by other anomalies. To examine this possibility, we sort stocks into twenty-five portfolios according different accounting and analysts' forecast measures. Table V reports the one-month excess returns and alphas to the alternative long-short trading strategy.

We first divide stocks into twenty-five portfolios according to TPERs alone. The long-short excess return is 2.69%. After controlling for the five risk factors (MKT, SMB, HML, UMD, DMU), the long-short alpha even higher, which means the profits obtained from the TPER-sorted strategy cannot explained by those five risk factors. Stocks are then sorted into twenty-five portfolios according to TPDs alone, producing an excess return of 2.63%, of which 0.16% (2.63%-2.47%) is absorbed by the five risk factors. We should acknowledge that the sample has been filtered through requiring the stocks who have both TPERs and TPDs. It makes us lose some stocks who have not enough target price forecasts to compute the dispersion, leading to higher excess returns and higher risk-adjusted alphas. Even so, the strategy sorted by TPER or TPD still does not obtain an higher excess return or higher risk-adjusted return than that of the combination strategy. Overall, these two strategies perform significantly positive profits, but no greater than excess returns or risk-adjusted returns of the TPER-TPD combination strategy.

TPER is defined as a ratio between target price and market price, and its current level is influenced by both its past return and past revisions in the target price. Big companies tend to have more target prices from different analysts; while growth companies are more likely to hold diversified analysts' forecasts, higher dispersion. Can either of these effects explain the returns to our combination strategy?

Although the other price ratios, such as book-to-price ratio and earnings price, obtain a positive and significant long-short excess returns and risk-adjusted alphas, neither one of them owns profits greater than 2%. Thus, the earning-to-price ratio, book-to-price ratio, and even the inverse of the price are likely to account for part of the profits from our TPER-TPD combination strategy. However, neither one of them can mimic the combination strategy with such a high long-short excess returns that reach over 3%.

As earlier studies (e.g. Womack (1996); Barber et al. (2001); Jegadeesh et al. (2004)) claim, the analysts stock recommendation is associated with stock returns. Thus, the anomaly of recommendation (the proxy is the most recent revision in recommendations, ΔRec) is examined and produces a significant risk-adjusted return of 1.54%. The anomalies of lagged one-month return and the interaction of ΔRec and one-month excess return are both examined and neither of them is statistically significant. The anomaly of changes in target price (DTP) provides a very low significantly positive risk-adjusted return, 0.20%. We note that the computation of DTP restricts us to the subsample of our stocks with target price announcements during the preceding month. We verify that the profit to our TPER-TPD combination strategy hardly changes when restricted to this subsample.

To summarize, changes in target prices and target price dispersions are positively related to future returns, as has been demonstrated by Da and Schaumburg (2011) and Feng and Yan (2016). Although some other price-ratio proxies measured by analysts forecasts produce positive anomalies, neither one of them alone can explain the profit to our TPER-TPD strategy. The profit comes from exploiting the relative valuation information implied in the TPER, which combines information from both the target price and the market price of a stock, and the target price dispersion information implied in the TPD, which contribute the information about the accuracy of the analyst forecasts and the quality of the analyst forecasts.

[Insert Table V here]

B. Cross-sectional regressions

The portfolio-sorting methodology has the advantage of non-parameter but has the drawback of the possibility that the findings are more driven by other characteristics so that TPER and TPD have low predictive power. It is possible that the stocks with higher target-price dispersion tend to belong to the growth and small companies who suffer higher systematic risks, or is coincident with other analyst's indexes such as stock recommendations and earning forecast revisions. In this case, the real factors contributed to high excess stock returns would be book-to-market ratio, firm size or other analyst's indexes. This section is to confirm that the excess stock returns formed through target price expected return and target price dispersion are not driven by other fundamentals or other analysts forecasts indexes. At the cost of assuming linearity, we can examine whether TPER and TPD have any incremental predictive power for returns after controlling for other stock characteristics in a cross-sectional regression framework.

Table VI shows us several alternative model specifications. The robust t-value is computed using Newey-West autocorrelation-adjusted standard error with six lags and are reported in the brackets. We first take only the price-related measures and fundamental factors into consideration. In Model 1, we implemented the Fama-Macbeth regression of one-month stock returns on TPERs and other price-related stock characteristics including the past one-month return (RET1M), the book-price ratio (BP), earnings-price ratio (EP), and SIZE. Model 1 shows that the loading of TPER is significantly positive, indicating incremental predictive power for short-run returns. Model 2 tests the predictive power of TPDs, indicating a positive relation at a significant level of 1%. The regression in Model 3 contains both TPER and TPD. It turns out that TPER and TPD simultaneously determine the one-month stock returns. The loading of TPER remains the same and keep significant at 1% level, while the loading of TPD is 0.1% lower compared to that in Model 2.

The variables related to analyst forecasts, stock recommendation changes and earning forecast revisions, are then added into the models. The results are shown in Model 4, 5 and 6 in Table VI. The two alternative proxies for the analysts recommendation are the most recent revision in the level of recommendations (ΔRec) and the number of recommendation upgrades minus the number of recommendation downgrades within the month ($AvgRecChg$). The measure of earning forecast revision is computed as I/B/E/S consensus one-year ahead forecast of month t minus the mean consensus two-year ahead forecast at month t, and then divided by the price at the end of month t-1 (Barth and Hutton (2004)). The reason why we use earning forecast revision rather than the earning forecast itself is that the earning-to-price ratio has been one of the explainable variables. The endogenous problem appears when the earning forecast measure added. In the presence of both price-related stock characteristics and other analyst-forecast-related variables, $RET1M$ still has a strong effect on the one-month stock returns. The average recommendation change (AvgRecChg) loadings keep positive and significant at 1% level. The loadings of the rest of analysts forecast measures, FREV and ΔRec, are either insignificant or significant at relatively low level. The predictive power of TPER and TPD is not influenced by adding those analysts measures. One unit higher value in TPER will increase 2.0% of one-month excess returns; while one unit higher value in TPD will increase 4.8% of one-month excess returns.

Overall, adding the stock characteristics factors and other analysts forecast factors does not eliminate the predictive power of TPER and TPD. The cross-sectional regression results further indicate that TPER and TPD have predictive power for short-run stock returns and that the predictive power is not entirely driven by any of the stock characteristics previously studies considered here.

[Insert Table VI here]

C. Sub-sample robustness test

The S&P 500 samples are mimicked through two requirements, that are, the market capitalization is located in the first eighty percent level of our full sample; and the stocks should have S&P 500 industry sector code. To validate our mimicking S&P 500 sub-sample, we first replicate the methodology of Da and Schaumburg (2011) that sort the stocks within GICS sectors into 9 portfolios, and obtain a significant and similar long-short strategy returns in term of the period 2000-2004. As Da and Schaumburg (2011) described, the GICS sector plays a crucial role in forming the TPER portfolios. The first month post-formation portfolio excess returns lose their significance if we instead form portfolios only based on TPERs across all stocks rather than within each GICS sector. To investigate the robustness of our TPER-TPD combination strategy, the excess returns and risk-adjusted returns are examined in sub-samples and sub-periods.

Following Da and Schaumburg (2011), we consider S&P 500 companies as sub-sample and the time period before 2005 as sub-period. We split the sampling-period into two, 2000-2004 and 2005-2017, and examine the performance of the combination long-short strategy in each of the sub-periods for both the sub-sample and the full sample.

The results of S&P 500 sub-sample are shown in Panel A of Table VI. The TPER-TPD combination strategy produces a significant risk-adjusted return, 3.49%. The four-factor and five-factor adjusted stock returns are 2.94% and 3.04%. We do not obtain extra benefits by sorting on the S&P 500 sub-sample rather the full sample. Panel B provides the sub-period results of full samples. We see that the S&P 500 sub-sample produces higher risk-adjusted returns during the period

2005-2017 compared to the same period for the full sample. In the meantime, the excess returns and risk-adjusted returns are both more significant than the results during the period 2000-2004. It is possible that there are much more observations from 2005 to 2017. Thus, it needs to further investigate that whether the predictive power of TPER and TPD performs better in recently years. Panel B provides the results of the full sample in different periods. The results are similar to those in Panel A. the excess returns and risk-adjusted returns in recent period are both higher than the results during the period 2000-2004.

Overall, the selection of either the S&P sub-sample or the full sample has little effect on the profits of the TPER-TPD combination strategy. The within GICS sector sorting formation is also tested both in sub-samples and sub-periods. Unlike the crucial role of GICS sector in TPER sorting strategy (Da and Schaumburg (2011)), the within GICS sector sorting formation of our TPER-TPD strategy cannot provide a higher profits than our original combination strategy.

[**Insert Table VII here**]

D. Separation of the effects between TPER and TPD

Although there are plenty of reasons to believe that TPER and TPD provide different sets of information independent to each other and there is a low correlation of 0.0067 between TPER and TPD, we provide additional proof that is consistent with the assumption. We decompose TPD into two components by regressing TPDs on TPERs. The first component is explained by TPER, and the second component is orthogonal to TPER (residuals). We introduce the second component of TPD, instead of TPD itself, to the Fama-Macbeth regressions. The results are shown in Table VIII. Orthogonalization of STP does not weaken the association between TPD and stock returns. The component orthogonal to TPER has a robust performance and all the loadings of TPD_orth remain statistically significant. Compared to the models in Table VII, the coefficients of TPD_orth are lower in Model 2 and Model 5. However, the loading of TPD_orth is still 0.048 in Model 6 and has a higher value in Model 3.

After separating the effects of TPER and TPD, Table VIII provides evidence that TPER and TPD contain independent information in the presence of the other.

[Insert Table VIII here]

E. Robustness test of the Value-weighted Fama-Macbeth regression

To avoid the bias from overweighting of microcap stocks, we follow the method in Green, Hand, and Zhang (2017), and implement the value-weighted Fama-Macbeth regression on the test, where the weight is the market value of equity for stock i at time $t-1$. In Table IX, we can see that the loading of $TPER$ drops to 0.011 from 0.020 in Model 1; while the loading of TPD increases to 0.070 from 0.051 in Model 2. It happens in the rest of the Models that the loading of TPER decreases and the loading of STP increases after applying the value-weighted least square to the Fama-Macbeth regression. Similar results are obtained for the regressions involved in orthogonal TPD, shown in Table X. Thus, the small stocks overweigh the effect of TPER and underweigh the effect of TPD in predicting stock returns. However, even after controlling for the bias of microcap stocks, the target price expected return (TPER) and the target price dispersion (TPD) are still significantly positive.

[Insert Table IX here]

[Insert Table X here]

VI. Conclusion

Most existing studies of equity analysts found abnormal profits based on target prices implied expected returns(TPER). In this paper, we create a long-short trading strategy by combining the target price expected return with the target price dispersion. Target prices, as opposed to recommendation or earnings forecasts, represent a direct measure of the fundamental value perceived by analysts. Target price dispersion reflects additional information such as the accuracy of analyst forecasts, the quality of analyst forecasts and the overall market performance. Our results show that our TPER-TPD combination strategy outperforms than either one of the single long-short strategy solely sorted by target price expected returns (TPER) or target price dispersion (TPD). By implementing the combination strategy on the stocks in NYSE, AMEX and NASDAQ, it gives us 3.48% of risk adjusted premium. Moreover, the predictive power of target prices for subsequent returns is economically and statistically significant even after including fundamental measures and other analysts forecast indexes. The profitability of the TPER-STP combination strategy is also barely affected by sorting stocks within GICS sectors or not.

Our results are remarkably robust to changes in the specifics of the portfolio construction strategy, choice of samples and sampling periods, and alternative risk-adjustment models. We have also shown that the information contained in the TPER or TPD variable is not subsumed by other analyst forecasts and other stock level characteristics commonly used to predict returns. Finally, we confirm the abnormal profits can be applied to both large full sample and S&P 500 sub-sample over the sampling period from 2000 to 2017. However, we still need to acknowledge that our results are likely built on particular samples since the requirement of stocks with its target price and target price dispersion is itself a process of sample screen. We do not find a big difference when we set up the combination strategy sorted within GICS sectors rather than without GICS sectors. The reason could be that the target price dispersion is associated with the accuracy of target prices and the categories of stocks.

Interestingly, we find more significant but lower abnormal profits in more recent years. Future studies can investigate whether the target price analyst forecasts become more accurate over time, or whether the target price analyst forecasts have stronger effects on stocks returns over time so that the target price measures have higher predictive power for stock returns. Besides, what factors lead to the increase in the predictive power of the target price? Is it only because of the increasing number of analysts? The dimension of time series is valuable to be explored.

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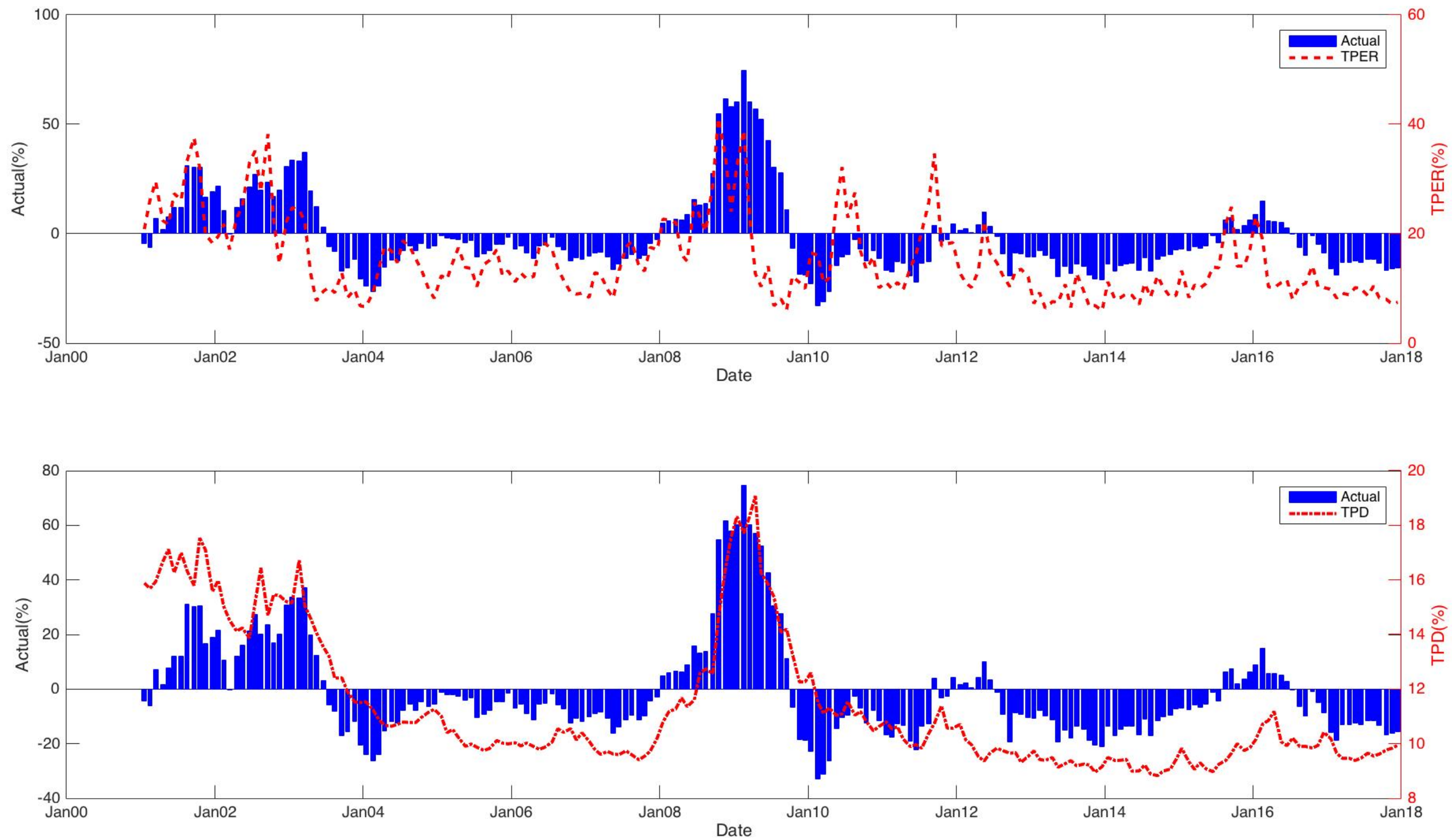

Figure 1. Target price implied one-year-ahead expected return (TPER) versus actual one-year return; the standard deviation of all non-duplicate forecasts during months $t-11,...,t$ scaled by the consensus target price (TPD) versus actual one-year return. At the end of month from Jan 2000 to Dec 2017, we compute the equity analysts' implied return forecast and its dispersion for the value-weighted value of the sample with analyst coverage that month (dashed red line). We compare this to the ex post realized 12-month return of the sample (solid bars).

Table I

Descriptive Statistics of Analysts Target Price Forecasts and its Dispersions

Year	Num of TP/ month	Num of stocks/month	Mean Mktcap (in mill$)	Median Mktcap (in mill$)	Mean TPER	Median TPER	Mean TPD	Median TPD	Mktcap %
2000	2.24	1254	7337	1153	39.03%	32.68%	20.66%	16.21%	64.25%
2001	2.45	1373	6228	1053	34.28%	24.44%	18.42%	15.11%	70.88%
2002	2.72	1503	5121	950	32.71%	23.51%	18.04%	14.08%	73.16%
2003	2.69	1572	5088	959	17.70%	10.88%	20.49%	15.82%	74.31%
2004	2.62	1860	5420	1045	17.91%	12.06%	15.51%	12.86%	76.63%
2005	2.56	2124	5515	1074	17.75%	12.80%	15.42%	12.33%	70.54%
2006	2.68	2370	5906	1194	17.28%	12.47%	14.59%	12.03%	76.02%
2007	2.83	2453	6631	1311	19.58%	14.38%	16.20%	13.66%	79.41%
2008	3.26	2258	5851	1117	34.77%	27.15%	17.76%	15.18%	79.29%
2009	3.42	2099	5001	1006	22.56%	15.41%	19.67%	16.06%	79.76%
2010	3.32	2426	5418	1146	22.40%	17.18%	16.93%	13.86%	80.58%
2011	3.63	2492	6123	1316	25.04%	18.07%	14.82%	11.96%	81.59%
2012	3.61	2500	6412	1390	22.46%	15.45%	15.22%	12.19%	81.33%
2013	3.84	2578	7573	1699	13.18%	8.58%	15.86%	12.06%	83.06%
2014	3.68	2761	8573	1846	18.02%	12.33%	13.79%	11.15%	85.58%
2015	3.73	2868	8669	1768	24.21%	16.67%	17.30%	11.27%	87.10%
2016	3.79	2845	8797	1731	21.16%	13.08%	15.21%	12.22%	88.50%
2017	3.69	2898	10257	1979	17.09%	10.18%	12.87%	10.48%	89.76%
Mean	3.15	2235	6662	1319	23.17%	16.52%	16.60%	13.25%	78.99%

Note:

The table reports descriptive statistics of target price forecasts available at the IBES database over the sample period from 2000 through 2017. The sample includes forecasts made by brokerage houses that provide no less than two target prices during previous 1 year. Variables are defined as follows. TP is the target price forecast; Mktcap is the market capitalization of sample firms; TPER is the target price implied return, calculated by subtracting one from the ratio of target price and the current stock price; TPD is the standard deviation of all non-duplicate forecasts during months $t-11, ..., t$ scaled by the consensus target price; Mktcap% is the proportion of the sample firms market capitalization to the total market value of the CRSP population.

Table II

Characteristics of 5 portfolios sorted by TPER and TPD

	TPER-sorted portfolios						TPD-sorted portfolios					
Portfolio	firm size	BP	EP	TPER	TPD	RET1M	firm size	BP	EP	TPER	TPD	RET1M
1	13.33	1.21	-0.022	53.23%	18.72%	-5.24%	13.64	0.96	-0.022	23.65%	33.45%	2.25%
2	14.12	1.10	0.022	27.33%	16.02%	-1.09%	14.15	0.87	0.013	22.62%	17.93%	0.92%
3	14.52	0.52	0.033	17.04%	14.31%	1.13%	14.44	1.16	0.027	21.08%	13.41%	0.60%
4	14.63	0.50	0.034	9.61%	14.83%	3.09%	14.60	0.51	0.034	19.50%	10.10%	0.41%
5	14.37	0.74	0.027	-0.67%	17.37%	6.57%	14.14	0.57	0.041	18.93%	6.81%	0.49%

Note:
BP is the book-to-price ratio; EP is the earnings-to-price ratio; firm size is the natural log of a firm's market capitalization; TPER is the target price implied return, calculated by subtracting one from the ratio of target price and the current stock price; TPD is the standard deviation of all non-duplicate forecasts during months $t-11, ..., t$ scaled by the consensus target price; and RET1M is the return during the month of portfolio formation.

Table III

Characteristics of 25 TPER-TPD sorted portfolios

Portfolio	size	BP	EP	TPER	TPD	RET1M
1	13.03	0.71	-0.073	56.79%	33.67%	-4.72%
2	13.43	1.62	-0.020	52.55%	18.59%	-5.65%
3	13.58	2.36	-0.004	50.98%	14.25%	-5.78%
4	13.54	0.63	0.002	50.41%	10.88%	-5.60%
5	13.20	0.66	0.011	53.76%	6.88%	-4.48%
6	13.58	1.25	-0.018	28.20%	33.45%	0.03%
7	14.09	1.06	0.019	28.04%	18.09%	-1.01%
8	14.36	2.02	0.028	27.42%	13.53%	-1.34%
9	14.47	0.53	0.034	26.72%	10.33%	-1.64%
10	14.01	0.59	0.043	26.31%	6.62%	-1.33%
11	13.81	0.56	0.003	17.38%	31.35%	2.71%
12	14.41	0.51	0.022	17.68%	17.82%	1.60%
13	14.71	0.48	0.038	17.33%	13.23%	0.98%
14	14.94	0.48	0.042	16.90%	9.95%	0.61%
15	14.43	0.55	0.047	16.16%	6.33%	0.44%
16	14.01	0.55	-0.000	9.86%	33.86%	5.05%
17	14.56	0.49	0.023	9.94%	17.57%	3.73%
18	14.86	0.46	0.037	9.89%	13.07%	3.26%
19	15.01	0.47	0.043	9.62%	9.80%	2.54%
20	14.50	0.55	0.050	9.01%	7.87%	1.87%
21	14.00	1.49	0.001	-2.42%	34.23%	9.20%
22	14.44	0.49	0.025	-0.91%	17.44%	7.21%
23	14.61	0.47	0.031	0.05%	13.01%	5.97%
24	14.70	0.48	0.042	0.41%	9.75%	5.00%
25	14.24	0.54	0.046	0.19%	6.12%	4.50%

Note:
BP is the book-to-price ratio; EP is the earnings-to-price ratio; firm size is the natural log of a firm's market capitalization; TPER is the target price implied return, calculated by subtracting one from the ratio of target price and the current stock price; TPD is the standard deviation of all non-duplicate forecasts during months $t-11, ..., t$ scaled by the consensus target price; and RET1M is the return during the month of portfolio formation.

Table IV

Returns on TPER-TPD-sorted portfolios

	First mth excess return	Five-factor model					
		Alpha	MKT	SMB	HML	UMD	DMU
1	3.75%***	2.90%***	1.169***	1.087***	-0.117**	-0.488***	0.003***
	(32.85)	(26.67)	(37.47)	(24.88)	(-2.39)	(-19.06)	(5.90)
2	1.80%***	0.93%***	1.169***	0.869***	0.072*	-0.412***	0.001*
	(17.53)	(9.83)	(44.95)	(23.36)	(1.75)	(-19.52)	(1.80)
3	1.52%***	0.81%***	1.104***	0.658***	0.094***	-0.345***	0.000
	(14.24)	(8.12)	(40.76)	(17.09)	(2.21)	(-15.81)	(0.83)
4	1.18%***	0.43%***	1.153***	0.461***	0.140***	-0.262***	-0.001*
	(10.65)	(4.09)	(41.05)	(11.60)	(3.13)	(-11.67)	(-1.76)
5	1.25%***	0.60%***	1.042***	0.542***	0.268***	-0.197***	-0.001**
	(11.51)	(5.88)	(38.29)	(13.87)	(6.18)	(-8.94)	(-2.56)
6	2.44%***	1.88%***	1.300***	0.792***	0.176***	-0.299***	0.001
	(20.57)	(17.52)	(45.38)	(18.38)	(3.76)	(-12.48)	(1.06)
7	0.92%***	0.38%***	1.167***	0.542***	0.234***	-0.195***	0.000
	(10.54)	(4.79)	(55.61)	(17.48)	(6.99)	(-11.08)	(-0.14)
8	0.54%***	0.04%	1.097***	0.355***	0.214***	-0.148***	0.000
	(7.00)	(0.05)	(58.49)	(12.89)	(7.24)	(-9.37)	(0.10)
9	0.41%***	-0.10%	1.045***	0.331***	0.312***	-0.146***	-0.002***
	(5.59)	(-1.46)	(58.68)	(12.93)	(11.22)	(-9.73)	(-4.99)
10	0.63%***	0.11%	0.942***	0.350***	0.283***	-0.045***	-0.001***
	(8.37)	(1.59)	(49.35)	(12.89)	(9.46)	(-2.89)	(-3.32)
11	2.66%***	2.06%***	1.194***	0.651***	0.325***	-0.210***	-0.000
	(21.89)	(18.51)	(40.87)	(14.77)	(6.92)	(-8.58)	(-0.84)
12	0.82%***	0.38%***	1.119***	0.651***	0.325***	-0.210***	-0.000
	(9.57)	(4.90)	(54.66)	(12.74)	(7.64)	(-5.73)	(-0.90)
13	0.46%	0.03%***	0.995***	0.291***	0.308***	-0.067***	-0.000
	(6.74)	(0.46)	(60.47)	(12.08)	(11.80)	(-4.78)	(-1.40)
14	0.34%***	-0.12%**	0.930***	0.171***	0.330***	-0.002	-0.000
	(5.72)	(-2.29)	(65.06)	(8.23)	(14.65)	(-0.13)	(-0.26)
15	0.42%***	-0.02%	0.839***	0.251***	0.363***	0.056***	-0.001***
	(7.67)	(-0.35)	(61.01)	(12.75)	(16.73)	(4.97)	(-5.04)
16	2.19%***	1.68%***	1.101***	0.634***	0.333***	-0.062***	0.000
	(19.88)	(16.45)	(41.09)	(15.95)	(7.70)	(-2.72)	(0.00)
17	0.71%***	0.20%***	1.049***	0.413***	0.302***	0.011	-0.000
	(8.83)	(2.76)	(54.06)	(14.39)	(9.74)	(0.68)	(-0.86)
18	0.36%***	-0.15%**	0.918***	0.284***	0.407***	0.028**	-0.001**
	(5.62)	(-2.53)	(58.41)	(12.52)	(16.26)	(2.16)	(-2.30)
19	0.17%***	-0.21%***	0.848***	0.200***	0.440***	0.099***	-0.001***
	(3.23)	(-4.28)	(65.11)	(10.39)	(21.20)	(9.01)	(-5.17)
20	0.32%***	-0.09%*	0.727***	0.246***	0.430***	0.125***	-0.001***
	(6.57)	(-1.95)	(60.98)	(14.10)	(23.11)	(12.59)	(-5.12)
21	1.30%***	0.83%***	1.048***	0.536***	0.259***	0.040*	-0.000
	(15.97)	(10.87)	(51.40)	(18.16)	(8.18)	(2.28)	(-1.19)
22	0.18%**	-0.30%***	0.946***	0.360***	0.298***	0.054***	-0.001*
	(2.52)	(-4.54)	(51.75)	(13.81)	(10.38)	(3.59)	(-1.92)
23	-0.25%***	-0.60%***	0.876***	0.247***	0.401***	0.107***	-0.001***
	(-3.66)	(-9.69)	(52.91)	(9.90)	(14.91)	(7.60)	(-4.18)
24	-0.23%	-0.59%	0.764***	0.205***	0.397***	0.168***	-0.000
	(-3.66)	(-10.22)	(49.54)	(8.72)	(15.82)	(12.77)	(-1.29)
25	-0.28%***	-0.58%***	0.631***	0.308***	0.483***	0.161***	-0.001***
	(-5.11)	(-11.19)	(45.76)	(14.15)	(21.13)	(13.09)	(-5.18)
1-25	4.03%***	3.48%***	0.538***	0.779***	-0.600	-0.649***	0.004
	(29.09)	(27.14)	(7.80)	(3.34)	(-1.09)	(-3.59)	(1.12)

*** Indicates significance at the 1% level.

** Indicates significance at the 5% level.

* Indicates significance at the 10% level.

Note: At the end of each month from January 2000 to December 2017, we rank the sample into 25 portfolios according to current month TPERs and TPDs and label them from 1 to 25 (1 with the highest and 9 with the lowest). For each stock, we compute the first month post-formation market-adjusted excess returns (in excess of the risk-free rate). Finally we equally weigh the excess returns of all stocks in the same portfolio. The table also reports the risk-adjusted alphas using a five-factor model. The five factors are the three Fama-French factors, a momentum factor (UMD), and a reversal factor (DMU). All returns and alphas are monthly. t-values are reported in the brackets.

Table V

Profits to alternative long-short strategies

	TPER	TPD	1/P	EP	BP	Ret1M	DTP	ΔRec	ΔRec×Ret1M
Long excess ret	2.51%***	2.49%***	2.01%***	0.34%*	1.43%***	1.08%***	0.76%***	1.41%***	0.67%***
	(31.24)	(16.22)	(32.73)	(1.54)	(25.52)	(7.04)	(3.59)	(15.09)	(4.38)
Short excess ret	-0.18%***	-0.13%***	0.03%***	-1.20%***	-0.15%*	1.15%***	0.55%***	-0.23%**	0.75%***
	(-74.63)	(-5.92)	(-5.66)	(-23.97)	(-1.81)	(9.71)	(49.28)	(-2.26)	(6.42)
L-S excess ret	2.69%***	2.63%***	1.97%***	1.55%***	1.58%***	-0.07%	0.21%***	1.64%***	-0.08%
	(28.28)	(21.07)	(14.18)	(14.82)	(27.18)	(-0.35)	(33.30)	(11.79)	(-0.43)
L-S alpha	2.86%***	2.47%***	1.96%***	1.58%***	1.82%***	-0.15%	0.20%***	1.54%***	-0.16%
	(34.75)	(22.34)	(18.61)	(16.84)	(32.63)	(-0.85)	(35.86)	(12.01)	(-0.93)

*** Indicates significance at the 1% level.

** Indicates significance at the 5% level.

* Indicates significance at the 10% level.

Note:

At the end of each month, we construct various long-short strategies using the stocks in our sample. For each strategy, we report the equal-weighted first month excess return (in excess of the risk-free rate) for long and short portfolios, the profit to the overall long-short strategy, and its associated five-factor alpha. All returns and alphas are monthly. t-values are reported in the brackets.

TPER: We sort stocks into twenty-five portfolios according to the current-month TPERs, then long stocks with the highest TPER and short stocks with the lowest TPER.

TPD: We sort stocks into twenty-five portfolios according to he current-month TPDs, then long stocks with the highest TPD and short stocks with the lowest TPD.

1/P: We sort stocks into twenty-five portfolios according to the inverse of the stock price (1/P) at the end of the month, then long stocks with the highest 1/P and short stocks with the lowest 1/P.

EP: We sort stocks into twenty-five portfolios according to the earning-price ration, then long stocks with the highest EP and short stocks with the lowest EP.

BP: We sort stocks into twenty-five portfolios according to the book-to-price ration, then long stocks with the highest BP and short stocks with the lowest BP.

Ret1M: We sort stocks into twenty-five portfolios according to the lagged one-month returns, then long past winners and short past losers.

DTP: We sort stocks into twenty-five portfolios according to the current month DTP (change in target price), which we define as $\Delta TP_t/TP_{t-1}$, then long stocks with the highest DTP and short stocks with the lowest DTP.

ΔRec: We sort stocks into twenty-five portfolios according to the most recent revision in recommendations (Δ), then long stocks with the highest ΔRec and short stocks with the lowest ΔRec.

$\Delta Rec \times Ret$: We conduct a five by five independent sort based on ΔRec and Ret, then long past winners and short past losers.

Table VI
Fama-Macbeth regressions

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
RET1M	-0.005	-0.029***	-0.010*	-0.007	-0.033***	-0.013***
	(-0.87)	(-4.66)	((-1.93))	(-1.25)	(-5.22)	(-2.68)
BP	0.000	0.001	0.000	-0.001	0.002	0.000
	(0.21)	(0.57)	(0.24)	(-0.31)	(0.94)	(0.17)
EP	0.004	0.004	0.003	0.018	-0.001	-0.000
	(0.98)	(0.95)	(0.85)	(1.02)	(-0.31)	(-0.07)
SIZE	-0.001***	-0.002***	-0.001*	-0.002***	-0.002***	-0.001*
	(-2.79)	(-3.10)	(-1.87)	(-2.66)	(-2.63)	(-1.86)
TPER	0.020***		0.020***	0.020***		0.020***
	(5.64)		(5.12)	(5.37)		(4.88)
TPD		0.051***	0.050***		0.049***	0.048***
		(8.71)	(8.21)		(6.71)	(6.55)
FREV				0.006	0.009	0.026*
				(0.37)	(0.62)	(1.82)
ΔRec				0.001	-0.004**	-0.000
				(0.50)	(-2.03)	(-0.28)
AgRecChg				0.001***	0.001***	0.001***
				(3.12)	(2.65)	(3.32)
Avg R-sq	13.92%	13.73%	14.58%	14.77%	14.68%	15.62%

*** Indicates significance at the 1% level.
** Indicates significance at the 5% level.
* Indicates significance at the 10% level.

Note: Each month from January 2000 to December 2017, we run cross-sectional regressions of one-month returns on sets of explanatory variables. These include the lagged one-month return(RET1M); book-to-price ratio (BP); log market cap (SIZE); target price implied expected return (TPER);target price dispersion (TPD); the analyst earnings forecast revision (FREV); the most recent revision in recommendations (ΔRec); a recommendation change variable used in Boni and Womack (2006), which we define as the number of recommendation upgrades minus the number of recommendation downgrades within the month (AvgRecChg). The reported slope coefficients are averaged across time and the robust t value is computed using Newey-West autocorrelation-adjusted standard error with six lags and are reported in the brackets.

Table VII

Returns on portfolios in sub-periods

Panel A: S&P 500 sample									
	2000-2004			2005-2017			2000-2017		
Portfolio	First month excess ret	4-f alpha	5-f alpha	First month excess ret	4-f alpha	5-f alpha	First month excess ret	4-f alpha	5-f alpha
1	3.99%***	3.22%***	3.22%***	2.41%***	2.10%***	2.08%***	3.06%***	2.39%***	2.47%***
	(9.38)	(8.00)	(7.65)	(13.94)	(14.65)	(14.50)	(17.56)	(15.02)	(15.55)
25	0.13%	-0.14%	-0.14%	-0.47%***	-0.59%***	-0.61%***	-0.42%***	-0.55%	-0.57%***
	(0.38)	(-0.39)	(-0.41)	(-5.71)	(-7.93)	(-8.11)	(-5.25)	(-7.53)	(-7.74)
1-25	3.86%***	3.35%***	3.35%***	2.87%***	2.69%***	2.69%***	3.49%***	2.94%***	3.04%***
	(4.00)	(3.94)	(4.68)	(11.20)	(14.79)	(15.31)	(13.66)	(12.81)	(13.28)
PanelB: Full Sample									
	2000-2004			2005-2017			2000-2017		
Portfolio	First month excess ret	4-f alpha	5-f alpha	First month excess ret	4-f alpha	5-f alpha	First month excess ret	4-f alpha	5-f alpha
1	2.73%***	3.64%***	3.55%***	2.27%***	1.61%***	1.76%***	3.31%***	2.18%***	2.50%***
	(8.21)	(7.81)	(7.65)	(13.92)	(10.33)	(11.2)	(29.74)	(17.85)	(23.76)
25	0.17%	-0.08%	-0.09%	-0.32%***	-0.49%***	-0.50%***	-0.45%***	-0.46%	-0.63%***
	(0.5)	(-0.24)	(-0.26)	(-4.72)	(-7.6)	(-7.77)	(-9.61)	(-7.28)	(-14.40)
1-25	2.56%***	3.72%***	3.64%***	2.59%***	2.10%***	2.26%***	3.76%***	2.63%***	3.13%***
	(4.83)	(4.22)	(4.15)	(11.20)	(10.07)	(10.43)	(12.38)	(17.18)	(11.49)

*** Indicates significance at the 1% level.

** Indicates significance at the 5% level.

* Indicates significance at the 10% level.

Note: We rank stocks into twenty-five groups according to the TPER-TPD combination strategy. For each sock, we compute its next one-month excess returns (in excess of the risk-free rate). Finally, we equally weigh the excess returns of all stocks within each portfolio. We report the average excess returns and risk-adjusted alphas (using four- and five-factor models) for portfolio 1, 25 and 1-25. All returns and alphas are monthly. t-values are reported in the brackets.

Table VIII

Fama-Macbeth regressions

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
RET1M	-0.005	-0.030***	-0.010*	-0.007	-0.034***	-0.013***
	(-0.87)	(-4.67)	(-1.85)	(-1.25)	(-5.40)	(-2.69)
BP	0.000	0.001	0.000	-0.001	0.002	0.000
	(0.21)	(0.76)	(0.21)	(-0.31)	(1.17)	(0.17)
EP	0.004	0.002	0.005	0.018	-0.006	-0.000
	(0.98)	(0.58)	(1.57)	(1.02)	(-0.78)	(-0.07)
SIZE	-0.001***	-0.002***	-0.001*	-0.002***	-0.002***	-0.001*
	(-2.79)	(-3.25)	(-1.87)	(-2.66)	(-2.70)	(-1.86)
TPER	0.020***		0.021***	0.020***		0.021***
	(5.64)		(5.31)	(5.37)		(5.07)
TPD_orth		0.049***	0.051***		0.046***	0.048***
		(8.53)	(8.41)		(6.02)	(6.55)
FREV				0.006	0.010	0.026*
				(0.37)	(0.64)	(1.82)
ΔRec				0.001	-0.004**	-0.000
				(0.50)	(-2.10)	(-0.28)
AgRecChg				0.001***	0.001***	0.001***
				(3.12)	(2.62)	(3.32)
Avg R-sq	13.92%	13.71%	14.64%	14.77%	14.62%	15.64%

*** Indicates significance at the 1% level.
** Indicates significance at the 5% level.
* Indicates significance at the 10% level.

Note: Each month from January 2000 to December 2017, we run cross-sectional regressions of one-month returns on sets of explanatory variables. These include the lagged one-month return(RET1M); book-to-price ratio (BP); log market cap (SIZE); target price implied expected return (TPER); TPD component that is orthogonal to TPER (TPD_orth); the analyst earnings forecast revision (FREV); the most recent revision in recommendations (ΔRec); a recommendation change variable used in Boni and Womack (2006), which we define as the number of recommendation upgrades minus the number of recommendation downgrades within the month (AvgRecChg). The reported slope coefficients are averaged across time and the robust t value is computed using Newey-West autocorrelation-adjusted standard error with six lags and are reported in the brackets.

Table IX

Value-weighted Fama-Macbeth regressions

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
RET1M	-0.006	-0.023**	-0.013	-0.005	-0.026***	-0.015*
	(-0.59)	(-2.40)	(-1.44)	(-0.60)	(-2.68)	(-1.65)
BP	0.001	0.001	-0.000	0.001	0.001	0.001
	(0.22)	(0.21)	(-0.18)	(0.22)	(0.63)	(0.24)
EP	-0.018	-0.019	-0.012	-0.022	-0.027	-0.014
	(-0.61)	(-0.59)	(-0.44)	(-0.76)	(-0.74)	(-0.55)
SIZE	-0.002***	-0.001***	-0.001***	-0.002***	-0.001***	-0.001***
	(-4.28)	(-3.10)	(-3.01)	(-4.12)	(-3.25)	(-3.08)
TPER	0.011**		0.011**	0.014***		0.012**
	(2.44)		(2.33)	(2.81)		(2.44)
TPD		0.070***	0.072***		0.071***	0.072***
		(6.91)	(6.95)		(6.72)	(6.91)
FREV				0.035	0.061**	0.072***
				(1.19)	(2.25)	(2.83)
ΔRec				0.003**	-0.002	0.001
				(2.33)	(-1.25)	(0.94)
AgRecChg				0.001***	0.001***	0.001***
				(2.82)	(2.63)	(2.80)
Avg R-sq	19.25%	19.03%	20.80%	20.64%	20.60%	22.09%

*** Indicates significance at the 1% level.

** Indicates significance at the 5% level.

* Indicates significance at the 10% level.

Note: Each month from January 2000 to December 2017, we applied value-weighted least squares (VWLS) to the Fama-Macbeth regression. These include the lagged one-month return(RET1M); book-to-price ratio (BP); log market cap (SIZE); target price implied expected return (TPER); TPD component that is orthogonal to TPER (TPD_orth); the analyst earnings forecast revision (FREV); the most recent revision in recommendations (ΔRec); a recommendation change variable used in Boni and Womack (2006), which we define as the number of recommendation upgrades minus the number of recommendation downgrades within the month (AvgRecChg). The reported slope coefficients are averaged across time and the robust t value is computed using Newey-West autocorrelation-adjusted standard error with six lags and are reported in the brackets.

Table X

Value-weighted Fama-Macbeth regressions

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
RET1M	-0.006	-0.024**	-0.013	-0.005	-0.027***	-0.015*
	(-0.59)	(-2.51)	(-1.44)	(-0.60)	(-2.80)	(-1.65)
BP	0.001	0.001	-0.000	0.001	0.002	0.001
	(0.22)	(0.27)	(-0.18)	(0.22)	(0.69)	(0.24)
EP	-0.018	-0.020	-0.012	-0.022	-0.028	-0.014
	(-0.61)	(-0.60)	(-0.44)	(-0.76)	(-0.75)	(-0.55)
SIZE	-0.002***	-0.001***	-0.001***	-0.002***	-0.001***	-0.001***
	(-4.28)	(-3.14)	(-3.01)	(-4.12)	(-3.30)	(-3.08)
TPER	0.011**		0.013***	0.014***		0.014***
	(2.44)		(2.63)	(2.81)		(2.75)
TPD_orth		0.068***	0.072***		0.069***	0.072***
		(6.91)	(6.95)		(6.63)	(6.91)
FREV				0.035	0.059**	0.072***
				(1.19)	(2.16)	(2.83)
ΔRec				0.003**	-0.002	0.001
				(2.33)	(-1.40)	(0.94)
AgRecChg				0.001***	0.001***	0.001***
				(2.82)	(2.61)	(2.80)
Avg R-sq	19.25%	18.92%	20.80%	20.64%	20.51%	22.09%

*** Indicates significance at the 1% level.

** Indicates significance at the 5% level.

* Indicates significance at the 10% level.

Note: Each month from January 2000 to December 2017, we applied value-weighted least squares (VWLS) to the Fama-Macbeth regression. These include the lagged one-month return(RET1M); book-to-price ratio (BP); log market cap (SIZE); target price implied expected return (TPER); TPD component that is orthogonal to TPER (TPD_orth); the analyst earnings forecast revision (FREV); the most recent revision in recommendations (ΔRec); a recommendation change variable used in Boni and Womack (2006), which we define as the number of recommendation upgrades minus the number of recommendation downgrades within the month (AvgRecChg). The reported slope coefficients are averaged across time and the robust t value is computed using Newey-West autocorrelation-adjusted standard error with six lags and are reported in the brackets.