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The value of combining the information content of analyst recommendations and target prices

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Abstract

In assessing the usefulness of the analysts' stock picking advice, the extant literature has largely focused on the profitability of either their stock recommendations or target prices in isolation. In this paper, we examine the profitability of investment strategies that exploit the information analysts convey through revisions in *both* their stock recommendations and target prices. We find that these strategies significantly outperform the comparable strategies that make use of only one analyst output.

JEL classification: D14; D21; G24

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Given the prominence of equity analysts in modern day financial markets, it is not surprising that financial economists over the last decade or so have become increasingly interested in examining whether investors could construct profitable investment strategies based on the investment advice of analysts. Earlier studies in this literature focus solely on analysts' stock recommendations and conclude that changes in recommendations indeed embody useful investment signals—stocks upgraded (downgraded) by analysts generate

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positive (negative) risk-adjusted returns in the future (see, for example, Womack, 1996; Barber et al., 2001; Jegadeesh et al., 2004; Green, 2006).[1]

Increasingly, however, academic researchers are recognizing that, besides the stock recommendation, an analyst report also usually includes a target price estimate that provides an alternative summary statistic of the analyst's view about the investment potential of the stock. The target price estimate reflects the analyst's opinion about the price level the stock is likely to achieve during the subsequent 6- to 12-month period. When combined with the prevailing market price of the stock, the target price estimate yields the analyst's estimate of the future expected return from the stock. A few recent studies examine the profitability of analysts' target prices in the presence of their stock recommendations and document that target prices have investment value independent of recommendations (Brav and Lehavy, 2003; Asquith et al., 2005; Da and Schaumburg, 2007).

The results in these studies raise the possibility that investment strategies that combine the information content of both target prices and recommendations could outperform those that rely solely on any one of these analyst outputs. We explore this possibility in this paper. We double sort stocks according to revisions in recommendations and target prices to assess the profitability of the strategies that combine the information content of both recommendations and target prices. We then compare the profitability of these strategies with similar strategies that rely solely on either recommendations or target prices. While the previous studies cited above are concerned with showing the marginal value of target prices in the presence of recommendations, our focus is on documenting the superiority of the combination investment strategies.

A priori, there are several reasons to expect that the stock recommendation and the target price of a stock would contain useful independent information in the presence of the other. A stock recommendation provides only a coarse measure of the analyst's view of the stock—he or she has only a few discrete categories to choose from when issuing a stock recommendation.[2] A target price, in contrast, allows the analyst more flexibility in expressing his or her refined views about the investment potential of the stock (Asquith et al., 2005). Moreover, perhaps as a reflection of the difference in the coarseness, analysts revise price targets far more often than they revise their stock recommendations (Brav and Lehavy, 2003). Furthermore, while a target price reflects the opinion of the analyst about the *expected* returns from the stock, a stock recommendation is the outcome of the comparison of this *expected* return with the *required* return that the analyst determines after assessing the risk of the stock. A stock recommendation, therefore, might contain additional information (about the required return) not directly discernable from a target price. Finally, as Bradshaw and Brown (2005) argue, the two outputs may not be equally distorted by the incentive structure analysts face. If analysts incorporate their biases

[1]Specifically, analyst recommendations provide useful investment signals when one focuses on *changes* in recommendations rather than on *levels* (Womack, 1996; Jegadeesh et al., 2004; Boni and Womack, 2006), and when one recognizes that analysts are industry specialists and create value mainly through ranking stocks within industries (Boni and Womack, 2006). In addition, the profitability of analyst recommendations also varies with sample period (see, for example, Barber et al., 2003) and country ([Jegadeesh and Kim, 2006).

[2]A stock recommendation represents a rating chosen from a discrete range, usually labeled as strong sell, sell, hold, buy, and strong buy. In practice, though, the choice is even limited to the three categories of hold, buy, and strong buy, as most analysts prefer not to issue unfavorable recommendations for various reasons (see, for example, Jegadeesh et al., 2004).

differently in the two summary statistics, each is likely to contain incremental information in the presence of the other.[3]

We obtain analyst recommendations from I/B/E/S and target prices from the Thomson First Call dataset. Constrained by the target price dataset, the time period of our analyses ranges from March 1997 through May 2004. A consensus recommendation for a stock is computed as simply the mean of the individual broker recommendations for the stock. To compute our measure of the consensus target price for a stock, we first divide each broker's target price by the stock price prevailing on the day of the announcement of the target price, and then subtract one from this ratio to obtain the broker's target price expected return (*TPER*). The mean of the *TPER* across all the brokers covering the firm then represents the consensus *TPER* in our analyses. We examine the returns from various calendar–time portfolio strategies that buy or sell short stocks each month according to the information signals analysts provide through their recommendation and *TPER* revisions over the preceding month.

We document that a combination strategy that buys (sells short) the stocks with the most favorable (unfavorable) revisions in *both* consensus recommendation and *TPER* outperforms the comparable strategies that rely solely on recommendations or *TPER*. While we do not claim to have examined all, or even the most optimal, of the possible strategies that could be constructed from the two analyst outputs, we find that for a range of simple strategies that we consider, the outperformance of the combination strategies is both economically and statistically significant. In industry-neutral equally weighted portfolios, which we focus on for reporting our main findings, the four-factor alpha associated with the combination strategy is about 50% larger than the corresponding alphas associated with the comparable strategies based on recommendations and *TPER* alone.

That revisions in analyst recommendations and target prices contain information signals that are largely orthogonal is further confirmed by the low rank order correlation between stocks sorted, within industries, on changes in recommendations and target price. This correlation is only 0.07 for our sample. This low correlation also makes the abnormal returns from the combination strategy more predictable over time. Consequently, this strategy appears less risky, results in fewer months with negative alphas, and produces superior Sharpe ratio relative to the comparable strategies based on single analyst output.

As noted above, a contemporaneous paper by Da and Schaumburg (2007) also looks at the profitability of analyst target prices, albeit primarily for the S&P 500 stocks. They attribute the ability of the *TPER* to predict returns to its ability to identify temporary changes in liquidity. One of the key arguments they use in favor of this interpretation is that the stocks that enter the long and short portfolios using the *TPER* tend to exhibit return reversals. Our paper shows that the profitability of the *TPER* could be improved significantly by combining it with analyst recommendations *and* that the long and short portfolios that are formed by combining the information signals of both target prices and recommendations do not exhibit any return reversals. This suggests that temporary shifts

[3]Another reason why a *consensus* recommendation and a *consensus* target price might contain incremental investment value in the presence of the other could be that the groups of analysts that make up the two consensus measures are not identical. In addition, there is a general agreement in the forecasting literature that, even if the two signals are predicting the same metric or outcome, a linear combination of the forecasts outperforms each of the individual forecasts (see, for example, Figlewski and Urich, 1983).

in liquidity are not the cause of the profitability of analyst investment advice that we document in our study. Our results seem more consistent with the traditional inference in the analyst literature—that the usefulness of the analyst investment advice stems from their informational advantage, which in turn is predicated on the large amounts of resources that are spent to support the analyst activities. This inference is also consistent with the Grossman and Stiglitz (1980) view of the markets. They observe that market prices cannot reflect all available information; otherwise, information gatherers like security analysts would not be rewarded for their costly activities.

We expect our results to be of interest to both finance academics and practitioners. From an academic perspective, our paper underlines the importance of studying the multiple analyst outputs jointly in the context of ascertaining the usefulness of analysts' stock picking advice. Our results suggest that the extant analyst literature, which primarily focuses on either recommendations or target prices in isolation, has underestimated the profitability of the analyst investment advice. From the perspective of practitioners, our paper helps identify superior investment strategies that could be constructed from the analyst output. We document that the strategies that rely on both recommendations and target prices perform significantly better than those that rely on only one analyst output.

The rest of the paper is organized as follows. In Section 1, we discuss our dataset and the sample selection criteria. Section 2 discusses how we form our portfolios based on changes in consensus recommendations and target prices. In Section 3, we report our main results and discuss the profitability of the various investment strategies. In Section 4, we show that the combination strategy continues to outperform individual strategies for several alternative portfolio formation procedures. Section 5 concludes the paper.

1. The data and sample selection criteria

Our dataset consists of the Thomson First Call data on analyst target prices, the I/B/E/S data on analyst recommendations, the Center for Research in Security Prices (CRSP) monthly stock returns and market capitalizations, and the Global Industry Classification Standard (GICS) sector codes. The time frame for our studies is from March 1997 through May 2004. The choice of our time period is determined by the availability of the Thomson First Call target price data. The data starts from January 1997. We begin constructing consensus level target prices at the end of January. Changes are then computed at the end of February before returns are tracked from March 1997 onwards. Our data of target prices end in May 2004.

The target price data we employ come from Thomson First Call. We only retain real-time records (with 'source' = 8) that comes with the date stamp to indicate the date on which the target price was issued. The dataset also provides information about the issuing broker (but not the analyst). Each target price indicates the analyst's view as to the likely stock price in the near future. The forecasting horizon usually tends to be the next six to twelve months (see, for example, the discussion in Brav and Lehavy, 2003). We divide the target price by the market price of the stock prevailing on the day of the announcement of target price, and subtract one from this ratio, to obtain the target price expected return (*TPER*). An initial examination of the distribution of *TPER* indicates some extreme observations. Accordingly, to ensure that erroneous or extreme individual analyst *TPER* do not influence the consensus *TPER*, we remove those individual broker *TPER*s that are outside of the 1% and 99% of the overall *TPER* distribution. This initial filtering leaves us

with a total of 402,731 broker-firm-target price observations issued over the period of January 1997 through May 2004.

To obtain the recommendations data, we utilize the I/B/E/S Detail History-Recommendation file, which provides an entry for each recommendation issued by each analyst and broker. I/B/E/S assigns a rating of 1 through 5 for each entry. A rating of 1 reflects a strong buy recommendation, 2 a buy, 3 a hold, 4 a sell, and 5 a strong sell. In this study, we reverse the order of the rating scale to make 5 a strong buy, 4 a buy, 3 a hold, 2 a sell, and 1 a strong sell. This is done to code the levels of recommendations in the same order as that of *TPER*. Other important variables provided in each entry include the date the recommendation was issued, the name of the analyst, and the name of the brokerage house.

We obtain CRSP monthly returns of NYSE, AMEX, and NASDAQ companies that could be matched with a GICS industry code available from Compustat. Recent studies document the superiority of GICS industry classification, especially for examining the sell-side analyst output and for more accurately depicting the industry specializations of the sell-side analysts (see, for example, Boni and Womack, 2006). We include CRSP ordinary shares and ADRs (American Depository Receipts) but exclude closed-end funds, shares of beneficial interest, and units. Specifically, CRSP share codes of 10, 11, 12, 18, 30, and 31 are included. ADRs are included because a substantial portion (over 50%) has analyst coverage, as pointed out in Boni and Womack (2006).

We retain the stocks that appear in both the I/B/E/S and First Call datasets and for which we could obtain the GICS sector codes and the stock price information from CRSP. Table 1 reports, for each calendar year, the extent of the firm-level coverage for I/B/E/S recommendations data, for the First Call target price data, and for our merged sample. Column (2) reports the total number of the listed firms on NYSE, AMEX, and NASDAQ, as depicted in CRSP, for which we could find GICS codes from Compustat. Columns (3) through (5) provide the information about the coverage of the I/B/E/S recommendations data. The I/B/E/S dataset coverage ranges from 97% to 99% of all the listed firms in terms of market capitalization, and from 58% to 70% in terms of the number of companies. This level of coverage is similar to that reported by Barber et al. (2001) for their sample, and seems to increase through our sample period. Columns (6) through (8) indicate a slightly lower level of firm-level coverage by the First Call target price dataset.

In column (9) of Table 1, we report the number of the firms in the merged sample. On this merged sample, we apply our final filter and exclude stocks that trade at or below a price of \$5 at the end of each month. As we will be devising investment strategies that involve short selling, including these stocks may not be a reasonable reflection of reality. D'Avolio (2002), for example, shows that stocks priced $<$\$5/share are difficult to borrow. The firm-level coverage after applying this additional filter is shown in the last three columns of Table 1. Our final sample contains about 3,000 firms, accounting for about 90% of the market capitalization and about 42% of the number of all listed firms.[4]

[4]It is worth pointing out that the numbers reported in the last three columns of Table 1 are meant to provide an indication of the coverage of the raw broker-level recommendation and target price datasets that we begin with. Not all of these recommendations and target prices feature in our final sample. Specifically, we use the criteria and the methodology set out in Section 2 to convert these raw data into *revisions* in *consensus* recommendations and TPER. The summary statistics of the stocks that finally make up our investment strategies are reported in Table 2.

Table 1
Firm-level coverage of the I/B/E/S, first call, and the merged filtered datasets.

This table provides indicative information about firm-level coverage in the I/B/E/S recommendations, FC target price, and the merged and filtered datasets for each of the eight years in our sample. The years in column (1) are calendar years. Column (2) reports the total number of the firms listed on the NYSE, AMEX, and NASDAQ as depicted in CRSP, which can be matched with an annual GICS code from Compustat. Columns (3) through (5) depict the information about firms that appear in both the I/B/E/S recommendations dataset and the CRSP dataset for the same year. Market capitalization (mkt. cap.) for each firm is computed by taking the average of 12 month-end market capitalizations during the year. Columns (6)–(8) depict the information about firms that appear in both first call target price and CRSP datasets. The number of firms for each year that appear in all three datasets—I/B/E/S, first call, and CRSP—are reported in column (9). Once we remove firms for whom the stock price at the end of any of the month in the respective year is $<\$5$, we obtain our final set of firms. The statistics for these are reported in columns (10) through (12).

Year	No. of all listed firms	Firms in I/B/E/S recommendations data that could be matched with CRSP and GICS			Firms in FC target price data that could be matched with CRSP and GICS			No. of firms matched across I/B/E/S, FC target price data, CRSP and GICS	Final sample		
		No. of firms	No. as % of listed firms	Mkt. cap. as % of listed firms	No. of firms	As a % of listed firms	Mkt. cap. as % of listed firms		No. of firms	As a % of listed firms	Mkt. cap. as % of listed firms
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1997	8,648	5,440	63	97	4,183	48	85	3,913	3,606	42	84
1998	8,466	5,484	65	97	4,410	52	88	4,192	3,541	42	87
1999	8,209	5,270	64	98	4,528	55	91	4,248	3,662	45	90
2000	8,065	4,938	61	98	4,447	55	94	4,080	3,239	40	91
2001	7,344	4,292	58	98	3,830	52	96	3,537	2,815	38	93
2002	6,654	4,299	65	99	3,688	55	96	3,590	2,655	40	91
2003	6,189	4,063	66	99	3,591	58	95	3,464	2,683	43	93
2004 (January–May)	6,013	4,184	70	98	3,179	53	93	3,056	2,701	45	91

2. Portfolio construction and performance evaluation

Our investment strategies revolve around forming long and short portfolios at the end of each calendar month based on the revisions in analysts' consensus recommendations and *TPER*. We then track the return performance of these long and short portfolios over the subsequent month. In order to determine the consensus recommendation (*TPER*) for stock i at the end of month $t-1$, we include the latest recommendation (*TPER*) outstanding on the 25th day of month $t-1$ of each broker that covers stock i. To avoid the problem of stale recommendations (*TPER*), an individual broker recommendation (*TPER*) is assumed to be valid until the broker issues a new recommendation (*TPER*) or until six months after the issue date, whichever is earlier.[5] We do not consider recommendations (*TPER*) that are issued after the 25th day of month $t-1$ to ensure that our results are not driven by an immediate market reaction to the announcement of a new recommendation (*TPER*), and to make our investment strategies easier to implement since investors on average are given five days to collect and react to the recommendation (*TPER*). The consensus recommendation (*TPER*) for stock i at the end of month $t-1$ is then computed as the mean of the outstanding individual broker recommendations (*TPER*).[6]

Next, the change in the consensus recommendation for the stock at the end of month $t-1$ is computed by taking the difference between the consensus recommendations of month $t-1$ and month $t-2$. If the consensus recommendation for month $t-2$ is not available, we substitute it with the consensus recommendation for the most recent of the preceding six months. The greater the magnitude of the revision, the more favored the stock is assumed to be. The change in the consensus *TPER* is computed in the same way except that we scale the monthly change in *TPER* by the *TPER* of month $t-2$, to control for the cross-sectional differences in the scale of the *TPER*s. As mentioned earlier, we focus on changes in recommendations (*TPER*) as the basis of our primary analyses as the prior research finds changes to be far more informative than levels (Womack, 1996; Jegadeesh et al., 2004; Boni and Womack, 2006). We drop those firm-month observations for which we do not have both the change in consensus recommendation and the change in consensus *TPER*. This yields us our final sample of stock-month observations that we employ to examine the profitability of various investment strategies.

It is worth pointing out here that we employ *revisions* in *consensus* values of analyst outputs as the basis for converting analyst advice into actual portfolio strategies. This is the treatment adopted in Jegadeesh et al. (2004). However, we do not claim that this is the only way of forming portfolios based on analyst advice. Some recent studies use alternative ways to convert analyst outputs into investment signals (e.g., Boni and Womack, 2006; Da and Schaumburg, 2007). In Section 4, we report the robustness of our conclusions to the use of some of these alternative techniques.

[5]A consensus recommendation (TPER), therefore, includes all individual broker recommendations (TPER) issued over the period from the 26th day of month $t-7$ through 25th of month $t-1$. As we mention in a later section, our results remain robust to making the alternative assumptions about the length of time an unrevised individual recommendation remains valid (TPER).

[6]Even though I/B/E/S data provide recommendations issued by all *analysts covering a stock*, we compute the consensus recommendation for the stock by aggregating the recommendations of each *broker*. This is done in order to be consistent with our treatment for target prices (where only broker-level information is available). Nevertheless, our results remain robust to computing consensus recommendations by aggregating recommendations of the individual analysts.

Having identified the revisions in consensus recommendation and *TPER* for each stock for each month end, we are ready to examine the profitability of various portfolios formed on the basis of these two analyst signals in isolation and in combination. Specifically, we examine the profitability of three investment strategies. The first strategy relies on changes in consensus recommendations alone to identify the winner and loser stocks. Within this strategy, we create three portfolios—a long portfolio, a short portfolio, and a long–short portfolio—at the end of month $t-1$. We do so by first sorting all stocks within each sector into nine groups based on the changes in consensus recommendations. The long (short) portfolio for each sector contains firms with the largest upwards (downwards) revisions in the consensus analyst recommendation. Stocks are equally weighted in a portfolio.[7] The long and short portfolios for each sector are then aggregated by equally weighting each sector to form the overall long and short portfolios for the strategy. A third zero-cost long–short portfolio is then created that captures the difference in the performance of the long and short portfolios. The second strategy also involves the construction of the long, short, and long–short portfolios similar to that of the first strategy except that changes in *TPER*s are used to sort stocks in place of changes in recommendations.

We compare and contrast the profitability of the three portfolios constructed under each of the first two strategies with the corresponding portfolios constructed under a third strategy that relies on changes in both consensus recommendations and *TPER*s to identify the winner and loser stocks. In this third strategy, which we label as the combination strategy, we sort firms independently into three groups at the end of each month based on changes in recommendations as well as changes in *TPER*s. This is done within each sector. The firms that are ranked the best on both recommendation and *TPER* revisions make up the long portfolio of each sector, whereas the firms that are ranked the worst on both recommendation and target price revisions are part of the short portfolio. Portfolios formed for each sectors are then aggregated by equally weighting each sector to form the overall long and short portfolios of the combination strategy.

Overall, therefore, we obtain three portfolios—long, short, and long–short—for each of the three strategies yielding us a total of nine portfolios. After determining the composition of each of portfolio p at the end of month $t-1$ as outlined above, monthly returns $R_{p,t}$ are computed for the portfolio for month t. Portfolios are rebalanced at the end of each calendar month.

Besides reporting the average of the raw monthly returns for each portfolio, we also report four risk-adjusted return measures. First, the market-adjusted returns are calculated by subtracting the corresponding monthly return on the NYSE/AMEX/NASDAQ value-weighted index, $R_{m,t}$, from $R_{p,t}$. In addition, the alphas from the time series regressions of the monthly portfolio returns on various risk-factors provide the other three measures of risk-adjusted returns for each portfolio. We obtain these alphas from a simple CAPM regression (our second measure of abnormal returns), from regressions on the Fama–French (1993) three factors (our third measure), and from the Carhart (1997) four-factor regressions that include the Fama–French three factors, as well as the momentum factor. The risk-adjusted returns associated with the long, short, and long–short portfolios of the combination strategy are then compared to those of the corresponding portfolios of each of the first two strategies to see whether relying on both analyst outputs yields better investment signals.

[7]In a later section, we report the robustness of our conclusion to value-weighting of the stocks.

It is worth reiterating that all three of our investment strategies sort stocks within a sector first before aggregating sector portfolios. This is done in view of the recent research, which documents that analysts do a much better job of ranking firms within the industry (Boni and Womack, 2006; Da and Schaumburg, 2007). Following Da and Schaumburg (2007), we use the first two digits of the GICS to divide all our stocks into 10 GICS sectors. These include energy, materials, industrials, consumer discretionary, consumer staples, health care, financials, information technology, telecommunication services, and utility.[8]

3. Characteristics and profitability of the portfolios based on analyst recommendations and target prices

3.1. Descriptive statistics and characteristics of the portfolios

The descriptive statistics of our final sample of the stock-month observations that we employ to implement our various investment strategies are provided in Table 2. For each year, we report the average number of stocks per month in column (2). As the last row indicates, on average, we have 2,722 stocks at each month-end to implement our analyst-oriented investment strategies. Columns (3) through (6) report the statistics on the number of recommendations (i.e., number of brokers) that make up a consensus recommendation in our sample. On average, about four broker recommendations make up a typical consensus recommendation in our sample. Similarly, columns (7) through (10) report the statistics about the number of *TPER* (i.e., number of brokers) that make up a consensus *TPER*. On average, the number of brokers that make up a consensus *TPER* is five, somewhat higher than that for a consensus recommendation.

In Table 3, we report the composition and characteristics of the various portfolios we create according to the methodology outlined in the preceding section. The table is divided into Panel A, B, and C to corresponding to each of the three investment strategies that are based, respectively, on recommendations alone, *TPER* alone and on both recommendations and *TPER*. Within each panel, the first row describes the portfolio of the stocks that experience the most favorable revisions, whereas the second row describes the portfolio of stocks with the most unfavorable revisions in the respective analyst output(s). The third row in each panel describes the zero-cost portfolio that is formed by being long in the stocks with the most favorable revisions and short in those with the most unfavorable revisions.

Beginning with the recommendations-based strategy depicted in Panel A of Table 3, the long and short portfolios formed for each month on the basis of the recommendations include on average about 300 stocks. As depicted in columns (3) and (4), these stocks tend to be of large companies. The mean (median) market capitalization of an included stock is about $3 billion ($1 billion). This reflects the well-known bias of the analyst datasets such as I/B/E/S and First Call. By design, the stocks included in the long and short portfolios in

[8]The S&P/MSCI Global Industry Classification System (GICS) classifies companies at four levels; each company belongs to one of 10 sectors, 23 industry groups, 59 industries, and 122 sub-industries. The 59 industry classification can be considered to mimic the approximately 70 industry categories the annual *Institutional Investor* poll requests buy-side managers to rate sell-side analysts. Although Boni and Womack (2006) document that using the 59-industry classification would be ideal for sector control, this would result in sector portfolios having too few stocks in our context, whereby we retain only those firms that have both target prices and recommendations.

Table 2
Descriptive statistics of the final sample of the matched firm–month observations.

This table presents the summary statistics for the final sample of firm–month observations obtained over 87 months from March 1997 to May 2004. These are the firm–month observations for which we could compute both a change in consensus recommendation and a change in consensus target price expected return (*TPER*). Column (2) reports the average (across all available months of the year) number of firms for each month. All our portfolio strategies are based on sorting this set of firms on one or more of analyst outputs. Columns (3) though (6) provide statistics about the number of analysts that make up a consensus recommendation for each of the included firm. Similarly, columns (7) through (10) report the statistics about the number of analysts that contribute towards a consensus *TPER* for the included firms.

Year	Avg. no. of firms per month	Number of recommendations per firm–month				Number of *TPER* per firm–month			
		Mean	Median	Min	Max	Mean	Median	Min	Max
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1997 (March–December)	2,359	3.18	2.64	1.00	20.09	3.63	3.00	1.00	19.27
1998	2,520	5.29	4.17	1.00	29.58	5.64	4.25	1.00	32.17
1999	2,568	4.22	3.00	1.00	29.67	5.12	4.00	1.00	27.08
2000	2,597	5.19	3.75	1.00	30.83	5.12	4.00	1.00	29.00
2001	2,757	4.52	3.25	1.00	30.50	5.58	4.00	1.00	32.50
2002	2,874	3.89	3.00	1.00	24.42	4.93	4.00	1.00	29.33
2003	3,010	4.11	3.00	1.00	24.25	4.59	3.38	1.00	26.92
2004 (January–May)	3,091	3.60	3.00	1.00	23.33	4.12	3.00	1.00	25.08
Average all years	2,722	4.25	3.23	1.00	26.58	4.84	3.70	1.00	27.67

Panel A experience large absolute changes in their consensus recommendations. As reported in the first row of column (5), an average stock included in the long portfolio experiences a revision of 0.57 whereas a stock included in the short portfolio experiences a revision of −0.64. Interestingly, the average change in consensus *TPER*, reported in column (6) of Panel A, is not much different across the long and short portfolios based on the recommendations. This suggests a lack of correlation between changes in consensus recommendations and *TPER* across stocks, and opens up the possibility that the investment value contained in one analyst output is orthogonal to that contained in the other analyst output. Columns (7) through (10) report the coefficients and the associated *t*-statistics of a four-factor regression of monthly raw returns. Consistent with the prior literature, the positive coefficients for the SMB and HML factors suggest that extreme changes in analyst recommendations happen for small and value stocks (see, for example, Jegadeesh et al., 2004).

Panel B of Table 3 reports similar statistics for the portfolios formed on the basis of changes in the consensus *TPER*. The stocks in these long and short portfolios are smaller than those in the portfolios depicted in Panel A. The mean (median) market capitalization of a stock is about $2.5 billion ($0.9 billion). Not surprisingly, examining columns (5) and (6), we observe that the long and short portfolios experience very different changes in consensus *TPER*. The average change in *TPER* is 14% (−12 + %) for an average stock included in the long (short) portfolio. The change in consensus recommendation, however, is not different across the long and short portfolios, again suggesting that the information contents of the two analyst output are orthogonal to each other.

Table 3
Descriptive statistics and characteristics for the portfolios formed.

This table provides summary statistics and characteristics of the portfolios formed on the basis of changes in consensus recommendation, changes in consensus *TPER*, and changes in both recommendations and *TPER*s, respectively, in Panels A, B, and C. All statistics shown in columns (2) through (7) are first computed for each month, and then averaged across all 87 months of our sample. Column (2) reports the number of average number of firms in each portfolio. Columns (3) and (4) report the mean and median market capitalization, respectively, of a firm that is included in the respective portfolio. Column (5) and (6) report the average change in consensus recommendation and consensus *TPER*, respectively, for a firm included in the portfolio. Columns (7) through (11) relate to the output of the time series regressions of monthly portfolio returns on the four factor model. The *t*-statistics are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The statistical significance is computed for the null hypothesis that the estimates are equal to zero (equal to one for market excess return in column (7) for the long and short portfolios).

Portfolio	Mthly avg. no. of firms	Avg. mkt. cap. ($000)	Med. mkt. cap ($000)	Avg. chg in Mn rec	Avg. chg in Mn *TPER*	Coefficient estimates for the four-factor model				Adjusted R^2
						R_m-R_f	*SMB*	*HML*	UMD	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: *Portfolios formed on the basis of changes in consensus recommendation*										
Long	300	3,666,835	1,155,076	0.57	0.90%	1.077	0.459	0.409	−0.060	0.92
						(1.81)*	(10.90)***	(7.48)***	(−2.14)**	
Short	298	3,040,657	954,049	−0.64	−0.12%	1.046	0.535	0.428	−0.142	0.93
						(1.14)	(13.28)***	(8.20)***	(−5.31)***	
Long–short	598	3,353,746	1,054,562	NA	NA	0.031	−0.076	−0.020	0.082	0.09
						(0.79)	(−1.97)**	(−0.39)	(3.21)***	
Panel B: *Portfolios formed on the basis of changes in consensus TPER*										
Long	299	2,491,654	894,179	0.03	13.67%	1.202	0.561	0.454	−0.192	0.92
						(4.09)***	(11.49)***	(7.18)***	(−5.93)***	
Short	298	2,536,200	930,648	−0.04	−11.47%	1.135	0.538	0.414	−0.073	0.91
						(2.74)***	(11.04)***	(6.55)***	(−2.26)**	
Long–short	597	2,513,927	912,414	NA	NA	0.067	0.024	0.041	−0.119	0.13
						(1.23)	(0.44)	(0.58)	(−3.34)***	
Panel C: *Portfolios formed on the basis of changes in both consensus recommendation and TPER*										
Long	253	7,092,720	2,271,391	0.34	6.28%	1.154	0.347	0.432	−0.102	0.92
						(3.40)***	(7.75)***	(7.43)***	(−3.42)***	
Short	268	6,548,149	2,175,340	−0.35	−5.54%	1.045	0.413	0.411	−0.088	0.91
						(1.00)	(9.22)***	(7.08)***	(−2.95)***	
Long–short	521	6,820,435	2,223,365	NA	NA	0.109	−0.066	0.020	−0.014	0.06
						(2.20)**	(−1.35)	(0.32)	(−0.43)	

In Panel C of Table 3, we report the characteristics of the portfolios that we form based on the combination strategy that relies on a three by three independent sorting of stocks on both changes in consensus recommendations and changes in consensus *TPER*. The number of stocks included in these long and short portfolios is similar to those included in the single output-based strategies depicted in the first two panels. However, average market capitalization of the constituent stocks is somewhat larger. The mean (median) market capitalization is now about \$6.5 billion (\$2 billion). Columns (5) and (6) indicate that the stocks included in the long and short portfolios now differ in terms of both changes in recommendation as well as changes in *TPER*. The stocks included in the long portfolio have a mean change in recommendation of 0.34 and a mean change in *TPER* of 6.3%. This contrasts with the mean change in recommendation of −0.35 and the mean change in *TPER* of −5.5% for stocks in the short portfolio.

Table 4
Equally weighted monthly returns earned by investment strategies.

This table provides returns from the portfolios formed on the basis of changes in consensus recommendation, changes in consensus *TPER*, and changes in both recommendations and *TPER*s, respectively, in Panels A, B, and C. Column (2) reports the average monthly raw returns. Column (3) reports the average monthly market-adjusted returns where market returns are represented by the NYSE/AMEX/NASDAQ value-weighted index. Columns (4) through (6) represent intercepts from the monthly regressions of the CAPM model, the Fama–French three-factor model, and the Carhart four-factor model, respectively. The *t*-statistics are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Portfolio	Raw return	Mkt-adj ret	Intercept from		
			CAPM	Fama–French	Four-factor
(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *Portfolios formed on the basis of changes in consensus recommendation*					
Long (%)	1.476	0.794	0.801	0.394	0.464
	(2.42)**	(2.96)***	(2.95)***	(2.18)**	(2.58)***
Short (%)	0.688	0.006	0.012	−0.442	−0.275
	(1.10)	(0.02)	(0.04)	(−2.27)**	(−1.60)
Long–short (%)	0.788	0.788	0.788	0.836	0.739
	(4.78)***	(4.78)***	(4.74)***	(4.90)***	(4.49)***
Panel B: *Portfolios formed on the basis of changes in consensus TPER*					
Long (%)	1.402	0.720	0.664	0.180	0.406
	(1.94)*	(2.08)**	(1.96)**	(0.74)	(1.94)*
Short	0.745	0.063	0.041	−0.398	−0.312
	(1.12)	(0.20)	(0.13)	(−1.90)*	(−1.50)
Long–short (%)	0.657	0.657	0.623	0.578	0.718
	(2.79)***	(2.79)***	(2.69)***	(2.42)**	(3.13)***
Panel C: *Portfolios formed on the basis of changes in both consensus recommendation and TPER*					
Long (%)	1.579	0.898	0.881	0.496	0.616
	(2.48)**	(3.44)***	(3.36)***	(2.48)**	(3.22)***
Short (%)	0.441	−0.241	−0.222	−0.617	−0.514
	(0.74)	(−0.90)	(−0.83)	(−3.14)***	(−2.69)***
Long–short (%)	1.139	1.139	1.104	1.114	1.130
	(5.56)***	(5.56)***	(5.52)***	(5.47)***	(5.43)***

3.2. Profitability of the portfolios

We report the returns from the three investment strategies in Table 4. As in Table 3, Panels A and B depict the returns performance of the strategies based on the individual analyst outputs, whereas Panel C reports the returns performance of the combination strategy. Column (2) in the table reports the average monthly raw returns, whereas column (3) reports the market-adjusted returns. Columns (4), (5), and (6) report the intercepts, respectively, of the CAPM, the Fama–French three-factor model, and the Carhart four-factor model. These intercepts represent the abnormal risk-adjusted returns earned by each portfolio after adjusting for the specific factors known to be associated with the cross-section of stock returns. Unlike the long and long–short portfolios, a larger negative return for a short portfolio indicates its superior return performance.

The results are quite similar across various measures of abnormal returns. So, for our discussion here, we focus only on the intercepts of the four-factor model reported in column (6) of Table 4. Consistent with Boni and Womack (2006) and Jegadeesh et al. (2004), in Panel A, we report positive returns of 0.74% (t-statistics = 4.49) associated with the long–short portfolio formed on the basis of changes in consensus recommendations. Furthermore, consistent with Da and Schaumburg (2007), we also find that a long–short strategy based on changes in *TPER* produces a positive four-factor alpha of 0.72% (t-statistic = 3.13).

The returns from the combination strategy that relies on both changes in recommendations and *TPER* to identify good and bad stocks are depicted in Panel C of Table 4. It can be noted that the incremental returns that could be obtained from examining the two analyst outputs in tandem are significant. The returns reported in Panel C for the long, short, and long–short portfolios all clearly dominate the returns from the corresponding long, short, and long–short portfolios reported in the first two panels.

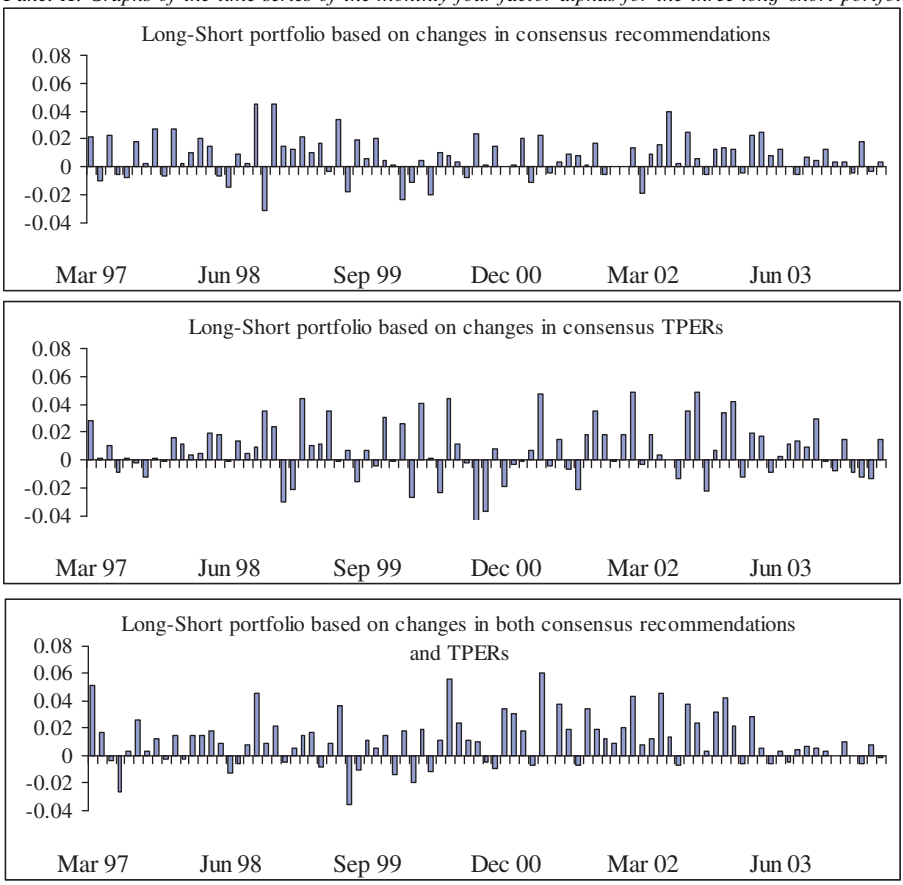
The long portfolio in Panel C of Table 4 yields a positive alpha of 0.62%, which is highly statistically significant (t-statistics = 3.22). This is greater than the returns on the two corresponding long portfolios that are based on either changes in recommendations or *TPER* alone. Similarly, the short portfolio in Panel C that relies on changes in both recommendations and *TPER* to identify loser stocks, produces a negative alpha of −0.51% (t-statistic = 2.69). This is clearly superior to the performance of the short portfolios in Panels A and B, both in terms of economic and statistical significance. The comparison of the performance of the long–short portfolio in Panel C with those in Panels A and B highlights the superiority of the combination strategy. The long–short portfolio of the combination strategy yields 1.13% alpha per month (t-statistic = 5.43). This is about 50% more than the corresponding alphas of the long–short portfolios, reported in Panel A and B, for the strategies that rely on solely recommendations and target prices, respectively.

To further highlight the benefits of relying jointly on the two analyst outputs, in Table 5, Panel A, we plot the monthly time series of the four-factor alphas for the long–short portfolios of the three investment strategies. Reflecting the structure of the previous tables, the first two plots depict the strategies based on the individual analyst outputs, whereas the third plot depicts the strategy that exploits the information contained in both the analyst outputs. A visual inspection of the three time series indicates that the combination strategy produces positive alphas on a more consistent basis. In Panel B of Table 5, we report the ratio of the mean to the standard deviation of the alphas for each strategy. This ratio is

Table 5
Monthly time series of the four-factor alphas for the three long-short portfolios.

This table provides information about the time series of the monthly four-factor alphas for the long-short portfolios of the three strategies: the first based on changes in consensus recommendation, the second based on changes in consensus *TPER*, and the third based on changes in both consensus recommendation and *TPER*. Panel A provides graphs of the monthly time series for our sample period of March 1997 through May 2004. Panel B provides some statistics about the time series of the four-factor alphas.

Panel A: *Graphs of the time series of the monthly four-factor alphas for the three long–short portfolios*



Panel B: *Summary statistics for the monthly four-factor alphas of the three long–short portfolios*

	Portfolio based on changes in recommendations	Portfolio based on changes in *TPER*s	Portfolio based on changes in both recommendations and *TPER*s
Mean (%)	0.739	0.718	1.130
Standard deviation (S.D.) (%)	1.430	1.993	1.809
Sharpe ratio (mean/ standard deviation)	0.52	0.36	0.62

Table 6
Spearman rank-order correlations between stocks sorted on changes in consensus recommendation and *TPER*.

This table reports the Spearman rank correlation coefficients, within each industry, for stocks sorted on the basis of changes in consensus recommendations and consensus *TPER*. We first compute the correlation coefficient for each month; the averages of the monthly correlations across all the 87 months of our sample are then reported in the table. The *t*-statistics are shown in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Energy GICS: 10	0.08 (7.04)***
Materials GICS: 15	0.08 (7.31)***
Industrials GICS: 20	0.06 (7.60)***
Consumer discretionary GICS: 25	0.04 (5.61)***
Consumer staples GICS: 30	0.07 (5.89)***
Health care GICS: 35	0.05 (5.20)***
Financials GICS: 40	0.08 (10.35)***
Information technology GICS: 45	0.03 (3.96)***
Telecommunication services GICS: 50	0.04 (2.80)***
Utilities GICS: 55	0.09 (6.61)***
Overall	0.06 (18.35)***

analogous to the traditional Sharpe ratio. The long–short portfolios of the strategies that rely only on recommendations and *TPER* alone have ratios of mean to standard deviation of 0.52 and 0.36, respectively. The ratio increases to 0.62 for the long–short portfolio of the combination strategy.[9] Overall, our results indicate that the combination strategy produces superior risk-adjusted returns, and does so on a more consistent basis.

That the information content of changes in the consensus analyst recommendation is largely orthogonal to that of changes in consensus *TPER* is further confirmed by Table 6 where we report correlations between changes in recommendations and *TPER*. As above, every month within each sector, we rank stocks based on changes in their consensus recommendations and *TPER*. Spearman rank correlation is then computed and reported in the table. The results in Column (2) indicate that even though the correlations are all positive and statistically significant, they are not very high. The highest correlation

[9]Employing the traditional Sharpe ratio, which uses raw returns in excess of the risk-free rate as the numerator, yields even stronger inference about the superiority of the combination strategy.

coefficient for any sector is 0.09. The overall average correlation coefficient is 0.06. These low correlation coefficients reiterate the message that changes in consensus recommendations and target prices do contain investment value that is largely orthogonal to each other.

3.3. Robustness checks

3.3.1. Role of return reversals in the profitability of the portfolios

It is possible that the abnormal returns generated by our target price-based strategies are due simply to standard return reversals documented in earlier studies (see, for example, Jegadeesh, 1991).[10] To understand how return reversals might play a role in the profitability of our target price-based strategies, it is worth recalling how we generate investment signals from analyst target prices. We first compute the target price expected returns (*TPER*) by scaling the individual analyst target prices by the current market price of the stock. We then compute consensus *TPER* for each stock for each month, and use changes in this consensus *TPER* over successive months as the basis to identify stocks that should be bought and sold. If an analyst does not continuously update his or her target price estimates and re-issues a stale target price, then any changes in the analyst's *TPER*s over successive months could be simply due to changes in the market price of the stock. If so, a stock whose market price has fallen (increased) in the recent past would experience systematic increases (decreases) in *TPER*. Since the long (short) portfolio in our target price-based strategy buys stocks with largest increases (decreases) in the consensus *TPER* in the formation month, it is possible that positive (negative) returns from this portfolio in the subsequent month are simply due to the standard return reversal documented in the earlier literature.

To confirm that our results are not simply driven by the standard return reversal documented in the prior literature, we augment the four-factor abnormal return model, which we employ for most of our earlier results, with a return reversal factor. This short-term reversal factor, DMU, is constructed as the return on a zero investment portfolio, which is long last month's losers and short last month's winners. The monthly time series of the factor realizations as well as the detailed description of the computation are available from Ken French's website. The intercepts from this five-factor model would then provide us abnormal returns from each portfolio after controlling for the return reversal effect. Furthermore, by observing the coefficient for the return reversal factor for each portfolio, we could find out if a portfolio is tilted towards stocks that are past month's losers (winners).

The coefficient estimates of the five-factor return model are reported in columns (2) through (7) of Table 7. The results in Panel B for the strategy that relies on target price alone are broadly consistent with those in Da and Schaumburg (2007). The coefficient on the long–short portfolio for the reversal factor is positive, and the five-factor alpha (i.e., the intercept reported in column (7)) of this portfolio is now 0.53%, somewhat lower than the four-factor alpha of 0.72% reported in Table 4. Nevertheless, the five-factor alpha is economically and statistically significant. More importantly, though, the coefficients for the reversal factor in Panel C, column (6), for the combination strategy are insignificant. The long and short portfolios under the combination strategy, therefore, do not exhibit

[10] Jegadeesh (1991) finds that stocks with the most positive (negative) returns in a month produce large and statistically significant abnormal negative (positive) returns in the following month.

Table 7
Examining the role of return reversals in the profitability of analyst-oriented investment strategies: Estimates of the five-factor model.

This table provides estimates of the time series regressions of the monthly portfolio returns from various investment strategies on the five-factor returns model. Panels A, B, and C report, respectively, the results for the equal-weighted portfolios formed on the basis of changes in consensus recommendations, changes in consensus *TPER*s, and changes in both recommendations and *TPER*s. The five factors include the three Fama-French factors, a momentum factor, and a return reversal factor. Columns (2) through (6) report the estimates of the coefficients for the five factors. Column (7) reports the intercepts of the model, which represents the abnormal returns of the respective portfolio. The *t*-statistics are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Coefficient estimates of the five-factor model						
	R_m-R_f	*SMB*	*HML*	*UMD*	*DMU*	Intercept	Adjusted R^2
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: *Portfolios formed on the basis of changes in consensus recommendation*							
Long	1.075	0.456	0.409	−0.059	0.012	0.444%	0.92
	(1.75)*	(10.51)***	(7.44)***	(−2.10)**	(0.32)	(2.33)**	
Short	1.044	0.530	0.430	−0.141	0.024	−0.314%	0.93
	(1.07)	(12.78)***	(8.19)***	(−5.22)***	(0.67)	(−1.72)*	
Long–short	0.031	−0.073	−0.021	0.081	−0.012	0.759%	0.08
	(0.80)	(−1.85)*	(−0.41)	(3.16)***	(−0.35)	(4.35)***	
Panel B: *Portfolios formed on the basis of changes in consensus TPER*							
Long	1.187	0.533	0.457	−0.186	0.109	0.225%	0.93
	(3.90)***	(11.05)***	(7.49)***	(−5.93)***	(2.67)***	(1.06)	
Short	1.136	0.539	0.414	−0.073	−0.004	−0.306%	0.91
	(2.72)***	(10.74)***	(6.51)***	(−2.25)**	(−0.10)	−(1.38)	
Long–short	0.052	−0.006	0.044	−0.113	0.113	0.531%	0.19
	(0.97)	(−0.11)	(0.65)	(−3.26)***	(2.51)**	(2.27)	
Panel C: *Portfolios formed on the basis of changes in both consensus recommendation and TPER*							
Long	1.147	0.334	0.432	−0.099	0.052	0.529%	0.92
	(3.23)***	(7.32)***	(7.49)***	(−3.34)***	(1.36)	(2.64)***	
Short	1.045	0.413	0.411	−0.088	0.001	−0.516%	0.90
	(0.99)	(8.93)***	(7.03)***	(−2.92)***	(0.03)	(−2.54)**	
Long–short	0.101	−0.079	0.021	−0.011	0.051	1.045%	0.07
	(2.05)**	(−1.59)	(0.33)	(−0.35)	(1.21)	(4.78)***	

any systemic tendency to include recent short-term winner or loser stocks. The five-factor alpha from the combination strategy, even though slightly lower than the four-factor alpha reported in Table 4, is still economically and statistically significant at 1.05% (*t*-statistic = 4.78). Overall, the results in Table 7 indicate that the superior performance of the combination strategy relative to the individual output-based strategies does not originate from its additional focus on recent winner or loser stocks.

In supplementary tests, we also compute the returns from the long–short portfolios for the three strategies after eliminating those stocks from our sample that fall in the extreme return deciles (of the overall CRSP stock universe) during the formation month. In the Jegadeesh (1991) study, these are the stocks that experience the greatest return reversals in the following month. The four-factor alphas of the long–short portfolios after eliminating these stocks are 0.61% (*t*-statistics = 3.91), 0.54% (*t*-statistics = 2.48), and 1.01%

(t-statistics = 5.29) for the recommendations-alone, target-price-alone, and the combination strategies, respectively. As a final robustness check, we also compute the average lagged one-month returns for the stocks included in the long and short portfolios of the combination strategy. In untabulated results, we find that the long and short portfolios of the combination strategy have very similar average prior month returns of 2.30% and 1.98%, respectively. Hence, differential exposure to the prior month's winner and loser stocks cannot explain the abnormal returns of the long–short portfolio of the combination strategy. In sum, these results suggest that return reversals are not the primary reason driving the superior performance of our combination strategy.

3.3.2. *Differences in the turnover of the portfolios*

It is possible that the superior performance of the combination strategy is due to the higher turnover for this strategy. The results reported so far in Tables 4 and 5 have been the gross, before transactions costs, returns that do not account for the possible differential turnover across the strategies. Given the nature of our strategies and the monthly rebalancing involved, execution of each of our strategy is likely to involve significant turnover at the end of each month. Hence, it is useful to examine whether the three strategies involve differential turnover.

To answer this question, we compute the turnover for each of the portfolios to see if the turnover really varies significantly across the three strategies. The calendar–time strategies that we employ allow the computations of the turnover. Specifically, we follow Barber et al. (2001) to estimate the turnover for each of our portfolio as follows. Turnover for portfolio p for month t is defined as the percentage of the portfolio's holdings as at the end of month $t-1$ that has been sold off at the end of month t. That is, it is the percentage of the portfolio that has been turned over into some other stocks.

To compute turnover, we first calculate for each stock i that makes up portfolio p at the end of month $t-1$, the fraction it would have comprised of the portfolio at the end of month t if there were no portfolio rebalancing. Denoted as $G_{i,t}$, it is computed as follows:

$$G_{i,t} = \frac{w_{i,t-1}(1 + R_{i,t})}{\sum_{t=1}^{n_{p,t-1}}[w_{i,t-1}(1 + R_{i,t})]}, \tag{1}$$

where $w_{i,t-1}$ is the weight of stock i in the portfolio at the end of month $t-1$, $R_{i,t}$ is the return for stock i during month t, and $n_{p,t-1}$ is the number of stocks in the portfolio. Next, $G_{i,t}$ is compared to the actual fraction $F_{i,t}$ that the stock i makes up of the portfolio at the end of month t after taking into account any portfolio rebalancing that is required under the respective investment strategy. Monthly portfolio turnover is the decrease (if any) in the percentage holding of each of the month's $t-1$ securities. Denoted by $U_{i,t}$, it is formally given by

$$U_{i,t} = \sum_{i=1}^{n_{p,t}} \max\{G_{i,t} - F_{i,t}, 0\}. \tag{2}$$

Finally, the average of the time series of the monthly turnovers for each portfolio is computed, and compared across portfolios to see if the three strategies involve differential turnover. The results indicate that it is not the case. The turnover across the three strategies is very similar. The average monthly turnovers for the long, short, and long–short portfolios formed on the basis of changes in recommendations are, respectively, 95%,

96%, and 191%. The monthly turnovers for the long, short, and long–short portfolios formed on the basis of changes in *TPER*s are 94%, 95%, and 189%, respectively. Importantly, the corresponding long, short, and long–short portfolios of the combination strategy involve similar turnovers of 95%, 95%, and 190%, respectively. Hence, the differential performance of the combination strategy that we document in this paper cannot be ascribed to the higher turnover for this strategy.[11]

4. Relative profitability of the combination strategy for alternative portfolio formation procedures

As outlined in Section 2, there are several steps involved in forming the portfolios whose performance we have reported so far in Tables 4 and 5. In this section, we examine whether the performance of the combination strategy still dominates if we were to modify some of the steps in the formation of our portfolios. In our first alternative portfolio formation procedure, we examine the differential performance of three strategies if we were to value-weight stocks instead of the equal weighting we have assumed so far. The returns for each long and short portfolios within an industry are computed by value-weighting the individual stocks, before aggregating (by equal-weighting) the industry returns. The results are reported in Table 8. Consistent with the prior studies, which find that analysts are more adept at forecasting the performance of small rather than large stocks (Barber et al., 2001; Boni and Womack, 2006), value-weighting reduces the returns from each of the three strategies. The return from the recommendations-alone strategy is now 0.30%, which is less than half of what was reported in Table 4 for the equal-weighted strategy. Nevertheless, value-weighting is especially damaging to the target-price-alone strategy. The abnormal returns from this strategy becomes small and statistically indistinguishable from zero when we value-weight the stocks. In contrast, as reported in Panel C of Table 8, the strategy that relies on both analyst outputs still produces a large and statistically significant four-factor alpha of 0.55% per month (t-statistic = 2.21).

We also examine how a combination strategy fares if we were to alter our assumption about how long an individual analyst recommendation (*TPER*) remains valid. Recall that in our main results reported in Tables 4 and 5, we assume an individual recommendation (*TPER*), if unrevised, to be relevant for investors for six months after the issue date. In untabulated results, we examine the four-factor alphas for the three strategies when we assume that a recommendation (*TPER*) is valid for three through six months. It is worth noting that the longer we assume the validity of an unrevised recommendation (*TPER*), the larger is the number of firms included in the various portfolios. We find that altering the assumption of how long a recommendation (*TPER*) is valid does not change our main conclusion that the combination strategy performs significantly better than the comparable strategies based on single analyst outputs.

Our primary results include all firm-month observations for which at least one analyst issues a recommendation or a *TPER*. We also check the robustness of our results when we limit out firm-month observations to those covered by at least two or at least three analysts. Our conclusion about the superior performance of the combination strategy still holds.

[11] It is also possible that the analysts' working environment changed after the bursting of the technology bubble in the year 2000, which brought increased media scrutiny and new regulations (such as the NASD 2711 in 2002). In untabulated results, we confirm the robustness of our results in the later sub-period of our sample that ranges from July 2000 through to the end of our sample period in May 2004.

Table 8
The four-factor alphas from the three strategies when stocks are value-weighted.

This table provides the returns from the three investment strategies when stock are value-weighted instead of equally weighted within their respective industry portfolio. As in earlier tables, the portfolios are formed on the basis of changes in consensus recommendation, changes in consensus *TPER*, and changes in both recommendations and *TPER*s, respectively, in Panels A, B, and C. The abnormal returns reported are the intercepts of the Carhart four-factor regressions of monthly portfolio returns. The *t*-statistics are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Portfolio	Intercept from the Four-Factor Model
(1)	(2)
Panel A: *Portfolios formed on the basis of changes in consensus recommendation*	
Long	0.343%
	(1.84)*
Short	0.041%
	(0.33)
Long–short	0.302%
	(2.27)**
Panel B: *Portfolios formed on the basis of changes in consensus TPER*	
Long	0.053%
	(0.25)
Short	0.078%
	(0.67)
Long–short	−0.025%
	(−0.15)
Panel C: *Portfolios formed on the basis of changes in both consensus recommendation and TPER*	
Long	0.351%
	(2.17)**
Short	−0.198%
	(−1.00)
Long–short	0.549%
	(2.21)**

The investment strategies we have examined so far identify stocks that enter long and short portfolios based on changes in consensus recommendations and target prices. However, this is only one of the possible ways to convert analyst outputs into implementable investment signals, and one could conceivably think of many other ways in which to exploit the information content of analyst recommendations and target prices. To check the robustness of our claim about the superior value of the combination strategy, and also to make our results comparable to recent studies, we compute the four-factor alphas of alternative strategies that make use of analyst recommendations as in Boni and Womack (2006) and of analyst target prices as in Da and Schaumburg (2007). The results are reported in Table 9.

Specifically, in Panel A of Table 9, we compute the returns from an investment strategy that mimics the portfolio formation procedures of Boni and Womack (2006). Stocks enter into long and short portfolios based on the number of net recommendation upgrades. Stocks that experience positive net upgrades form the long portfolio and those that experience negative net upgrades form the short portfolio. To remain as close as possible to

Table 9
The four-factor alphas from the alternative investment strategies.

This table reports the four-factor alphas of the strategies that adopt alternative ways of generating buy and sell signals from analyst recommendations and target prices. In Panel A, the portfolios are formed by replicating the strategy of Boni and Womack (2006) for analyst recommendations. Stocks enter into long and short portfolios based on the number of net upgrades. Stocks that experience positive (negative) net upgrades form the long (short) portfolio in this strategy. In Panel B, we form portfolios by following a strategy similar to that of Da and Schaumburg (2007). This strategy identifies stocks that should go into long and short portfolios based on target prices alone. Specifically, we divide the consensus target price of a stock in each month by the end-of-the-month stock price, and use this ratio to sort stocks within each industry. Please note that in Panel B, stocks are sorted into three groups according to their mean target price to price ratio, and not into nine groups as Da and Schaumburg (2007) do. In Panel C, we report the results of a strategy that takes long (short) positions in stocks labeled favorable (unfavorable) according to both the Boni and Womack (2006) and the Da and Schaumburg (2007) strategies in Panels A and B, respectively. The *t*-statistics are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Portfolio	Intercept from the four-factor model	Avg. number of stocks per month in the portfolio
(1)	(2)	(3)
Panel A: *Recommendations-only portfolios formed by mimicking the* Boni and Womack (2006) strategy		
Long	0.774%	238
	(4.04)***	
Short	−0.160%	269
	−(0.74)	
Long–short	0.935%	507
	(4.26)***	
Panel B: *Target-price-only portfolios formed by mimicking the* Da and Schaumburg (2007) strategy		
Long	0.601%	230
	(2.27)**	
Short	−0.070%	215
	−(0.38)	
Long–short	0.671%	445
	(2.14)**	
Panel C: *Combination Strategy that uses signals contained in both the* Boni and Womack (2006) *strategy for recommendations and in* Da and Schaumburg (2007) *strategy for target prices*		
Long	1.347%	66
	(3.08)***	
Short	−0.821%	72
	−(2.73)***	
Long–short	2.181%	138
	(4.71)***	

Boni and Womack, we also employ the 59-industry classification scheme. As reported in the last row of Panel A, the long–short portfolio generated by replicating the Boni–Womack strategy on our sample generates a four-factor alpha of 0.935% (*t*-statistic = 4.26). This is comparable to the four-factor alpha of 1.165% that Boni and Womack report in their paper. In Panel B, we apply the Da and Schaumburg (2007) strategy on the target prices to identify stocks that should go into long and short portfolios based on target prices alone. Specifically, we divide the consensus target price of a stock in each month by the end-of-the-month stock price, and use this ratio to sort stocks within each industry. The returns from the long–short portfolio generated by replicating the Da

Table 10
The four-factor alphas for the long-short portfolios for the three strategies assuming delayed investor response to analyst output.

This table examines the sensitivity of our results when one varies the time lag with which the individual analyst recommendations (*TPER*) that make up the consensus are noted. As in earlier tables, the portfolios are formed on the basis of changes in consensus recommendation, changes in consensus *TPER*, and changes in both recommendations and *TPER*, respectively. In column (2), we report the results when the consensus recommendations (*TPER*) used to form portfolios for month t are based on the individual analyst recommendations (*TPER*) available on the 25th of month $t-1$. Moving to the right from column (3) through columns (5), the consensus recommendations (*TPER*) used to form portfolios for month t are based on individual analyst recommendations (*TPER*) noted with two-week, three-week and one-month lags, respectively. The abnormal returns reported in column (2) through (5) are the intercepts of the Carhart four-factor regressions of monthly portfolio returns. The t-statistics are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	The date for constructing the consensus recommendation and *TPER* for month t			
	Base case: 25th of month $t-1$	2-Weeks before the end of month t	3-Weeks before the end of month t	Beginning of month $t-1$
(1)	(2)	(3)	(4)	(5)
Long–short portfolio based on recommendation alone	0.739%	0.571%	0.247%	0.268%
	(4.49)***	(3.72)***	(1.28)	(1.65)*
Long–short portfolio based on *TPER* alone	0.718%	0.552%	0.368%	0.217%
	(3.13)***	(2.74)***	(1.91)*	(1.09)
Long–short portfolio based on both recommendation and *TPER*	1.130%	0.677%	0.440%	0.434%
	(5.43)***	(3.41)***	(2.18)**	(2.11)**

and Schaumburg (2007) strategy on our sample is 0.671% (t-statistic = 2.14).[12] In Panel C, we report the results of a strategy that takes long (short) positions in stocks labeled favorable (unfavorable) according to *both* the Boni–Womack and the Da–Schaumburg strategies in Panels A and B, respectively. This combination strategy produces a four-factor alpha of 2.181% (t-statistic = 4.71), which is clearly superior to the returns reported for the individual strategies in Panels A and B. Overall, Table 9 indicates that the recommendation-only strategy of Boni–Womack and target-price-only strategy of Da–Schaumburg when applied to our sample generate similar returns as reported in their studies. More importantly, it shows that a combination strategy that combines these two individual strategies generates returns that are significantly superior to those in reported in the prior studies.[13]

[12]Please note that in Panel B, stocks are sorted into three groups according to their mean target price to price ratio, and not into nine groups as Da–Schaumburg do. This is done to ensure we retain enough stocks for our combination strategy in Panel C. Nevertheless, it is worth pointing out that if we were to divide stocks into nine groups, the long-short portfolio in Panel B would produce a four-factor alpha of 1.349% (t-statistic = 2.95), which is comparable to the returns Da–Schaumburg report in their paper.

[13]However, despite higher alphas, we retain Table 9 as part of our robustness checks rather than making it our base result. There are two reasons for this. One, we prefer to use the results in Table 4 as our main results as the table employs similar investment strategies for recommendations and target prices. Second, the number of stocks

As in other prior studies (see, for example, Barber et al., 2001; Boni and Womack 2006), we next examine the profitability of the various strategies if investors were to react to analyst output with delay. Recall that in our primary analyses, the consensus recommendation (*TPER*) for a stock at the end of month $t-1$ is based on the individual analyst recommendations (*TPER*) outstanding as on the 25th day of month $t-1$. This allows investors to respond to analyst output with about a five-day lag. In Table 10, we report the results of alternative assumptions about this lag. For example, in column (2) we report the results for the base case where we form consensus recommendation (*TPER*) at the end of month $t-1$ based on the outstanding analyst recommendations (*TPER*) five days before the end of month $t-1$. Moving to the right from column (3) through columns (5), we report the four-factor alphas when the consensus recommendations (*TPER*) are computed based on the outstanding analyst recommendations (*TPER*) two weeks, three weeks, and one month before the end of month $t-1$, respectively. As expected, the profitability of the various strategies goes down the older the analyst information that investors use in constructing the consensus recommendations (*TPER*). For information that is more than 3 weeks old, for example, the first two strategies produce returns indistinguishable from zero. Even the returns from the combination strategy, although still statistically significant at the 5% level, are now about one-third of what they were for the base case. Nevertheless, our primary assertion that a combination strategy outperforms the comparable individual output-based strategies remains valid.

Finally, we examine the importance of industry controls for the profitability of the three investment strategies. In our base strategies reported in Table 4, revisions in analyst outputs are used to rank stocks within each 10-digit GICS industry, before forming overall long and short portfolios. Prior studies find that ranking stocks in the overall universe, without the industry controls, reduces the returns associated with the recommendations-alone strategies (Boni and Womack, 2006) and eliminates the profits associated with the target-price-alone strategies Da and Schaumburg (2007). In untabulated results, we find results consistent with these assertions. Without industry controls, the long–short portfolio of the recommendations-only strategy produces a four-factor alpha of 0.50% (t-statistics = 3.23), which is lower than the corresponding four-factor alpha of 0.74% reported in Table 4. The long–short portfolio of the target-prices-only strategy produces statistically insignificant abnormal return of 0.25% (t-statistics = 0.61). The long–short portfolio of the combination strategy produces abnormal returns of 0.63% (t-statistics = 2.42). Overall, therefore, removing industry controls reduces the returns from all three strategies, although these controls are more important for the target-price-only strategy.

5. Conclusion

In assessing the value of the investment advice that analysts communicate to investors, the extant literature has largely focused on either the stock recommendations or the target prices in isolation. It is, however, commonly known that analysts gather, process, and disseminate a variety of information about the stocks they cover. They are also known to operate in an environment characterized by complex incentive structure. An examination

(*footnote continued*)
in the combination strategy in Table 4 is significantly larger than the corresponding number for the combination strategy in Table 9, perhaps making it a more representative strategy for investors.

of the multiple analyst outputs in conjunction could, therefore, provide a better appreciation of the information that analysts convey to the market.

In this paper, we focus on the question of the usefulness of the analysts' stock picking advice by investigating the profitability of the investment signals analysts convey through revisions in *both* their stock recommendations and target prices. We find that the portfolios formed on the basis of changes in both consensus recommendations and target prices earn much higher risk-adjusted returns than those formed based on the basis of only one output of analysts. The combination strategy also produces more consistent performance. Our results suggest that the extant literature has so far underestimated the profitability of the analyst investment advice by focusing either on recommendations or target prices in isolation. Analysts' investment advice, when gleaned from their multiple outputs, is significantly more useful than that gleaned from either of their two summary outputs in isolation.

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