Do Sell-Side Analysts Exhibit Differential
Target Price Forecasting Ability?*

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Comments welcomed

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Do Sell-Side Analysts Exhibit Differential Target Price Forecasting Ability? **Abstract**

We examine the overall and individual analyst accuracy of 12-month-ahead target price forecasts. On average, 24-45 percent of analysts' target prices are met, and analysts do not exhibit persistent differential abilities to forecast target prices. We show that the market acts as if it understands analyst inability to consistently forecast target prices and discounts more optimistic target prices. These results are reconciled with those of prior research that finds analysts differentiate themselves on the basis of earnings forecasts, demonstrating that our sample analysts do exhibit persistent skills in forecasting earnings, but not target prices. We interpret our results as follows. Analyst earnings forecast accuracy is subject to considerable scrutiny, and analyst compensation and job tenure are related to, *inter alia*, earnings forecast accuracy. In contrast, we know of no evidence that analyst target price forecasts are related to analysts' compensation or job tenure. Thus, analysts either have limited abilities to forecast target prices or may be trading off precision in target price forecasts for deliberate optimism that is not subject to ex post scrutiny.

Do Sell-Side Analysts Exhibit Differential Target Price Forecasting Ability?

1.   Introduction

Sell-side analysts predict earnings, make stock recommendations, and predict stock prices (i.e., target prices). Hundreds of studies have examined analysts' earnings predictions and their stock recommendations, but few have examined analysts' target price forecasts.[1] The literature has shown analysts' earnings forecasts, stock recommendations, and target price forecasts all affect stock prices. Additionally, studies document that analysts exhibit differential abilities to predict earnings and make stock recommendations; no prior studies have examined whether analysts have differential abilities to predict target prices. We fill this void in the literature.

There are several reasons why it is important to examine whether or not analysts have differential abilities to predict target prices. First, stock prices incorporate earnings forecasts, and target prices are direct statements about future stock prices. Thus, reliable target prices are of potentially high relevance to investors. Second, the link between earnings forecasts, valuations, and stock recommendations implies that analysts skilled at earnings forecasting and/or stock recommendations should also be skilled at valuations, quantified and communicated as target prices. A finding that analysts have differential target price forecasting abilities provides corroborative evidence related to studies concluding analysts have other differential abilities. Third, prior research reveals a number of characteristics, such as brokerage resources and firm-specific experience that are related to earnings forecasting and stock picking abilities. An analysis of the drivers of analysts' abilities with respect to target price forecasts will increase our understanding of characteristics that are correlated with valuation abilities. Fourth, if analysts do have differential

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[1] Brown (2000) abstracts over 575 studies on expectations research, most of which are devoted to sell-side analysts' earnings forecasts and their stock recommendations.

abilities to predict target prices and if markets are efficient with respect to this information, stock

prices should move relatively more when target price forecasts are issued by those analysts with

better track records.

Our alternative hypothesis is that analysts exhibit differential abilities to predict target

prices, but there are reasons to expect no rejection of the null (i.e., no differential abilities). On one

hand, target prices are related to both earnings forecasts and stock recommendations, and analysts

have been shown to have differential abilities on these two dimensions. Therefore, analysts should

also exhibit differential target price forecasting ability. On the other hand, forecasting price

movements is quite different from forecasting earnings, and the quantification of a target price is a

more precise statement than is a standard three-tiered stock recommendation. Further, analyst

compensation increases in the accuracy of their earnings forecasts and stock recommendations but

not in the accuracy of their target price forecasts, so rational analysts might expend less effort on

distinguishing themselves through differential target price ability.[2] Thus, if analyst wealth is

unrelated to the accuracy of their target price forecasts, target prices may serve alternative means

such as deliberate optimism that is unchecked by any ex post settling up mechanism.

Our empirical analysis proceeds in three stages. First, we quantify the overall frequency that

target prices are met, measured two ways (discussed below). Second, we investigate whether

analysts exhibit persistent differential abilities to forecast target prices after controlling for analyst,

firm, and market factors. Third, we examine if investors respond more (less) to target price

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[2] Membership on the *Institutional Investor* All-American Research Team is based on four factors: earnings forecast
accuracy, quality of stock recommendations, quality of research reports, and overall service, and such membership is
associated with lucrative compensation (Stickel 1992, Cooper, Day, and Lewis 2001). As noted at career information
website www.thevault.com, "Once a research analyst finds himself listed as an II-ranked analyst, the first stop is into his
boss's office to renegotiate his annual package."

announcements of analysts' with better (worse) track records of predicting target prices. Fourth, we examine whether our results might be due to a sample selection bias arising from the data imposition that analysts provide target price forecasts. In the process, we reconcile our results with prior research on differential abilities to forecast earnings.

We restrict our sample to '12-month' target price forecasts, so the one-year period following a target price forecast release date is the forecast horizon. It is not clear what criterion to use to determine whether a target price is met, so we use two definitions.[3] Our first measure is an indicator variable equal to one if the actual closing price *as of* the end of the one-year forecast horizon is at or above the target price. This definition is motivated by the notion that a target price implies that the actual price will be at or above the target price level by the end of the forecast horizon. While intuitively appealing, this definition excludes target prices that are met sometime during the forecast horizon, but not at the end of it (e.g., bad news arrives shortly before the end of the 12 month forecast horizon). To allow for this possibility, our second measure is an indicator variable equal to one if the target price is met *at any time* during the 12-month horizon. This definition is much less restrictive, implicitly assuming that analysts making target price forecasts predict that the stock price will meet or beat the target price sometime during the next 12 months, but may not necessarily remain there. If descriptive, investors following such target price-based investment strategies would have to actively trade, placing limit orders to sell shares once the actual price attains the target price.

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[3] Our two alternatives are guided by intuition, confirmed through several conversations with analysts. While most indicated the intent of target prices is consistent with our first definition; some analysts also indicated the second definition.

We show that 24-45 percent of analysts' target prices are met on average, depending on the definition of target price accuracy. In contrast to research on differential abilities to forecast earnings (Stickel 1992; Sinha, Brown, and Das 1997; Mikhail, Walther, and Willis 1997, 1999; Clement 1999; Jacob, Lys, and Neale 1999; Clement, Rees, and Swanson 2003) and make profitable stock recommendations (Loh and Mian 2004; Mikhail, Walther, and Willis 2004), we find no evidence of differential abilities to forecast target prices. Consistent with the lack of persistence in abilities to forecast target prices, we find no differential stock price reactions to analysts with good (bad) track records. It is conceivable that our sample of analysts who forecast target prices differs somehow from the larger samples used in prior research on persistence of earnings forecasting and stock picking abilities. We reconcile our results with prior research on differential abilities to forecast earnings by showing that both superior and inferior earnings forecasters exhibit indistinguishable target price forecasting ability.

Control variables in multivariate analyses provide insights into the determinants of attainable target price forecasts. Not surprisingly, we find that the higher the target price forecast relative to the prevailing stock price, the less likely the target price forecast will be met. We also show that target price forecasts are more likely to be met when: (i) market returns over the 12 forecast horizon are higher, (ii) analysts have more experience, and (iii) analysts are employed by the largest brokerage houses. Surprisingly, we find that target prices are less likely to be met for firms with higher stock price volatilities.

We use the term 'ability' when assessing the ex post performance of analysts' target price forecasts even though analysts' behavior may actually be driven by incentives that conflict with providing unbiased target prices (thus confounding statements regarding innate 'ability' *per se)*.

Indeed, we show that no analysts issue a large percent of accurate target prices on a persistent basis, yet these analysts do exhibit persistent differential abilities to forecast earnings per share. We interpret our results as analysts having stronger incentives for making accurate earnings forecasts in comparison to target prices.

Prior research maintains that earnings forecasting and stock recommendation activities are affected by analysts' career concerns and compensation factors (Stickel 1992; Hong, Kubik, and Solomon 2000; Cooper, Day, and Lewis 2001). There exist many analyst rankings and tracking services that measure analysts' earnings forecast accuracy and stock recommendation profitability (e.g., *Institutional Investor* All-America Research Team, *The Wall Street Journal* Best of the Street, Investar, Starmine SmartEstimate). In contrast, we are unaware of any rankings based on analysts' target price forecasts or of any medium wherein target price performance is even assessed. Overall, our evidence is consistent with analysts using target prices as a means of expressing optimism, without consequence for being wrong ex post.[4]

The next section discusses background and predictions. The sample and descriptive statistics are discussed in section 3. The primary results are presented in section 4. Section 5 concludes.

2. Background and Research Design

2.1.1 Prior research – Earnings forecasts

Research on analysts' earnings forecasts developed in response to early literature on the time-series properties of earnings. The early research showed that analysts' earnings forecasts were

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[4] If analysts are not held accountable for errors in their target price forecasts, these outputs might be a means of expressing optimism to curry favor with management or generating trading revenues for brokerage firms (Francis and Philbrick 1993; Jackson 2005).

more accurate than extrapolations from earnings time-series models (Brown and Rozeff 1978), but one explanation for analyst forecast superiority is that they enjoy a timing advantage over time-series predictions (Fried and Givoly 1982). Subsequent research showed that analyst forecast superiority was attributable to both a timing advantage and an information advantage (Brown , Griffin, Hagerman and Zmijewski 1987). Early research fails to reject the null hypothesis that analysts are identical in their ability to forecast earnings (e.g., O'Brien 1990; Butler and Lang 1991), but subsequent research incorporating refined controls for forecast recency documents differences in individual forecast accuracy (Stickel 1992; Sinha, Brown, and Das 1997, Mikhail, Walther, and Willis 1999). Subsequent research (Mikhail, Walther, and Willis 1997; Clement 1999; Jacob, Lys, and Neale) identified determinants of forecasting ability such as experience, task complexity, and brokerage size.

2.1.2 Prior research – Stock recommendations

Womack (1996) shows that stock prices rise (fall) when analysts upgrade (downgrade) their recommendations. Mikhail, Walther, and Willis (2004) document that security analysts exhibit persistence in stock picking ability, showing that analysts whose recommendation revisions earned the higher (lower) returns in the past also earn higher (lower) returns in the future. Moreover, they show that the market partially recognizes these differences at the time of recommendation revisions, but that a trading strategy based on the incomplete reaction is unprofitable after transaction costs.

2.1.3 Prior research – Earnings forecast and stock recommendations

Several studies suggest that analysts' differential abilities to predict earnings are related to their differential abilities to make stock recommendations. Loh and Mian (2004) show that analysts issuing more accurate earnings forecasts make more profitable stock recommendations. They

document that the average factor-adjusted return of recommendations of analysts in the highest earnings-forecast accuracy quintile is 1.48% per month higher than those in the lowest earnings-forecast accuracy quintile. Mikhail, Walther, Wang and Willis (2004) show that some of the factors that distinguish analysts who make good (bad) earnings forecasts are the same as those that distinguish analysts who make good (bad) stock recommendations. For example, analysts who make better stock recommendations follow fewer industries (i.e., face less task complexity) and have more resources at their disposal (i.e., work for larger brokerage houses). Sorescu and Subrahmanyam (2004) analyze the relation between the market reaction to analysts' stock recommendation revisions and the years of experience and reputation of the analysts' brokerage house. Using the latter to proxy for analyst ability, they find revisions by high-ability analysts outperform those of low-ability analysts.

2.1.3 Prior research – Target prices

Analysts often provide target prices to support their stock recommendations (Bradshaw 2002). Bandyopadhyay, Brown, and Richardson (1995) document that near-term (long-term) forecasted earnings revisions explain approximately 30 (60) percent of the variation in target price revisions, suggesting that target prices are correlated with value-relevant fundamentals such as earnings expectations (Frankel and Lee 1998). Brav and Lehavy (2003) report mean five-day abnormal returns around the release of target prices range from –3.9 percent to +3.2 percent, depending on whether the announcement is a negative or positive revision. Asquith, Mikhail, and Au (2005) also find significant reactions to target prices incremental to other information, providing additional evidence that investors consider target price forecasts to be valuable.

2.2 Research design

We extend research on analysts' forecasting abilities by examining their target price

forecasts. Examining target prices offers potential benefits over prior research. Stickel (1992) finds

that analysts ranked the highest by *Institutional Investor* have the most accurate earnings forecasts,

and Sinha, Brown, and Das (1997) extend Stickel's results to analysts in general, showing that

analysts who are superior in the cross-section also are superior in holdout periods. However, in

order to document differential earnings forecast ability, careful controls for forecast timeliness must

be made because timeliness is a major determinant of accuracy. Examining recommendations is

also problematic in that the length of the presumed holding period is not stated so the researcher's

choice of holding period is imprecise. An advantage of examining target price forecasts is that the

differential timing problem does not exist as long as one focuses on forecasts with the same

horizons, which is 12 months ahead for the majority of target prices.

We first provide univariate evidence to quantify the overall frequency that target prices are

met. As we have no benchmark for expected target price forecast performance, this univariate

analysis is descriptive. After quantifying average target price forecast performance, we investigate

whether some analysts are better than others at forecasting target prices, and whether the market

reacts more (less) to information in target prices of analysts whose past target prices were relatively

more (less) accurate. Finally, we examine whether our results are affected by a selection bias in the

sense that analysts who issue target price forecasts may differ from the larger population examined

in prior studies on differential earnings forecasting ability.

To measure ability, we first use a {0,1} indicator variable equal to one if the actual closing

price *as of* the end of the 12-month forecast horizon is at or above the target price (TPMET12); we

also use a {0,1} indicator variable equal to one if the target price is met *at any time* during the 12-month horizon (TPMETANY).[5] To investigate individual analyst abilities, we perform univariate and multivariate analyses. We examine if analysts' past target price forecasting performance is related to future performance. We measure past performance (LagTPMET) based on either TPMET12 or TPMETANY. Additionally, we report descriptive statistics on target price forecast error, TPERROR, defined as closing price at the end of the forecast horizon minus the target price, scaled by stock price as of forecast date.

We partition target price forecasts into semi-annual periods to provide a reasonable number of periods for assessing persistence. Our selection of periods six months in length is an attempt to strike a balance between having a sufficient number of periods for measurement while including a reasonable number of forecasts for each analyst during the period.[6] In univariate tests, our unit of analysis is the performance of individual analysts across the portfolio of stocks s/he covers. We allocate analysts to performance quintiles based on the percent of the analyst's target prices that were met during the semi-annual measurement period (under both definitions). We then measure the percent of target price forecasts met during subsequent (non-overlapping) semi-annual periods.

Multivariate tests are operationalized using logit regressions with the unit of analysis being an individual target price forecast. We control for a number of factors expected to be correlated with a target price being met, and estimate coefficients for the following model:

$$\text{TPMET}_{\text{Var}} = \sum_{t=2}^{49} \delta_t \text{Industry}_{49} + \sum_{t=1998}^{2002} \sum_{s=1}^{2} \delta_{t,s} \text{Time}_{t,s} + \alpha + \beta_1 \text{LagTPMET}_{\text{Var}} + \beta_2 \text{TP/P} + \beta_3 \text{PM} + \beta_4 \text{CVPRICE} \quad (1)$$
$$+ \beta_5 \text{MktRET} + \beta_6 \text{FEXP} + \beta_7 \text{DTOP10} + \beta_8 \text{LOGMV} + \varepsilon$$

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[5] We also considered a third measure, formed by summing the days during the forecast horizon on which the trading price closes at or above the target price and dividing by the number of trading days, generally 252. This measure quantified the *fraction of trading days* during the forecast horizon the stock closes at or above the target price. The results are similar so, for brevity, we do not report these results.
[6] We also partitioned the sample into annual periods and find similar results.

TPMET$_{Var}$ is our measure of whether the target price is met, and the subscript Var = {TPMET12, TPMETANY}. We control for industry and time-period effects using indicator variables. LagTPMET$_{Var}$ is the analyst-specific past performance ranking measured based on the dependent variable ([quintile-1]/4). If analysts exhibit persistent abilities to forecast target prices, the coefficient on LagTPMET$_{Var}$ will be positive. When we estimate this model, we ensure that there is no overlap between the TPMET and LagTPMET time periods so as not to artificially induce a positive and significant estimated β_1.

Our first control variable is the ratio of target price to current trading price, TP/P. We expect the relation to be negative for the simple reason that, *ceteris paribus*, it is more difficult to attain a higher hurdle. Our next two controls are price-level variables. PM is a proxy for price momentum, measured as the six-month cumulative raw return ending prior to the semi-annual period in which the target price release date falls (Jagadeesh and Titman 1993). If momentum stocks are more likely to achieve target prices, the coefficient on PM will be positive. However, if the target price levels forecasted by analysts are influenced by recent price momentum (i.e., 'chasing' momentum stocks), then the relation may be negative due to the reversal taking place during the forecast horizon, so we make no sign prediction for PM. CVPRICE is a proxy for stock price variability, calculated as the coefficient of variation of closing price per share over the prior one-year period. Based on option pricing theory, we expect stocks whose prices are more volatile will have higher probabilities of attaining target price forecasts. We also include an ex post market return control because target prices are not stated in terms of expected 'abnormal' appreciation (or depreciation in a very few cases). MktRET is the value-weighted market return excluding

dividends during the 12-month target price forecast horizon. Because most stocks have positive

market betas, we expect the coefficient on MktRET to be positive.

We include two control variables often used in research examining differential abilities of

analysts to predict earnings and to make profitable stock recommendations: (i) FEXP is an analyst's

firm-specific experience in following a particular firm, measured in months;[7] (ii) DTOP10 is an

indicator variable equal to 1 if the analyst's brokerage is in the top decile based on the number of

analysts providing forecasts. Based on the results of related literature, we expect both coefficients

to be positive. Our final control variable is LOGMV, the natural logarithm of market value three

days prior to the target price release, which is included to proxy for omitted variables correlated

with firm size. We have no expectation regarding this variable.

We examine short-window announcement returns surrounding the release of target prices

using the following model:

$$
\text{ABRET}_{-1,+1} = \sum_{t=2}^{6} \delta_t \text{Industry}_i + \sum_{t=1998}^{2002} \sum_{s=1}^{2} \delta_t \text{Time}_{t,s} + \alpha + \beta_1 \Delta \text{TP} + \beta_2 \text{LagTPMET}_{\text{Var}} + \beta_3 \text{TP/P} + \\
\beta_4 \text{PM} + \beta_5 \text{FEXP} + \beta_6 \text{DTOP10} + \beta_7 \text{LOGMV} + \varepsilon
\tag{2}
$$

The dependent variable is the buy-and-hold size-adjusted return for the three-day window centered

on the target price release date identified by First Call. We exclude observations if an earnings

announcement occurs at any time during the three-day window. We include the issuing analyst's

past performance ranking (LagTPMET$_{\text{Var}}$) as an independent variable in the regression to test for

whether the market places more weight on target prices issued by analysts with a demonstrated

history of issuing attainable target prices. A positive coefficient on LagTPMET$_{\text{Var}}$ is consistent with

the market identifying superior analysts' target price forecasts and expecting the superiority to

persist. We include all of the control variables that we included in equation (1) except for

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[7] We also examine GEXP, which is an analyst's general experience (also measured in months). Due to the high
correlation between FEXP and GEXP ($\rho \approx 0.50$), we exclude GEXP from reported analyses.

CVPRICE and MktRET, which are omitted due to the short measurement window. We include one additional variable, ΔTP, which is the change in target price, scaled by P. We calculate ΔTP when we have a previously issued target price by the same analyst within the preceding 12 month period, and omit observations if we cannot locate a prior target price.

3. Data and Descriptive Statistics

Target prices are provided by First Call, which collects data from a number of sources, including formal analyst research reports and daily broker notes. The data file provides close to 300,000 individual target prices. We retain target price observations spanning the calendar years 1997-2002 that meet certain criteria, discussed below.

First, we restrict our analysis to target prices that are specifically identified as being '12-month' target prices. Analysts occasionally provide target prices for different time-horizons, but these are less common.[8] Second, the First Call database identifies the submitting brokerage firms but not individual analysts so we identify individual analysts and the brokerage firms that employ them by accessing the I/B/E/S detail files. We assume that an analyst identifier on I/B/E/S maps to the target price data on First Call via brokerage-CUSIP pairings within calendar months. Our assumption is problematic if broker firms employ multiple analysts who simultaneously cover the same stock, but this is unlikely based on our discussions with both analysts and personnel at Thomson Financial.[9] Also, in an examination of changes in analyst coverage around firm breakups, Gilson et al. (2001) report that a detailed analysis revealed less than 8% of firm years with multiple

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[8] First Call also identifies target prices with forecast horizons of (i) less than 12 months, (ii) 12 to 18 months, and (iii) greater than 18 months. The majority of the observations lost by retaining only 12-month target prices were missing horizon identifiers. For the full sample, more than 92% with horizon identifiers are 12-month target prices.
[9] Both First Call and I/B/E/S are products of Thomson Finanical, Inc. Per discussion with Steven Sommers of Thompson Financial, this is a very reasonable approach.

analysts per brokerage firm covering the same stock, which almost exclusively represented overlaps around analyst turnover.

To be retained, we require that a target price be associated with an investment firm and a calendar month for which we are able to identify the individual analyst from I/B/E/S. For each target price observation, we search for earnings forecasts from the same brokerage firm for the company during the same calendar month. When available, we obtain the analyst identifier from I/B/E/S. To ensure that we do not introduce noise by misaligning I/B/E/S analyst identifiers with individual target prices from First Call, we retain only observations with subsequent I/B/E/S earnings forecasts by the same analyst-brokerage-cusip combination. Some brokerage firm codes and names are ambiguous across the two databases, so we are conservative and exclude target price observations if we are unsure of the propriety of the brokerage firm matches. After deleting observations where we cannot identify the analyst code from I/B/E/S, we are left with 118,640 observations.

We impose three additional data constraints. First, we require data on the share price in effect as of three days prior to the date of the target price forecast and that share price exceeds $1 per share. Second, we require data on share price 12 months subsequent to the target price date. Third, to mitigate effects of extreme observations due to data errors or misaligned stock split factors, we delete the outer one percent of the tails of the distribution of observations based on the ratio of target price to actual price. Our final sample consists of 95,852 observations.

The six-year sample period is partitioned into 12 semi-annual periods, labeled 1997-1, 1997-2, 1998-1, etc., corresponding to January-June 1997, July-December 1997, January-June 1998, etc. Table 1 provides descriptive statistics for sample size, analyst and brokerage representation, and

industry composition. Panel A indicates that the sample represents 4,167 firms, 4,531 analysts, and

142 brokerage firms. The number of observations in each semi-annual period increases as First Call

expanded collection of this data after formal collection began in late 1996. Panel B presents the

distribution of sample firms across industries, benchmarked against coverage represented on

Compustat.[10] Consistent with the overall distribution of the general population of firms represented

on Compustat, our sample firms show some concentration in the business services (10.2 percent of

the sample), banking (9.7 percent), electronic equipment (6.3 percent), retail (5.4 percent), and

pharmaceuticals (5.3 percent).

Descriptive statistics for size, financial performance, and market pricing of the sample firms,

along with those for the Compustat benchmark, are presented in table 2. All differences are

significant at less than the 0.001 level. Mean (median) analyst following for the sample firms is 9.3

(7.0) relative to 3.4 (1.0) for all firms. Not surprisingly, conditioning on analyst following and

target price availability yields sample firms that are much larger than the full population. Mean

total assets and sales for the sample firms are approximately double that of the Compustat firms,

and mean market value is approximately four-fold that of Compustat firms. Financial performance

is much better for our sample firms. The mean (median) ROA of 0.9 percent (3.3 percent) and

mean (median) ROE of 6.4 percent (10.7 percent) are significantly above those for Compustat

firms. Additionally, the sample firms have higher P/E ratios (mean 22.1) and lower B/M ratios

(mean 0.57) than the full population, although the differences are not as striking as for financial

performance. The bottom section of table 2 presents (median) industry-adjusted financial

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[10] Industries are as defined in Fama and French (1997).

performance and market multiples. Again, sample firms exhibit much better financial performance, higher P/E ratios, and lower B/M ratios.

4. Results

4.1 Overall frequency that target price forecasts are met

Panel A of table 3 provides the distribution of the ratio of target price (TP) to actual price (P), where P is the closing price three days prior to the target price forecast date. This ratio provides an indication of the ex-dividend predicted return on a stock. Mean TP/P is 1.35 for the sample observations, rising slightly during the first half of the sample period and falling during the last half.[11] This pattern varies somewhat with the observed market returns over the sample period. Figure 1 presents data for the S&P 500 index (subsequent 12-month returns and index) and contemporaneous mean TP/P ratios for 1997-2002. While not formally tested, the figures suggest that analysts impound the information in stock prices into their target price forecasts with a lag (e.g., Abarbanell 1991; Hong, Lim, and Stein 2003).

The ex post achievability of target prices is affected by overall market movements during the forecast horizon. Unless analysts can predict overall market movements and establish their target prices accordingly, it is likely that target prices released later in the sample period will be met less frequently than those released earlier in the sample period. Evidence in the economics literature is consistent with low abilities to forecast interest rates (e.g., Belongia 1987), GDP (e.g., Loungani 2000), recessions (e.g., Fintzen and Stekler 1999), and turning points of business cycles

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[11] The minimum TP/P is 0.83 and the maximum is 3.91 (not tabulated). Target prices used in this study are coded by First Call as 'real time,' which typically indicates that they were released in morning notes that brokers release prior to trading each day. Thus, a TP/P ratio less than one cannot be attributed to stale target prices. It is possible that increases in price during the two days between the time we obtain P and the release of the target price could explain some of these observations. However, due to the low frequency of observations with TP/P below one, we perform no further analysis.

(Zarnowitz 1991). Thus, it is an empirical question whether sell-side analysts can forecast overall market movements as manifested in firm-specific price forecasts.

Panel A of table 3 also shows the percent of target price observations that are achieved using our two measures of target price accuracy, TPMET12 and TPMETANY. Across all semi-annual periods, 24 percent and 45 percent of target prices are met using TPMET12 and TPMETANY, respectively. In untabulated analyses, we examined TPMET12 and TPMETANY for sample periods partitioned into 'up' and 'down' markets based on the sign of the realized S&P500 return over the forecast horizon (i.e., perfect foresight), where forecasts made in semi-annual periods 1997-1 through 1998-2 and 2002-1 through 2002-2 are classified as spanning 'up' markets and the remainder are classified as 'down' markets. Measuring TPMET12, 26 percent of target prices are met in down markets, while 36 percent are met in up markets. However, when accuracy is measured by TPMETANY, target prices are met 36 percent of the time in down markets, but only 30 percent of the time in up markets. Differences across markets are significant, though conflicting across TPMET measures. Nevertheless, these results emphasize the importance of controlling for overall market movements when assessing target price performance.

One aspect of target prices that likely plays a significant role in whether they are met is the distance between the target price and current price. Panel B of table 3 repeats the analysis from panel A, but partitions the sample into portfolios based on the level of TP/P. In each semi-annual period, we rank observations by TP/P and assign them in equal numbers to quintiles. Mean TP/P across the quintiles ranges from 1.01 to 1.90. For all of the TPMET variables, there is a monotonically decreasing pattern across the quintiles. For the least optimistic TP/P quintile, target prices are met 41 percent of the time at 12 months (TPMET12), and 72 percent of the time on at

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least one day (TPMETANY). In contrast, for the most optimistic TP/P quintile, target prices are met just 7 percent of the time at 12 months, and just 21 percent of the time on at least one day. This negative correlation between TP/P and the target price being met illustrates the importance of also controlling for the level of TP/P in later analyses.

4.2 Persistence in individual analyst target price forecasting ability

The descriptive results show variation in the frequencies that different target prices are met, but are silent regarding variation among individual analysts. Although the overall accuracy of target prices appears to be unexceptional on average, *individual* analysts may still possess differential forecasting abilities. We provide univariate results for the persistence of individual analyst target price forecasting abilities in table 4, and results of multivariate tests in table 5.

To gauge whether an analyst has persistent ability to forecast target prices, we rank individual analysts and track their subsequent forecasting ability conditional on their initial ability. To be included in this analysis, an analyst must have released at least three target prices during a semi-annual period. Within each semi-annual period, analysts meeting this criterion are assigned to quintiles based on their mean portfolio performance for each of our target price performance measures (i.e., TPMET variables). After analysts are assigned to quintiles, we pool all analyst observations across time and report quintile means of analyst portfolio means.

To illustrate, in the semi-annual period 1997-1, we compute the percent of all target prices issued by a single analyst that are met as of the close of trading 12 months subsequent to the target price issue date (TPMET12). Analysts are assigned to quintiles based on the distribution of analysts' portfolio TPMET measures for the base measurement period. We retain only those

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analysts providing target prices in the subsequent semi-annual period.[12] Having assigned individual

analysts to a quintile in the base period, target price forecasts by that analyst are measured in the

subsequent test period. For example, the performance of an analyst's target price forecasts issued

during 1997-1 is assessed as of the end of the 12 months subsequent to the last target price issued by

the analyst (i.e., by the end of 1998-1). To avoid overlapping forecast periods, the period during

which we measure the analyst's subsequent target price forecasting ability is 1998-2.

If individual analysts differ in their abilities to forecast target prices, analysts providing

accurate target prices in one period should provide accurate target prices in subsequent periods, and

the monotonic relation in the TPMET variables induced in the base year ranking should persist

through time. Panels A and B of table 4 present the results for rankings based on TPMET12 and

TPMETANY, respectively. For each ranking across the panels, we report subsequent performance

measured using both TPMET variables. In panel A, for each base ranking period the portfolio

results reveal a spread in mean TPMET12 across portfolios ranging from 0 percent to 69 percent.

In contrast to persistent performance, there is significant reversion to the mean for subsequent

performance across quintile. In fact, subsequent measurement of TPMET12 yields at best a flat

relation across the lagged performance quintiles, and at worst, an inverse relation. For example,

analysts in performance quintile 1 who saw a mean of 0 percent of their target prices being met in

the forecast period see 24 percent of target prices being met in the subsequent measurement period;

on the other hand, analysts in performance quintile 5 who saw an average of 69 percent of target

prices being met subsequently see just 21 percent of their target prices being met.

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[12] Imbalances in the number of observations within portfolios 2 through 4 reflect (i) the manner that SAS handles ties in
its ranking procedure and (ii) losses of observations when we impose the subsequent target price requirement.

The results for TPMETANY in panel B mirror those for TPMET12 in panel A, but perhaps show an even clearer inverse relation between base period and subsequent target price forecasting ability. For example, the spread between the worst and the best performers spans 3 percent to 73 percent in the base period, but only 38 percent to 36 percent in the subsequent measurement period.

Although the univariate results suggest no persistence in individual analyst target price forecasting accuracy, analysts might still exhibit differential abilities after controlling for various firm- or time-period specific factors such as overall stock market returns during the forecast horizon, industry-level market returns, short-term price momentum effects, or stock price variability. We next attempt to control for these and other factors in multivariate tests.

Table 5 presents the estimation of equation (1). Coefficients for the time-period and industry fixed effects indicator variables are not tabulated. In panel A, the LagTPMET variables that measure analysts' prior target price forecasting ability are based on target prices released in the base semi-annual period.[13] Regardless of specification, there is no evidence that prior target price forecasting ability is related to subsequent forecast ability. In fact, all coefficients on the LagTPMET variables are negative and significant, consistent with the univariate evidence of immediate reversion to the mean in table 4. Analysts with the highest frequency of target prices being met (not met) have a lower (higher) frequency of their target prices being met in the subsequent period. These results appear more consistent with luck than skill.

Coefficients on control variables provide insight into firm and market characteristics associated with achievable target prices. The control variable with the greatest explanatory power is TP/P, which is negatively related to target prices being met. The obvious interpretation is that, all

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[13] The LagTPMET variables are transformed to range between 0 and 1 (i.e., [Quintile-1]/4).

else equal, the higher the target price is relative to current price, the less likely it is to be achieved. This is hardly surprising, but it is shows how important it is to control for the relative level of the TP 'hurdle' when examining target price forecasting persistence.

Price momentum measured over the year preceding the target price forecast (PM) provides mixed and inconclusive results, consistent with the conflicting evidence regarding industry-level momentum strategies (e.g., Grundy and Martin 2001, Lewellen 2002). There likely exists endogeneity between analysts' target prices and price momentum given the analogous findings in Stickel (1998) and Bradshaw (2004) for recommendations. If analysts react to price momentum with a delay, reversals like those identified by Jagadeesh and Titman (1993) would occur after our target price release dates but before the end of the 12-month forecast horizon. A negative sign on PM is consistent with analysts providing inflated target prices after seeing momentum in a stock.

Contrary to what an options pricing framework would predict, the proxy for stock price volatility (CVPRICE) is negatively related to a target price being met. However, this appears to reflect the positive correlation between TP/P and CVPRICE (significant in all periods). If an interaction term, TP/P*CVPRICE, is introduced into the regression, both TP/P and CVPRICE retain significant negative coefficients, but the interaction term is positive, consistent with more variable stocks achieving target price forecast levels for a given level of optimism. The value-weighted market return over the target price forecast horizon (MktRET) is also included as a control, and coefficients on MktRET are positive and significant in both regressions (TPMET12 and TPMETANY). Two variables shown in prior research to capture individual analyst earnings forecast skill are also included as controls (Clement 1999). Both firm-specific forecasting experience (FEXP) and association with a large brokerage (DTOP10) are positively correlated with

target prices being met. Finally, our proxy for firm size (LOGMV) is negative and significant in all regressions, consistent with target price forecasts for larger firms being less likely to be achieved.

The results tabulated in table 5 reflect pooled regressions with industry and time fixed effects. We also estimated the regressions separately for each semi-annual period (omitting the time fixed effects), and the results are similar but weaker. For example, coefficients on TPMET12 in the multivariate specification are negative in 7 of 9 semi-annual period regressions and negative and significant in 5 of 9 regressions. For all results in table 5, if we compute Fama-MacBeth t-statistics, all coefficients on TPMET variables are insignificant and coefficients on other variables are uniformly less significant, with the exception of FEXP and DTOP10, which are insignificant. These weaker results may reflect a decrease in power (i.e., 9 data points).

Overall, there is no evidence that analysts exhibit persistent abilities to forecast target prices. In contrast, there is a marked tendency for analysts' target price forecasting performance to revert quickly to the mean. This evidence differs from previous research that finds differential abilities among analysts at forecasting earnings and picking stocks, which we revisit in section 4.4. We next examine whether the market reacts differently to target prices released by analysts with recent success at forecasting target prices.

4.3 Market appreciation of past target price forecasting performance of individual analysts

Table 6 presents the results of regressions of three-day abnormal returns on proxies for analysts' past target price forecasting performance and control variables. As in Brav and Lehavy (2003), we introduce change in target price (ΔTP) as the driver of short-window announcement returns. In addition to the proxy for analyst target price forecasting ability (LagTPMET variables),

we include control variables from table 5 but omit CVPRICE due to the short measurement window and MktRET because we use size-adjusted returns as the dependent variable.

Consistent with changes in target prices affecting stock prices, the coefficient on ΔTP is positive and is the most significant explanatory variable. The coefficient on analysts' lagged target price forecasting ability is insignificant, consistent with the market not weighting recent target price forecasting performance. The only control variables that are significantly related to three-day returns are TP/P and PM. Both are negatively related to short-window abnormal returns, consistent with the market discounting extremely optimistic target prices and target price revisions for stocks with the highest recent price momentum.

4.4 Reconciliation of target price forecasting ability with earnings forecasting ability

Our results for target prices are inconsistent with the evidence that analysts demonstrate persistent abilities in forecasting earnings and making stock recommendations (e.g., Mikhail, Walther, and Willis 1997, 2004; Sinha, Brown, and Das 1997). Target prices are issued less frequently than earnings forecasts and recommendations. The fact that our sample analysts were required to have issued target prices may result in a selection bias if these analysts systematically differ from the larger population. To assess this possibility, we examine whether our sample of analysts exhibits persistent earnings forecasting ability, and if so, whether analysts who are superior (inferior) on the earnings forecast dimension also exhibit persistence at forecasting target prices.

For the analysts in our sample, we measure annual earnings per share forecast accuracy of forecasts made within a three-month window surrounding the target price forecasts. Similar to our construction of LagTPMET variables, we compute the mean earnings forecast accuracy for an analyst's portfolio of stocks s/he covers. Forecast accuracy is measured as the absolute value of

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reported earnings minus forecasted earnings, scaled by stock price at the date of the forecast. In each semi-annual period of the sample, we assign analysts to accuracy quintiles based on their recent one-year ahead earnings forecasts (LagFA1). We then compute portfolio means for subsequent earnings forecast accuracy (FA1) and subsequent target price forecasting accuracy (TPMET12, TPMETANY). If analysts have differential earnings forecasting abilities, portfolio assignments should rank order subsequent earnings forecast accuracy.

Results appear in table 7. Panel A shows results for quintiles based on lagged ability to forecast one-year ahead earnings per share. Consistent with Mikhail, Walther, and Willis (1997) and Sinha, Brown and Das (1997), analysts with superior earnings forecasting ability in the base period provide more accurate earnings forecasts in subsequent periods. However, the lagged earnings forecasting ability does not translate into subsequent target price forecasting ability. The means of target price forecast accuracy are flat across the LagFA1 quintiles.

In panels B and C, we rank on each of the target price forecasting measures, and measure subsequent forecasting accuracy as well as target price forecasting accuracy (i.e., replicate table 4).[14] We document that analysts whose target prices forecasts are met more often at the end of the forecast period (TPMET12) also provide the most accurate subsequent earnings forecasts, but this does not hold for TPMETANY. Nevertheless, in both panels, the significant relations between the lagged ranking and subsequent target price performance that we observe are in opposite directions than expected (similar to table 4). Overall, individual analysts' differential earnings forecasting abilities do not extend to target price forecasting ability.

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[14] The sample size in table 7 is smaller than in table 4, due to the earnings forecast data requirement.

5. Conclusion

We examine the overall accuracy of analysts' 12-month-ahead target price forecasts. We find that on average, 24-45 percent of target prices are met. Across analysts, we find no evidence of persistent differential abilities to forecast target prices and that the market appears to understand this inability. Finally, we reconcile our results with prior research by showing that our sample analysts exhibit persistent skills in forecasting earnings, but not target prices.

We provide new evidence regarding a forecast of considerable interest to investors. Our findings that analysts do not demonstrate differential target price accuracy contrasts with findings that analysts possess differential earnings forecast accuracy and recommendation profitability. We show that the market responds to changes in target prices (with substantial discounting of the embedded forecasted return), and the market does not incorrectly weight target price forecasts based on recent analyst track records. In contrast to the substantial evidence that analyst compensation and job tenure increases in earnings forecast accuracy and profitability of stock recommendations, there is no evidence of which we are aware that compensation is tied in any way to the accuracy of their target prices. Moreover, analysts' target prices are not subjected to the media scrutiny that their earnings forecasts and recommendations are. Consequently, it is perhaps not surprising that target price forecasts are overly optimistic on average, and that analysts demonstrate no abilities to persistently forecast target prices. This evidence is consistent with prior findings of low abilities of various experts to forecast interest rates, GDP, recessions, and business cycles.

References

Abarbanell, J., 1991. "Do Analysts' Earnings Forecasts Incorporate Information in Prior Stock Price Changes?" *Journal of Accounting and Economics* 14, June, 147-166.

Asquith, P., M.B. Mikhail, and A. Au, 2005. "Information Content of Equity Analyst Reports." *Journal of Financial Economics*, Vol. 75, No.1, pp. 245-282.

Bandyopadhyay, S.P., L.D. Brown, and G.D. Richardson, 1995. "Analysts' Use of Earnings Forecasts in Predicting Stock Returns: Forecast Horizon Effects." *International Journal of Forecasting* 11, 429-445.

Belongia, M., 1987. "Predicting Interest Rates: A Comparison of Professional and Market-Based Forecasts." *Federal Reserve Bank of St. Louis Review*, March, 9-15.

Bradshaw, M.T., 2002. "The Use of Target Prices to Justify Sell-Side Analysts' Stock Recommendations." *Accounting Horizons*, March, pp. 27-41.

-------, 2004. "How Do Analysts Use Their Earnings Forecasts in Generating Stock Recommendations?" *The Accounting Review*, Vol. 79, No.1, pp. 25-50.

Brav, A. and R. Lehavy, 2003. "An Empirical Analysis of Analysts' Target Prices: Short-Term Informativeness and Long-term Dynamics." *The Journal of Finance*, Vol. 58, No.5, pp. 1933-1967.

Brown, L.D., ed, 2000. I/B/E/S Research Bibliography: Sixth Edition. I/B/E/S International Inc.

--------, P. A Griffin, R. L. Hagerman and M. E. Zmijewski 1987. "Security Analyst Superiority Relative to Univariate Time-Series Models in Forecasting Quarterly Earnings." *Journal of Accounting and Economics*, Vol. 9 No. 1, pp. 61-87.

--------, and E. Mohd, 2003. "The Predictive Value of Analyst Characteristics." *Journal of Accounting, Auditing, and Finance*, pp. 625-647.

--------, and M.S. Rozeff, 1978. "The Superiority of Analyst Forecasts as Measures of Expectations: Evidence from Earnings." *Journal of Finance* 33, pp. 1-16.

Butler, K.C., and L.H.P. Lang, 1991. "The Forecast Accuracy of Individual Analysts: Evidence of Systematic Optimism and Pessimism." *Journal of Accounting Research*, pp. 150-156.

Clement, M.B., 1999. "Analyst Forecast Accuracy: Do Ability, Resources, and Portfolio Complexity Matter?" *Journal of Accounting and Economics*, Vol. 27 No. 3, pp. 285-303.

--------, L. Rees and E. P. Swanson, 2003. "The Influence of Culture and Corporate Governance on the Characteristics that Distinguish Superior Analysts." *Journal of Accounting, Auditing and Finance* Val. 18 No. 4: 593-618.

Cooper, R.A., T.E. Day, and C.M. Lewis, 2001. "Following the Leader: A Study of Individual Analysts' Earnings Forecasts." *Journal of Financial Economics* 61, 383-416.

Dechow, P.M., and R.G. Sloan, 1997. "Returns to Contrarian Investment Strategies: Tests of Naive Expectations Hypotheses." *Journal of Financial Economics* 43, 3-27.

Fama, E.F., and K.R. French, 1997. "Industry Costs of Equity." *Journal of Financial Economics* 43, 153-193.

Fintzen, D., and H.O. Stekler, 1999. "Why Did Forecasters Fail to Predict the 1990 Recession?" *International Journal of Forecasting*, Vol. 15, 309-323.

Frankel, R. and C. Lee, 1998. "Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns." *Journal of Accounting and Economics,* Vol.25, No.3, pp. 283-319.

Fried, D. and D. Givoly. 1982. "Financial Analysts' Forecsts of Earnings: A Better Surrogate for Market Expectations." *Journal of Accounting and Economics*, Vol. 4, No. 2, pp. 85-107.

Gilson, S.C., P.M. Healy, C.F. Noe, and K.G. Palepu, 2001. "Analyst Specialization and Conglomerate Stock Breakups." *Journal of Accounting Research*, Vol. 39, No. 3, December, pp. 565-582.

Grundy, B.D., and S.J. Martin, 2001. "Understanding the Nature of Risks and the Sources of Rewards to Momentum Investing." *Review of Financial Studies* 14, 29-78.

Hong, H., J.D. Kubik, and A. Solomon, 2000. "Security Analysts' Career Concerns and Herding of Earnings Forecasts." RAND Journal of Economics Vol. 31 No. 1, Spring, 121-144.

-------, T. Lim, and J. Stein, 2000. "Bad News Travels Slowly: Size, Analyst Coverage and the Profitability of Momentum Strategies." *The Journal of Finance*, Vol. 25, No. 1, Feb.

Jackson, A.R., 2005. "Trade Generation, Reputation, and Sell-Side Analysts." *The Journal of Finance* Vol. 60, No. 2, 671-717

Jacob, J., T. Lys and M. Neale 1999. "Expertise in Forecasting Performance of Security Analysts." *Journal of Accounting and Economics*, Vol. 28 No. 1, pp. 51-82.

Jagadeesh, N., and S. Titman, 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *The Journal of Finance* 48, pp. 65-91.

Lewellen, J., 2002. "Momentum and Autocorrelation in Stock Returns." *Review of Financial Studies* 15, 533-563.

Lin, H., and M.F. McNichols, 1998. "Underwriting Relationships, Analysts' Earnings Forecasts and Investment Recommendations." *Journal of Accounting and Economics* 25, pp. 101-127.

Loh, R. and M. Mian. 2004. "Do Accurate Earnings Forecasts Facilitate Superior Investment Recommendations?" Working Paper, August.

Loungani, P., 2000. "How Accurate Are Private Sector Forecasts? Cross-Country Evidence from Consensus Forecasts of Output Growth." IMF Working Paper No. 00/77, April.

Mikhail, M.B., B.R. Walther, and R.H. Willis, 1997. "Do Security Analysts Improve their Performance with Experience?" *Journal of Accounting Research* 35, pp. 131-166.

Mikhail, M.B., B.R. Walther, and R.H. Willis, 1999. "Does Forecast Accuracy Matter to Security Analysts?" *The Accounting Review* 74, pp. 185-200.

Mikhail, M.B., B.R. Walther, and R.H. Willis, 2004. "Do Security Analysts Exhibit Persistent Differences in Stock Picking Ability?" *Journal of Financial Economics,* Vol. 74, No.1, pp. 67-91.

Mikhail, M.B., B.R. Walther, X. Wang, and R.H. Willis, 2004. Determinants of Superior Stock Picking Ability. Working Paper, November.

O'Brien, P., 1990. "Forecast accuracy of Individual Analysts in Nine Industries." *Journal of Accounting Research* 28, pp. 286-304.

Sinha, P., L.D. Brown, and S. Das, 1997. "A Re-Examination of Financial Analysts' Differential Earnings Forecast Accuracy." *Contemporary Accounting Research* 14, pp. 1-42.

Sorescu, S.M. and A. Subrahmanyam. 2004. "The Cross-Section of Analyst Recommendations." Working Paper, September.

Stickel, S.E., 1992. "Reputation and Performance among Security Analysts." *Journal of Finance* 47, pp. 1811-1836.

--------, 1995. "The Anatomy of the Performance of Buy and Sell Recommendations." *Financial Analysts Journal*, September-October, pp. 25-39.

--------, 1998. "Analyst Incentives and the Financial Characteristics of Wall Street Darlings and Dogs." Working paper, LaSalle University.

Womack, K.L., 1996. "Do Brokerage Analysts' Recommendations Have Investment Value?" *The Journal of Finance*, March, pp. 137-167.

Zarnowitz, V., 1991. "Has Macro-Forecasting Failed?" *The Cato Journal*, vol. 11, no. 3, Winter.

Figure 1
S&P 500 Index and Sample Mean TP/P for Semi-Annual Periods 1997-2002

Figure 1a: S&P subsequent 12-month returns and contemporaneous TP/P
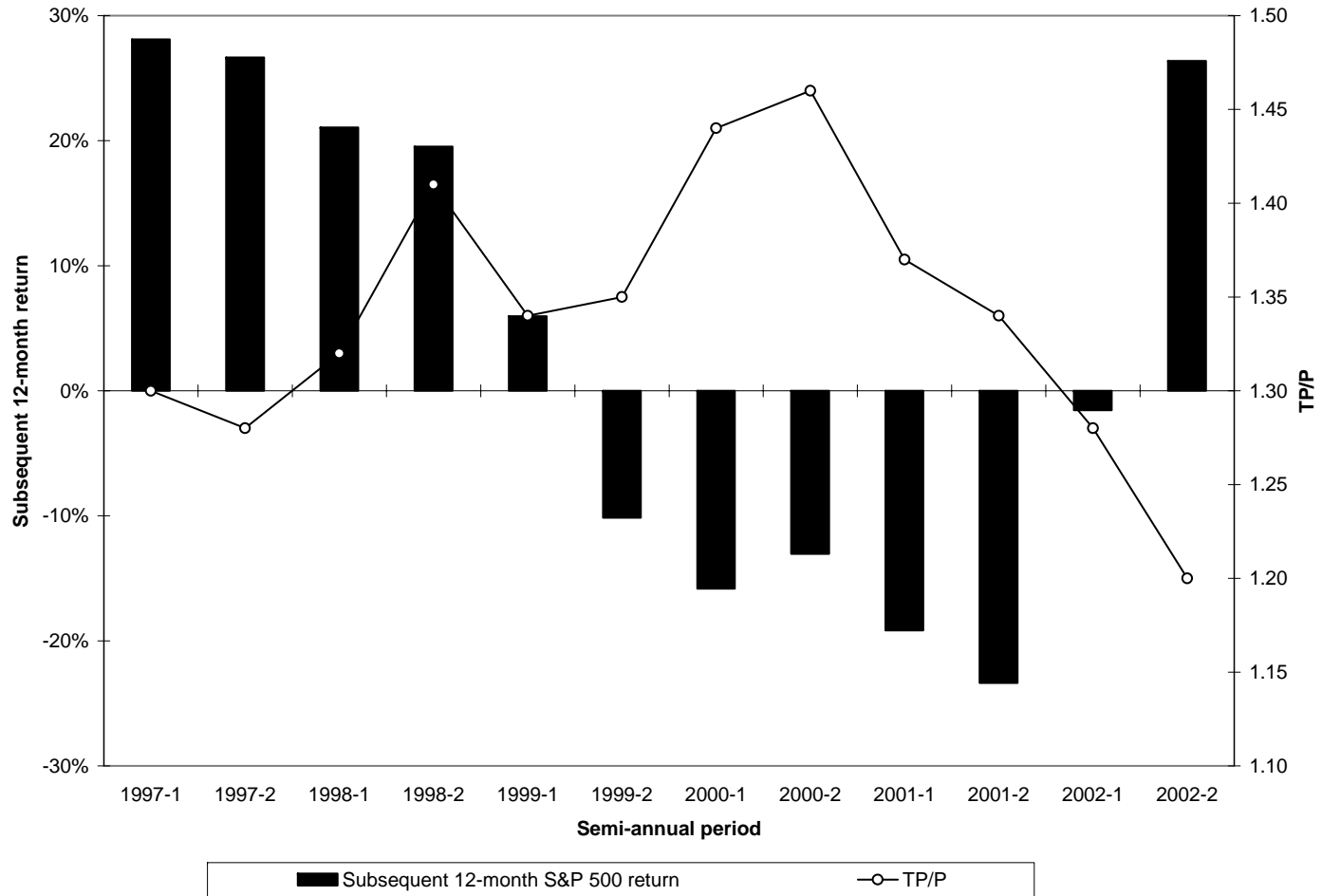
Figure 1 (cont.)
S&P 500 Index and Sample Mean TP/P for Semi-Annual Periods 1997-2002

Figure 1b: S&P Index and contemporaneous TP/P
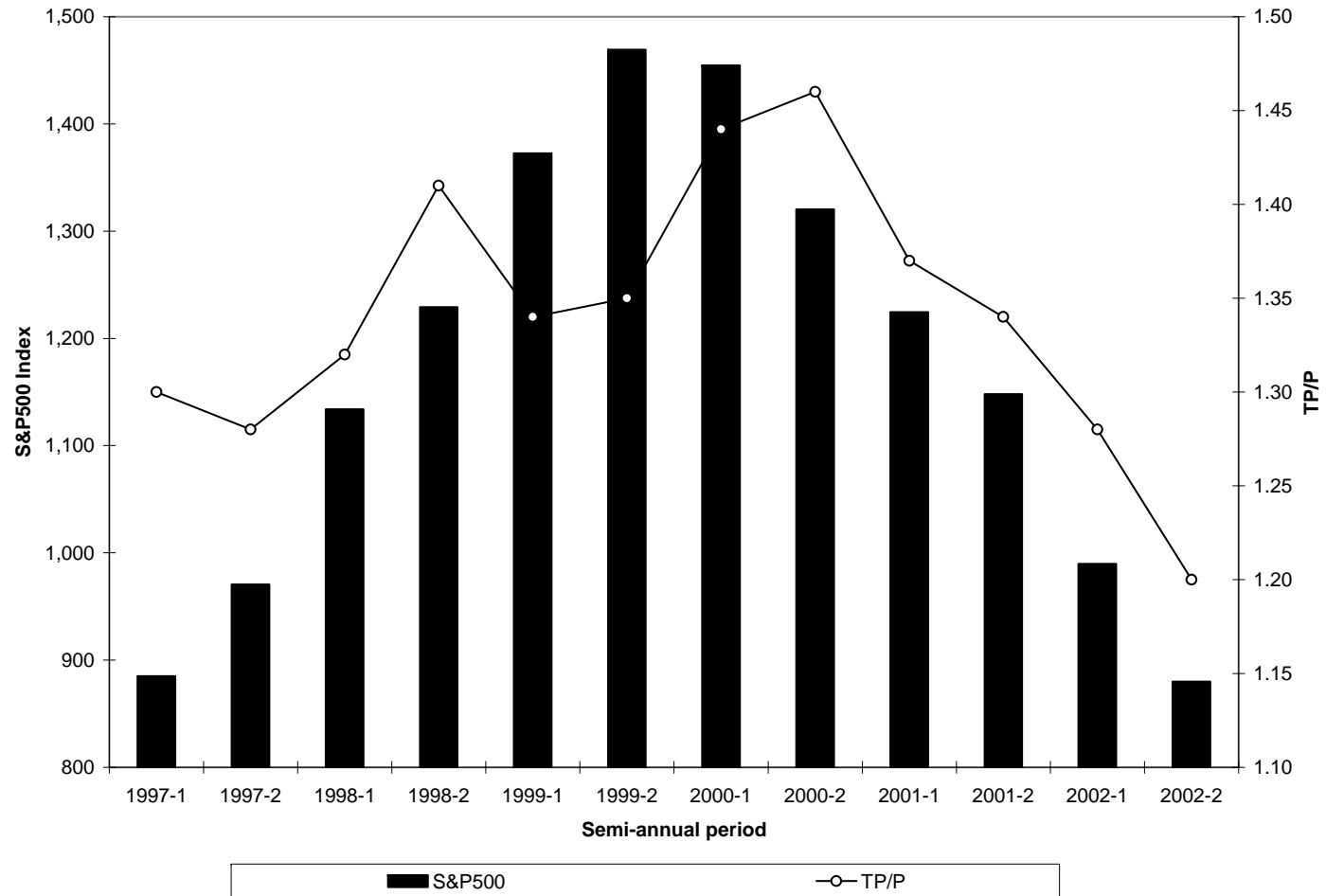
Table 1
Descriptive Statistics for Sample Size, Analyst and Brokerage Representation, and Industry Composition
For Sample Firms Relative to the Compustat Population

Panel A: Distribution of number of firms, analysts, and brokerages

Semi-Annual Period	#Firms	#Analysts	#Brokers	#Obs.
1997-1	1,056	891	52	2,893
1997-2	1,310	1,137	68	4,039
1998-1	1,577	1,311	69	5,447
1998-2	1,736	1,452	79	6,282
1999-1	1,828	1,640	91	7,341
1999-2	2,017	1,769	98	8,035
2000-1	2,152	1,908	109	9,846
2000-2	2,143	1,884	103	9,630
2001-1	2,098	1,889	105	10,089
2001-2	2,285	2,056	101	12,229
2002-1	2,420	2,180	103	14,427
2002-2	1,852	1,595	98	5,594
All periods	4,167	4,531	142	95,852

Table 1 (cont.)

Descriptive Statistics for Sample Size, Analyst and Brokerage Representation, and Industry Composition
For Sample Firms Relative to the Compustat Population

Panel B: Distribution of sample firms across industries

Industry	Sample Frequency	Sample %	Compustat %	Industry	Sample Frequency	Sample %	Compustat %
Agriculture	10	0.20%	0.30%	Measure/control equip.	76	1.80%	1.90%
Aircraft	9	0.20%	0.30%	Medical equipment	132	3.20%	3.00%
Alcoholic beverages	13	0.30%	0.30%	Miscellaneous	39	1.00%	1.60%
Apparel	54	1.30%	1.20%	Nonmetallic metals	12	0.30%	0.50%
Autos and trucks	51	1.20%	1.20%	Personal services	42	1.00%	0.90%
Banking	403	9.70%	10.40%	Petroleum/natural gas	137	3.30%	3.40%
Business services	621	14.90%	13.40%	Pharmaceutical products	221	5.30%	4.80%
Business supplies	9	1.20%	1.00%	Precious metals	18	0.40%	0.80%
Candy and soda	10	0.20%	0.20%	Printing and publishing	32	0.80%	0.70%
Chemicals	72	1.70%	1.50%	Real estate	14	0.30%	1.00%
Coal	5	0.10%	0.10%	Recreational products	22	0.50%	0.90%
Computers	188	4.50%	4.40%	Restaurants/hotel/motel	69	1.60%	1.80%
Construction	42	1.00%	1.10%	Retail	224	5.40%	4.20%
Construction materials	61	1.50%	1.60%	Rubber/plastic products	27	0.60%	0.90%
Consumer goods	54	1.30%	1.50%	Shipping containers	14	0.30%	0.30%
Defense	4	0.10%	0.10%	Ships, railroad equip.	9	0.20%	0.20%
Electric equipment	28	0.70%	0.80%	Steel works, etc.	62	1.50%	1.30%
Electronic equipment	261	6.30%	5.20%	Telecommunications	157	3.80%	3.60%
Entertainment	51	1.20%	1.70%	Textiles	17	0.40%	0.50%
Fabricated products	11	0.30%	0.40%	Tobacco products	5	0.10%	0.10%
Food products	59	1.40%	1.30%	Trading	102	2.40%	4.70%
Healthcare	56	1.30%	1.50%	Transportation	103	2.50%	2.00%
Insurance	146	3.50%	2.80%	Utilities	126	3.00%	2.70%
Machinery	124	3.00%	2.90%	Wholesale	125	3.00%	3.40%
					4,167	100%	100%

This table presents frequency distributions for the sample of target price forecasts. The sample period spans January 1997-December 2002, and is partitioned into ten semi-annual periods, labeled 1997-1, 1997-2, …, 2002-2, corresponding to January-June 1997, July-December 1997, …, July-December 2002. Panel B represents the distribution of the 4,167 firms across industries for the last year the firm is in the sample. Industries are as defined in Fama and French (1997).

Table 2
Descriptive Statistics for Size, Profitability, and Market Pricing of
Sample Firms Relative to Compustat Population

	Means			Medians	
	Sample	Compustat		Sample	Compustat
# Analysts following	9.3	3.4 ***		7.0	1.0 ***
Total assets ($M)	7,388	3,675 ***		773	143 ***
Sales ($M)	3,050	1,398 ***		524	82 ***
Market value ($M)	4,554	1,159 ***		672	95 ***
ROA	0.9%	-4.2% ***		3.3%	1.3% ***
ROE	6.4%	0.9% ***		10.7%	7.4% ***
P/E	22.1	20.3 ***		17.5	15.9 ***
B/M	0.57	0.65 ***		0.46	0.51 ***
Industry-adjusted ROA	0.5%	-4.9% ***		1.6%	0.0% ***
Industry-adjusted ROE	1.2%	-4.9% ***		3.4%	0.0% ***
Industry-adjusted P/E	5.6	3.7 ***		1.5	0.0 ***
Industry-adjusted B/M	0.03	0.13 ***		-0.06	0.00 ***

This table presents means and medians of select size and profitability measures for the sample firms relative to the Compustat population. Total assets is the year end value of total assets (data item #6). Sales is fiscal year net sales (data item #12). # of Analysts following is the number of I/B/E/S analysts comprising the consensus one-year ahead forecast as of the last month of the fiscal year. ROA is return on assets (data item #18/data item #6), ROE is return on equity (data item #18/data item #216), P/E is the fiscal year end price-earnings ratio (data item #199/data item #58), and B/M is the fiscal year end book-to-market ratio (data item #18/[data item #25*data item #199]). Industry-adjusted variables reflect the means and medians of the associated variables, after adjusting it for the Compustat population industry-specific median. The sample period spans January 1997-December 2002, and is partitioned into ten semi-annual periods, labeled 1997-1, 1997-2, …, 2002-2, corresponding to January-June 1997, July-December 1997, …, July-December 2002. Panel B represents the distribution of the 4,167 firms across industries for the last year the firm is in the sample. Industries are as defined in Fama and French (1997). *** indicates that means (medians) are significantly different from each other at the 0.001 level under a standard t-test (Z-test).

Table 3
Frequency that Target Prices are Met Across Semi-Annual Periods
and Conditional on the Ratio of Target Price to Current Trading Price

Panel A: Means across semi-annual periods

Semi-annual period	N	TP/P	TPERROR	% target prices met as of the end of the 12 month forecast horizon (TPMET12)	% of target prices met on at least one day during the 12-month forecast horizon (TPMETANY)
1997-1	2,893	1.30	-0.04	47%	59%
1997-2	4,039	1.28	-0.33	25%	42%
1998-1	5,447	1.32	-0.33	25%	38%
1998-2	6,282	1.41	-0.26	27%	47%
1999-1	7,341	1.34	-0.16	27%	46%
1999-2	8,035	1.35	-0.21	28%	49%
2000-1	9,846	1.44	-0.41	26%	46%
2000-2	9,630	1.46	-0.50	21%	44%
2001-1	10,089	1.37	-0.42	22%	43%
2001-2	12,229	1.34	-0.51	17%	52%
2002-1	14,427	1.28	-0.45	15%	35%
2002-2	5,594	1.20	-0.02	38%	55%
All	95,852	1.35	-0.35	24%	45%

Panel B: Means across portfolio based on the ratio of target price to current trading price

TP/P quintile	N	TP/P	TPERROR	% target prices met as of the end of the 12 month forecast horizon (TPMET12)	% of target prices met on at least one day during the 12-month forecast horizon (TPMETANY)
1	19,168	1.01	0.04	41%	72%
2	19,170	1.16	-0.13	32%	54%
3	19,170	1.26	-0.25	23%	44%
4	19,175	1.41	-0.44	16%	34%
5	19,169	1.90	-0.98	7%	21%
All	95,852	1.35	-0.35	24%	45%

This table presents the distribution of various measures of target price accuracy across portfolios based on the ratio of per share target price (TP) to actual trading price (P) in panel A and across semi-annual periods in panel B. All target prices are identified as one-year target prices. The actual trading price is the closing per share stock price as of three-days prior to the date of the target price release. Quintiles are formed by sorting observations in each semi-annual period based on the TP/P ratio. The results presented are pooled across semi-annual periods. TPMET12 is an indicator variable equal to 1 if $P12 \geq TP$, where P12 is the actual closing stock price per share on the last day of the forecast horizon and TP is the analyst's target price forecast. TPMETANY is an indicator variable equal to 1 if any closing price during the forecast horizon is greater than or equal to TP. TPERROR is the target price forecast error, computed as one plus the raw return over the target price forecast horizon minus the target price, scaled by stock price as of forecast date. The sample period spans January 1997-December 2002, and is partitioned into ten semi-annual periods, labeled 1997-1, 1997-2, …, 2002-2, corresponding to January-June 1997, July-December 1997, …, July-December 2002.

Table 4
Persistent ability of individual analysts to accurately forecast target prices

Panel A: Percent of an individual analyst's target prices met as of the end of the 12 month forecast horizon (TPMET12)

Lagged performance quintile	N	Lagged performance, measured by: TPMET12	Subsequent performance, measured by: % target prices met as of the end of the 12 month forecast horizon (TPMET12)	Subsequent performance, measured by: % of target prices met on at least one day during the 12-month forecast horizon (TPMETANY)
1	881	0%	24%	46%
2	569	14%	27%	51%
3	701	25%	24%	47%
4	695	42%	22%	45%
5	629	69%	21%	42%
Diff (5-1)		74%	-5%	-5%
t-test p-value		<0.0001	0.0018‡	0.0030‡
Z-test p-value		<0.0001	0.0032‡	0.0225‡

Panel B: Percent of an individual analyst's target prices met on at least one day during the 12-month forecast horizon (TPMETANY)

Lagged performance quintile	N	Lagged performance, measured by: TPMETANY	Subsequent performance, measured by: % target prices met as of the end of the 12 month forecast horizon (TPMET12)	Subsequent performance, measured by: % of target prices met on at least one day during the 12-month forecast horizon (TPMETANY)
1	788	3%	31%	38%
2	680	20%	28%	38%
3	664	33%	27%	39%
4	703	48%	24%	37%
5	640	73%	22%	36%
Diff (5-1)		70%	-9%	-2%
t-test p-value		<0.0001	<0.0001 ‡	<0.0001 ‡
Z-test p-value		<0.0001	<0.0001 ‡	0.0020 ‡

This table presents the subsequent target price forecasting ability of analysts conditional on lagged forecasting ability. All target prices are identified as one-year target prices. The sample period spans January 1997-December 2002, and is partitioned into ten semi-annual periods, labeled 1997-1, 1997-2, …, 2002-2, corresponding to January-June 1997, July-December 1997, …, July-December 2002. In each semi-annual sample period, individual analysts with target price forecasts for at least three different firms are allocated to quintiles based on the overall performance of their target price forecasts issued during that period. Target price forecasting performance is measured in three ways. TPMET12 is an indicator variable equal to 1 if P12≥TP, where P12 is the actual closing stock price per share on the last day of the forecast horizon and TP is the analyst's target price forecast. TPMETANY is an indicator variable equal to 1 if any closing price during the forecast horizon is greater than or equal to TP. Quintiles are formed by sorting analysts within each semi-annual period based on the ex post performance of target prices forecasted during that period. The results presented are pooled across semi-annual periods. Subsequent performance is measured similarly during the first semi-annual period following the end of the initial forecast horizon so as to maintain independence in prices. For example, the performance of an analyst's target price forecasts issued during 1997-1 will be assessed as of the end of twelve months subsequent to the last target price issued by the analyst (i.e., by the end of the 1998-1 period). Thus, when an analyst's forecasts issued during 1997-1 are the basis for the analyst's performance ranking, the subsequent performance is measured based on target prices issued during 1998-2. ‡ indicates statistical significance in the opposite direction predicted.

Table 5
Regression Analysis to Examine Analysts' Ability to Persistently Forecast Target Prices
(N=34,774)

$$TPMET_{Var} = \sum_{t=2}^{49} \delta_t Industry_{49} + \sum_{t=1998}^{2002} \sum_{s=1}^{2} \delta_{t,s} Time_{t,s} + \alpha + \beta_1 LagTPMET_{Var} + \beta_2 TP/P + \beta_3 PM + \beta_4 CVPRICE +$$

$$\beta_5 MktRET + \beta_6 FEXP + \beta_7 DTOP10 + \beta_8 LOGMV + \varepsilon$$

	Intercept	LagTPMET	TP/P	PM	CVPRICE	MktRET	FEXP	DTOP10	LOGMV	Likelihood Ratio or Adj. R^2
Panel A: TPMET_Var=TPMET12: Percent of an individual analyst's target prices met as of the end of the 12 month forecast horizon										
Coef.	-0.581	-0.372	-	-	-	-	-	-	-	1379.2
χ2 stat.	*27.0****	*96.6****								-
Coef.	3.536	-0.409	-3.202	0.027	-2.181	2.439	0.001	0.112	-0.139	4352.4
χ2 stat.	*405.6****	*98.7****	*1970.5****	*0.6*	*1.0*	*111.7****	*4.3**	*10.8***	*228.5****	-
Panel B: TPMET_Var=TPMETANY: Percent of an individual analyst's target prices met on at least one day during the 12-month forecast horizon										
Coef.	-0.506	-0.499	-	-	-	-	-	-	-	1459.4
χ2 stat.	*20.4****	*175.9****								-
Coef.	3.630	-0.554	-3.224	0.015	-2.182	2.444	0.001	0.114	-0.137	4437.9
χ2 stat.	*425.1****	*183.1****	*1981.7****	*0.2*	*1.0*	*111.9****	*3.3**	*11.2***	*227.7****	-

This table presents logit regressions of three target price performance measures on a proxy variable representing an analyst's target price forecast performance (LagTPMET) and various control variables. Coefficients on industry and time fixed effect variables are not tabulated for brevity. TPMET12 is an indicator variable equal to 1 if P12≥TP, where P12 is the actual closing stock price per share on the last day of the forecast horizon and TP is the analyst's target price forecast. TPMETANY is an indicator variable equal to 1 if any closing price during the forecast horizon is greater than or equal to TP. LagTPMET_Var is the quintile ranking for the individual analyst during the semi-annual period(s) prior to the semi-annual period in which the target price is released. TP/P is the ratio of TP to the actual closing stock price three days prior to the target price forecast date (P). PM is price momentum, measured as the six-month cumulative raw return ending prior to the semi-annual period in which the target price release date falls. CVPRICE is the coefficient of variation of per share stock price over the prior 12 months. MktRET is the value-weighted market return over the one-year forecast horizon. FEXP is an analyst's firm-specific experience in following a particular firm, measured in months. DTOP10 is an indicator variable equal to 1 if the analyst's brokerage is in the top decile based on the number of analysts providing forecasts. LOGMV is the natural logarithm of market value as of the end of the firm's fiscal year end. The sample period spans January 1997-December 2002, and is partitioned into ten semi-annual periods, labeled 1997-1, 1997-2, …, 2002-2, corresponding to January-June 1997, July-December 1997, …, July-December 2002. Significance levels are one-tailed where there is a predicted sign, two-tailed otherwise; ***/**/* represent significance at the 0.001/ 0.010/ 0.05 level.

Table 6
Tests for Stock Market Reactions to Individual Analyst Target Price Accuracy
(N=20,597)

$$\text{ABRET}_{-1,+1} = \sum_{t=2}^{6} \delta_t \text{Industry}_i + \sum_{t=1998}^{2002} \sum_{s=1}^{2} \delta_{t,s} \text{Time}_{t,s} + \alpha + \beta_1 \Delta \text{TP} + \beta_2 \text{LagTPMET}_{\text{Var}} + \beta_3 \text{TP/P} +$$

$$\beta_4 \text{PM} + \beta_5 \text{FEXP} + \beta_6 \text{DTOP10} + \beta_7 \text{LOGMV} + \varepsilon$$

	Intercept	ΔTP	LagTPMET	TP/P	PM	FEXP	DTOP10	LOGMV	Adj. R^2

Panel A: TPMET$_{Var}$=TPMET12: Percent of an individual analyst's target prices met as of the end of the 12 month forecast horizon

	Intercept	ΔTP	LagTPMET	TP/P	PM	FEXP	DTOP10	LOGMV	Adj. R^2
Coef.	0.002	0.063	0.000	-0.004	-0.005	0.0000	-0.000	-0.000	0.029
t-stat.	*0.5*	*16.9****	*0.3*	*-3.5****	*-4.5****	*0.4*	*-0.3*	*-1.5*	

Panel B: TPMET$_{Var}$=TPMETANY: Percent of an individual analyst's target prices met on at least one day during the 12-month forecast horizon

	Intercept	ΔTP	LagTPMET	TP/P	PM	FEXP	DTOP10	LOGMV	Adj. R^2
Coef.	0.002	0.063	0.001	-0.004	-0.005	0.000	-0.000	-0.000	0.029
t-stat.	*0.5*	*16.9****	*0.7*	*-3.5****	*-4.5****	*0.4*	*-0.3*	*-1.5*	

This table presents ordinary least squares regressions of three-day size-adjusted abnormal returns around the date of a target price forecast revision on a proxy variable representing an analyst's prior target price forecast performance (LagTPMET) and various control variables. Coefficients on industry and time fixed effect variables are not tabulated for brevity. TPMET12 is an indicator variable equal to 1 if P12≥TP, where P12 is the actual closing stock price per share on the last day of the forecast horizon and TP is the analyst's target price forecast. TPMETANY is an indicator variable equal to 1 if any closing price during the forecast horizon is greater than or equal to TP. ΔTP is the analyst's target price forecast revision, scaled by price as of three days prior to the date of the revision. LagTPMET$_{Var}$ is the quintile ranking for the individual analyst during the semi-annual period(s) prior to the semi-annual period in which the target price is released. TP/P is the ratio of TP to the actual closing stock price three days prior to the target price forecast date (P). PM is price momentum, measured as the six-month cumulative raw return ending prior to the semi-annual period in which the target price release date falls. FEXP is an analyst's firm-specific experience in following a particular firm, measured in months. DTOP10 is an indicator variable equal to 1 if the analyst's brokerage is in the top decile based on the number of analysts providing forecasts. LOGMV is the natural logarithm of market value as of the end of the firm's fiscal year end. The sample period spans January 1997-December 2002, and is partitioned into ten semi-annual periods, labeled 1997-1, 1997-2, …, 2002-2, corresponding to January-June 1997, July-December 1997, …, July-December 2002. Significance levels are one-tailed where there is a predicted sign, two-tailed otherwise; ***, **, and * represent significance at the 0.001, 0.01, and 0.05 level.

Table 7
Relation Between Earnings Forecasting and Target Price Forecasting Ability

Panel A: Quintiles based on individual analyst forecast accuracy for one-year ahead earnings (FA1)

LagFA1 quintile	LagFA1		FA1	TPMET12	TPMETANY
1 (most accurate)	0.001		0.016	0.243	0.469
2	0.004		0.017	0.237	0.484
3	0.008		0.019	0.226	0.480
4	0.015		0.017	0.241	0.494
5 (least accurate)	0.045		0.023	0.228	0.485
Diff (5-1)	0.043		0.006	-0.015	0.016
t-test p-value	<0.0001		0.0456	0.6732	0.4171
Z-test p-value	<0.0001		0.0003	0.2660	0.2782

Panel B: Quintiles based on an individual analyst's target prices met as of the end of the 12 month forecast horizon (TPMET12)

LagTPMET12 quintile	LagTPMET12		FA1	TPMET12	TPMETANY
1 (least accurate)	0.011		0.022	0.245	0.474
2	0.165		0.020	0.270	0.508
3	0.266		0.016	0.233	0.480
4	0.452		0.014	0.238	0.467
5 (most accurate)	0.731		0.017	0.193	0.412
Diff (5-1)	0.721		-0.005	-0.069	-0.067
t-test p-value	<0.0001		0.0240	<0.0001 ‡	<0.0001 ‡
Z-test p-value	<0.0001		0.0127	0.0019 ‡	0.0002 ‡

Panel C: Quintiles based on percent of an individual analyst's target prices met on at least one day during the 12-month forecast horizon (TPMETANY)

LagTPMETANY quintile	LagTPMETANY		FA1	TPMET12	TPMETANY
1 (least accurate)	0.044		0.021	0.293	0.519
2	0.212		0.019	0.233	0.471
3	0.351		0.015	0.232	0.458
4	0.477		0.017	0.213	0.459
5 (most accurate)	0.708		0.019	0.189	0.418
Diff (5-1)	0.664		-0.002	-0.105	-0.027
t-test p-value	<0.0001		0.4667	<0.0001 ‡	0.1216
Z-test p-value	<0.0001		0.1423	<0.0001 ‡	0.0574 ‡

This table presents means for earnings forecasting and target price forecasting ability. In each semi-annual sample period, individual analysts with target price forecasts for at least three different firms are allocated to quintiles based on the overall performance of their earnings forecasts (FA1) and target price forecasts (TPMET12, TPMETANY) issued during that period. If analysts' earnings forecasting and target price forecasting abilities are shared, there should be a negative relation between quintile rankings on one variable, and the quintile means of the other variable. Significance levels are one-tailed. ‡ indicates that the quintile difference is significant but is opposite this prediction. Earnings forecasting ability is measured as forecast accuracy, computed as the absolute value of the difference between actual earnings per share and an analyst's earnings forecast, scaled by stock price. All forecast accuracy variables are obtained from I/B/E/S. Target price forecasting ability is represented by three proxies. TPMET12 is an indicator variable equal to 1 if $P12 \geq TP$, where P12 is the actual closing stock price per share on the last day of the forecast horizon and TP is the analyst's target price forecast. TPMETANY is an indicator variable equal to 1 if any closing price during the forecast horizon is greater than or equal to TP. The sample period spans January 1997-December 2002, and is partitioned into ten semi-annual periods, labeled 1997-1, 1997-2, …, 2002-2, corresponding to January-June 1997, July-December 1997, …, July-December 2002. ‡ indicates statistical significance in the opposite direction predicted.