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SUBJECTIVE VALUATION AND TARGET PRICE ACCURACY

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In this paper, we analyze how subjective adjustments to baseline models by analysts affect the forecasting accuracy. For a panel of analyst reports, we show that target price forecasts that deviate significantly from simple multiple-based *pseudo*-target prices are (*ex-post*) more accurate. By controlling for various stock and broker characteristics, we also demonstrate that our results are not driven by the degree of sophistication of the valuation models. Furthermore, we show that investors know about this increased informativeness of forecasts as the abnormal market return around target price revisions is significantly higher if analysts deviate from simple *pseudo*-target prices when issuing their forecasts.

Keywords: Target prices; equity research; forecast accuracy; multiple valuation.

JEL Classifications: G14, G19, G24, M41

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"[We apply] a 20% discount to account for the 'conglomerate' nature of the business."[a]

"[T]he model leads us to a fair value of €46 per share and a price target of €50."[b]

1. Introduction

Sell-side analysts serve as information providers to investors in capital markets. Their research on listed companies is generally summarized in stock recommendations, earnings forecasts, and target price predictions (Asquith *et al.* 2005). Target prices have been extensively studied by academics and practitioners because they contain a straightforward prediction of future stock performance that is given by the difference between the forecast (which represents the analyst's assessment of the stock's fair value) and the stock price at the forecast publication date [see Bilinski *et al.* (2013) for a comprehensive set of references of studies in the US and international markets]. This prediction translates into abnormal positive portfolio performance, as shown by Da & Schaumburg (2011). Surprisingly, however, the process that analysts follow to estimate their target prices is still unclear. Analysts usually make subjective assessment about a stock and use an array of different valuation models to compute target prices that arguably yield predictions with different levels of accuracy (Imam *et al.* 2013, 2008). Several papers have investigated the extent to which the adoption of multiple versus residual income models, for example, results in more accurate forecasts (e.g. Liu *et al.* 2002, Demirakos *et al.* 2010, Gleason *et al.* 2012). However, it is unlikely that analysts take the output of one model at face value. Indeed, target prices are commonly obtained by subjectively adjusting the "fair value" outcome of one or more valuation models. While how adjustments are made is unobservable, quite surprisingly, the observable effects of subjective deviations from the baseline model(s) on price target accuracy are still unknown.

In this paper, we address this important issue by *uniformly* modeling deviations between observed price targets and estimated baseline forecasts, by computing their empirical distribution and by testing whether such deviations are informative. In particular, we argue that a deviation from a naive benchmark model is a signal of the analysts possessing additional, valuable information that she/he factors in the forecast. Adjustments are therefore idiosyncratic but cross-sectionally they provide statistically robust estimates of future prices. We develop these arguments in four steps.

First, we model deviations through a novel measure given by the difference between the published target price and a *pseudo*-target price, with the latter being computed extending the benchmark models proposed in Bradshaw (2002) and Gleason *et al.* (2012). We document that target prices heterogeneously deviate from this baseline valuation model and when they do the average difference is large, at approximately 26%. Second, our empirical results indicate that forecasts in which analysts considerably adjust the basic multiple-based outcome are (*ex-post*)

[a] Citigroup Smith Barney, equity report on Henkel, May 11, 2004.

[b] ABN Amro, equity report on Medion, March 26, 2002.

significantly more accurate. Controlling for a number of alternative explanatory variables, we show that accuracy is inversely related to the degree of boldness (as measured by the deviation of the target price from the prevailing stock price). However, subjective deviation partially compensates for this effect suggesting that boldness is not a unidimensional measure: When forecasts are bold but show also significant deviations from the baseline models, analysts likely incorporate in their estimates additional information or processing skills that are valuable to investors. Third, extending the findings in Liu *et al.* (2002), Demirakos *et al.* (2010), and Gleason *et al.* (2012), we acknowledge the potential influence of the valuation model on accuracy testing for the relative accuracy of forecasts based on a single valuation model or by mixing several models.[c] However, in extended multivariate tests, we find no evidence for a positive association between accuracy and the estimation of forecasts based on $n > 1$ valuation models. Finally, we investigate whether market participants are aware of systematic differences in accuracy among the forecasts. Focusing on the five-day and 10-day market reactions around the publication of a report, we find that the market reacts more strongly to positive target price changes when new target prices are characterized by significant deviations from the baseline model.

Our results provide insights for investors and capital markets with respect to a simple interpretation of target prices. In fact, those forecasts in which analysts decide to deviate from simple multiple-based models are (*ex-post*) more accurate and, hence, contain more valuable information, thus helping investors in their investment decision-making processes.

The remainder of the paper is organized as follows. Section 2 provides an overview about the related literature. Section 3 describes the sample selection process, introduces important model variables, and discusses summary statistics. Section 4 presents empirical results on the association between deviations from simple valuation models and target price accuracy alongside the results concerning short-term market reactions. Section 5 concludes.

2. Literature Review

This paper blends two different lines of research: a first set of contributions that has investigated the accuracy of valuation models *per se* and a second line of research that investigates target price accuracy and its determinants. Research on valuation models (Erkilet *et al.* 2021, Bradshaw *et al.* 2013) has found a widespread adoption of single-period multiple-based approaches such as price-to-earnings (PE) or price-to-book value (PTBV) ratios (which are compared to the historical or industry peer values). Multi-period discounted cash flow (DCF) methods are less frequently observed because of the complexity of reliably estimating a large number of necessary

[c] Demirakos *et al.* (2010) highlighted as "an interesting avenue for further research [...] the content analysis of reports that combine alternative valuation models and derive target prices based on averages of the value estimates".

inputs. Survey-based research (e.g. Barker 1999a, Block 1999) reveals that analysts prefer to apply the PE multiple models. This is confirmed by the empirical evidence in Demirakos *et al.* (2004) and Asquith *et al.* (2005), who show that virtually all analysts use multiple valuation methods. However, a few papers (Erkilet *et al.* 2021, Imam *et al.* 2013, 2008, Demirakos *et al.* 2010) suggest that DCF models are almost invariably a primary valuation tool. Hashim & Strong (2018) show a link between the granularity of DCF models' cash flow estimations and target prices accuracy. Glaum & Friedrich (2006), for example, argue that the increase in using DCF models for valuing telecommunication companies is due to the latest cash flow orientation (relative to the 1990s) for valuation purposes of this specific industry segment. Yet, Imam *et al.* (2013) reveal that price-to-earnings multiples have not faded and are similarly widespread. Based on their survey, the authors explain this finding by perceived limitations in the technical application of more sophisticated models. Although all models should (theoretically) lead to identical forecasts (Demirakos *et al.* 2010), findings with respect to this hypothesis are mixed. Liu *et al.* (2002), for example, show that multiples based on forward earnings (as compared to residual income models) explain stock prices better. In contrast, Gleason *et al.* (2012) compute *pseudo*-target prices based on residual income and PE-to-growth (PEG) heuristics to document that target price quality improves when analysts use residual income models relative to PEG models.[d] Brown *et al.*'s (2015) conclusion that earnings forecasts are "often a means to an end and not ends in themselves" suggests that analysts place more weight on their valuation outputs than their valuation inputs.

A second stream of literature focuses on target price accuracy and its determinants. Bonini *et al.* (2010) show that target price forecasting by analysts is a largely unmonitored activity. Furthermore, they show that prediction errors are large and increase with predicted growth in the stock price and size of the company as well as for loss-making firms. Bradshaw *et al.* (2013) report that analysts have limited abilities to persistently provide accurate target price forecasts. Furthermore, their results show no differential market reactions to analysts' target price revisions based on differences in the previous target price performance. Bilinski *et al.* (2013) find that target price accuracy differs significantly across countries, mainly due to differences in accounting disclosure quality, the origin of the legal system, and cultural traits. Contrary to the study of Bradshaw *et al.* (2013), Bilinski *et al.* (2013) show that analysts have persistent abilities to predict target prices, a result echoed by Loh & Stulz (2018) who show that analysts are more informative during bad market cycles. Although these findings demonstrate the limited accuracy of target price forecasts, the information included within such forecasts still contains value for capital markets. Brav & Lehavy (2003) and Asquith *et al.* (2005) document that target price revisions are informative, even if other types of information, such as stock recommendations and earnings forecast revisions, are also considered.

[d] The PEG ratio is the price-to-earnings multiple divided by the long-term earnings growth rate.

3. Data and Sample

3.1. *Sample selection*

Detailed information about the valuation model(s) used to set the price targets is absent from commercial databases. While complete analyst reports in PDF format can be obtained from several sources, the now-popular machine-reading software cannot, unfortunately, be effectively employed given the highly contextual nature of the information relevant to this exercise, e.g. the selected valuation model or the forward-looking PE multiple.[e] As a consequence, the only effective approach to such a research question is to collect the actual full reports and read each of them carefully. This strategy has some limitations: First, it naturally constrains the size of the dataset. Second, it limits the possibility of performing meaningful cross-country studies as the researcher needs to choose between a single country but relatively larger dataset with superior statistical properties, and smaller and econometrically weaker regional sets. In our paper, we opt for the superior robustness of a single-country approach and we focus on analyst reports issued by investment banks on German stocks in the three-year period from 2012 to 2014. We do not expect our focus on German companies to materially impact the generalizability across other countries for the following reasons: First, prior research (e.g. Bilinski *et al.* 2013) has shown that analyst forecasts on German stocks do not differ much from the forecasts on UK or other European companies. Hence, using purely German companies should not impact comparability across countries. Second, Bilinski *et al.* (2013) and Sonney (2009) have shown that country specialization by analysts positively affects accuracy. This may lead to more accurate target prices on an *absolute* level if we assume that analysts within our database have been covering German stocks before and therefore are country experts. Nevertheless, this should not undermine the generalizability of our results since we primarily focus on *relative* differences between analysts within our database that all cover German stocks. And third, with respect to our key dependent variable, i.e. analyst-specific forecast accuracy, our dataset is international as it covers forecasts from analysts that stem from different countries and that work for an international set of investment banks. Hence, one can assume that these international analysts use their country-specific cultural approaches to valuation and therefore sufficiently differ with respect to forecast variation.

We collect reports from the *Investext* database from *Thomson Research*, which provides PDF papers in their original form and claims to provide a database of company research that comprises more than two million full-text research reports. For the chosen time period, the *Investext* database contains 31423 reports on German stocks. We restrict our sample to reports that were published by banks that appear in the *Institutional Investors*' rankings at least once in the three-year time period of our analysis. A bank appears in these rankings if it employs analysts that

[e] This information can be expressed in different ways from a linguistic standpoint, hence, it is hard to write a code that can effectively retrieve it from the text.

have been members of the *Institutional Investors*' *All-European Research Team*. This selection criterion has been widely used in the US (e.g. Stickel 1992, Womack 1996, Fang & Yasuda 2013) because it has been shown that highly ranked analysts provide more accurate earnings forecasts and recommendations and lead to more pronounced stock price reactions. Based on this restriction, 13 banks that appear in the *Institutional Investors*' rankings remain in our database.[f] Furthermore, we restrict the database to reports that are between three pages and 20 pages in length. The lower bound is set to avoid including mere reiterations of previous reports, while the upper bound is motivated by the fact that extremely long reports are uncommon and generally related to either initial coverage or highly distressed cases, situations where the forecast might be driven by corner motivations thereby potentially adding idiosyncratic noise to the sample. We, additionally, exclude reports that focus on general industry and sector analysis. After filtering, the database shrinks to 10364 reports. Due to the effort that is associated with inspecting each full report, we draw a random sample of 1000 reports from the full sample for a total of about 6400 pages. Reports in the final sample were individually read to extract the information required to perform the econometric analysis.

3.2. *Variables*

Dependent and explanatory variables are summarized in Table 1.

3.2.1. *Dependent variable*

Our main research goal is to investigate whether analysts' accuracy varies with the degree of subjective adjustment of the baseline model(s)-estimated fair values. As our dependent variable, we compute the accuracy of target price forecasts (TP_ACCURACY) as one minus the absolute target price forecast error,

$$\text{TP\_ACCURACY} = 1 - \left|\frac{(12 - \text{month}\ \ \text{stock}\ \ \text{price} - \text{target}\ \ \text{price})}{\text{target}\ \ \text{price}}\right|. \tag{3.1}$$

If the 12-month stock price exactly matches the forecasted target price, the accuracy will be 100%. If the 12-month stock price either over- or under-achieves the target price, this will reduce the accuracy. Such an accuracy measure based on absolute forecast errors takes a perspective that strictly evaluates the abilities of each single analyst. Hence, exactly and precisely achieving the price forecast is positively acknowledged whereas any deviation, irrespective of the sign of the deviation, increases the forecast error and reduces the accuracy levels. Since we analyze if the analyst/forecast-specific subjective deviation from baseline models is a signal for better

[f] Namely, these banks are ABN Amro, BNP Paribas, Citigroup Smith Barney/Schroder Salomon Smith Barney, Credit Suisse First Boston, Deutsche Bank, ING Financial Markets, JP Morgan, Julius Baer Brokerage, Kempen & Co., Pictet & Cie, Sanford C. Bernstein & Co., Santander Central Hispano Bolsa, and UBS (Warburg).

Table 1. Definition of variables.

Name of variable	Definition
Dependent variables: target price accuracy/short-term market reaction	
TP_ACCURACY	Formula: TP_ACCURACY = 1-$\vert$(12-month stock price -target price)/target price$\vert$ The accuracy measure equals one minus the absolute forecast error(i.e. the absolute difference between 12-month stock price and target price, scaled by target price). If the forecast error is 0%, the accuracy is 100%. Any deviation of 12-month stock price from target price reduces the accuracy.
CAR[−2, +2]	Five-day cumulative "abnormal return" centering the report publication day. Event-study methodology to compute the market model is based on MacKinlay (1997). Estimation time dates from [−180, −11]. Abnormal returns are the differences between realized and normal returns. Realized returns are downloaded via the datatype *RI* from *Datastream.* To compute normal returns, we estimate OLS parameters in the estimation period while using the value-weighted CDAX as independent variable. The normal return on each day in the event period is defined as the return of the CDAX, adjusted by the estimated OLS parameters.
CAR[−5, +5]	Analogously to CAR[−2, +2] with an a 11-day event window.
Explanatory variables: valuation model characteristics	
PSEUDO_TP	Formula: PSEUDO_TP = PE * EPS The *pseudo*-target price is computed as the PE multiple multiplied with the corresponding earnings-per-share forecast. Both values are taken from the original analyst report as issued by *Investext.* Since analysts quite regularly issue a series of PE multiples and EPS forecasts (one for each of the upcoming years), those values are chosen that most closely match the time horizon of the 12-month target price.
SUBJ_DEVIATION	Formula: SUBJ_DEVIATION = $\vert$(target price - PSEUDO_TP)/PSEUDO_TP$\vert$ The subjective deviation measures the absolute difference between the (issued) target price and the *pseudo*-target price, scaled by the *pseudo*-target price. Hence, this variable measures the relative amount of deviation from the most basic model.
SIGNED_SUBJ_DEVIATION	Formula: SIGNED_SUBJ_DEVIATION = (target price - PSEUDO_TP)/PSEUDO_TP The signed subjective deviation measures the value and sign of the difference between the (issued)target price and the *pseudo*-target price, scaled by the *pseudo*-target price. Hence, if analysts issue a target price which is above (below) the *pseudo*-target price, this variable represents the positive (negative) degree of deviation.
ADD_MODEL	Dummy variable that equals one if within the report and the target price valuation section, the analyst bases his target price forecast on additional, more sophisticated models such as DCF or EVA models in addition to multiple models.
Explanatory variables: forecast-specific characteristics	
BOLDNESS	Formula: BOLDNESS = $\vert$(Target price/current price) −1$\vert$ The absolute value of the implicit return (i.e. the ratio of current target price and current stock price).
OVERACHIEVEMENT	Dummy variable that equals one in the case of the 12-month stock price being higher compared to the target price forecast and zero otherwise.

Table 2. (continued).

EPS_forecast	Current earnings forecast
EPS_ERROR	Formula: EPS_ERROR= |(EPS_actual-EPS_forecast)/EPS_forecast| EPS_ERROR measures the absolute earnings-per-share (EPS) forecast error.
REPORT_LENGTH	Number of pages of a specific report. We restricted the report sample to reports between 3 pages and . . .. This is done to exclude both very short updating reports that contain no original, new research as well as very long and extensive industry or sector analyses.
TP_REV	Percentage change of the current target price issued for a firm at the publication day compared to the previous target price of the firm (published within the previous report). If the previous target price is not included within the report at the publication day, we take the most recent report available in the *Investext* database on the specific firm (if released within 60 days prior to the publication day) to extract the previous target price manually.
TP_REV_pos	This variable basically represents those cases where the revision of target prices is positive. TP_REV_pos equals TP_REV for positive target price revisions, otherwise TP_REV pos is zero.
TP_REV_neg	This variable basically represents those cases where the revision of target prices is negative. TP_REV_neg equals TP_REV for negative target price revisions, otherwise TP_REV_neg is zero.
EPS_REV	Analogously to TP_REV, focusing only on earnings-per-share forecast for the upcoming financial year.
UP	Dummy variable that equals one if the analyst's recommendation for the company is upgraded within the published report, zero otherwise.
DOWN	Dummy variable that equals one if the analyst's recommendation for the company is downgraded within the published report, zero otherwise.
	continued on the next page
Explanatory variables: broker-specific characteristics	
TOPBANK	Dummy variable that equals one for those reports written by one of the three banks that employed the highest average number of top analysts in the three-year sample period. Top analysts are identified by the yearly *All Institutional Investors'* rankings issued by the *Institutional Investor* magazine.
EXPERIENCE	EXPERIENCE measures the total number of reports an analyst has written prior to the specific report.
Explanatory variables: company-specific characteristics	
MV	Market capitalization is downloaded from *Datastream* at the publication day of the analyst's report. Within all regressions, we use the log form of MV (LOG_MV).
PTBV	Price-to-book values are downloaded from *Datastream* at the publication day of the analyst's report.
1_YEAR_HISTORIC_RETURN	One-year performance prior to the publication day of the analyst's report. The one-year performance is the ratio of the 12-months stock price and the prevailing stock price at the report issuance date, adjusted by the one-year historic stock return.
VOLATILITY	Standard deviation based on daily returns for the one-year period prior to the publication day of the analyst's report.

forecasting abilities, we consider an absolute forecast error as more useful, compared to using relative forecast error measures which evaluate forecasting activities from the investors' perspective.[g] Also, given the highly idiosyncratic nature of forecasts, all regressions will include analyst-specific fixed effects among several other time-invariant controls.

If analysts possess valuable information that is incorporated in target prices by deviating significantly from the baseline fair values, this should be associated with higher short-term stock performance. As a second-order level of analysis, we perform a simple event study (MacKinlay 1997). The publication date of each report is transferred into event time, representing the event day [0]. The estimation period encompasses the window [−180; −11]. We compute abnormal returns as the difference between realized and normal returns[h] that are estimated through a standard market model (Brown & Warner 1985).[i] We then calculate the five- and 11-day cumulative abnormal returns (CAR[−2, +2] and CAR[−5, +5]) around the official publication date of each report.

3.2.2. *Explanatory variables*

3.2.2.1. Valuation model characteristics

Analysts issue target prices as part of their research papers. However, it is difficult to gauge the extent to which these estimates are the direct outcomes of the valuation models applied by analysts or are developed through subjective methodologies. It could be argued, for example, that inexperienced analysts may issue a target price that is a direct outcome of some mainstream valuation model, whereas more experienced analysts may be more likely to apply adjustments to the baseline model result to come up with a more informative target price. Such adjustments could be based on more (private) information, broader industry insights, or more experience in general.[j] These adjustments can be large and can be the main source of one analyst's accuracy (or inaccuracy). Yet, no study has so far attempted to measure the contribution of subjective deviations from the adopted model to the forecast accuracy. We introduce

[g] Within the relative forecast measures, a forecast is only inaccurate as long as the stock price does not reach the forecasted target price. Once the stock price overshoots the target price, it is considered to be highly accurate, from the investors' perspective. Hence, even if the 12-month stock price heavily deviates from the previously issued stock price, investors will consider it as accurate since they benefit from prices that are higher compared to their expectation based on the previously issued price target. Apart from the investors' perspective, the usage of relative forecast errors also implies that it would be rational for analysts to only forecast target prices that are close to the current stock price since these will be more easily met (and overachieved). By using absolute forecast errors, this problem can also be circumvented.

[h] Realized returns are computed based on the data type *RI*, which we download from *Datastream*. This data type includes adjustments for dividends and stock splits.

[i] We therefore estimate OLS parameters in the estimation period for each recommended stock based on the value-weighted CDAX as the independent variable. The CDAX represents the entire universe of stocks that are traded on the *Frankfurt Stock Exchange*. In the second step, we compute the normal return of each day within the event period as the return of CDAX adjusted by the previously estimated OLS parameters.

[j] Within a slightly different context, the literature finds that experienced analysts deviate more from consensus forecasts relative to their inexperienced counterparts (e.g. Hong *et al.* 2000) and the so-called bold forecasts are more accurate (Clement & Tse 2005).

a novel measure of subjective adjustment (SUBJ_DEVIATION) by computing the (absolute) difference of the issued target price and a benchmark given by a *pseudo*-target price, scaled by the *pseudo*-target price,[k]

$$\text{SUBJ\_DEVIATION} = \left|\frac{(\text{Target price} - \text{PSEUDO\_TP})}{\text{PSEUDO\_TP}}\right|. \tag{3.2}$$

One of the advantages of SUBJ_DEVIATION as a proxy for additional information is that it is a direct and forecast-specific proxy as it reflects the individual amount of new information in each specific forecast. By construction, our measure can vary for each individual report and we confirm this intuition documenting the considerable within-analyst variation (see Appendix). Differently, commonly used measures such as past experience are analyst-specific and therefore cannot capture the specific "private" information content of each report.

The benchmark *pseudo*-target price (PSEUDO_TP) is constructed following Bradshaw (2002) and Gleason *et al.* (2012) based on forward-looking PE multiples and current financial year earnings-per-share (EPS) forecasts. We select PE multiple-based *pseudo*-target prices as benchmarks because all reports in our database use PE multiples for valuation purposes whereas only a small subset of reports additionally selects more sophisticated valuation models, such as the DCF or economic value-added (EVA) models.[l] We then compute *pseudo*-target prices as the product of one-year-forward EPS forecasts and industry-adjusted PE multiples that incorporate analysts' one-year- and two-year-ahead earnings forecasts,

$$\text{PSEUDO\_TP} = \text{PE} * \text{EPS}. \tag{3.3}$$

In general, target prices are 12-month forward-looking forecasts (relative to the publication date of each report), whereas EPS forecasts and the corresponding PE multiples are forecasts for the financial year-ends. Hence, to compare *pseudo*-target prices with the target prices disclosed in analyst reports, we select PE multiples and EPS forecasts for the financial year-end that most closely matches the target price forecast horizon.[m]

Analysts mention the usage of (standard) PE multiple models within all reports; only a subset of analysts additionally selects more sophisticated models (such as DCF

[k] We focus on absolute values within the computation because we try to measure the magnitude of deviation from the basic (multiple-based) model rather than its directional (positive versus negative information) characteristic.

[l] For a majority of our reports, analysts include EPS forecasts for the current and several future years and, correspondingly, the forward-looking PE multiples for the same years. Only in a minority of reports was there just one PE multiple instead of a series of forward-looking PE multiples for each of the upcoming financial years.

[m] If a report is written at the end of December, the (12-month) target price lasts till the end of December of the following year. In this case, taking the forward-looking PE multiple and the corresponding EPS forecast for the next year-end perfectly matches the forecasting horizon. On the other hand, if a report is issued at the end of June, the target price forecasting horizon (end of June of the following year) and EPS/multiple forecast (end of the current financial year) display a time mismatch of a maximum of 180 days. Hence, on average, there is a difference of three months between the target price forecasting horizon and the *pseudo*-target price horizon.

or EVA) for company valuation. Demirakos *et al.* (2010), despite not testing this hypothesis in their paper, reckoned that the joint use of multiple estimates could have a significant impact on accuracy. To control for these cases, we introduce a dummy variable called "additional model" (ADD_MODEL) that equals one when analysts report estimates from more than one model and zero otherwise.[n]

3.2.2.2. Forecast-specific characteristics

Prior research (e.g. Bonini *et al.* 2010, Kerl 2011, Bradshaw *et al.* 2013) has shown that forecasts that deviate significantly from the prevailing stock price are (*ex-post*) less accurate because it is less likely that such forecasts will be exactly met after the forecast horizon. To control for such forecast inflation, we compute analyst-specific "boldness" (BOLDNESS) as the absolute difference between the target price and the stock price (on the day the report is issued), scaled by the stock price. We consider forecasts to be bold if they considerably differ from the prevailing stock price.

From an investor perspective, it is desirable to observe that the stock price exceeds the forecast at the end of the investment horizon. Analysts may therefore have an incentive to willingly cut the "true" forecast to increase the likelihood of investors experiencing this sort of outperformance. We control for this possible behavior through a dummy variable (OVERACHIEVEMENT) that equals one if the 12-month stock price is higher than the target price forecast and zero otherwise.[o]

Bilinski *et al.* (2013) show that analysts who are more skillful or experienced issue better earnings forecasts as well as target prices, and also make more sophisticated subjective adjustments to the simple *pseudo*-target prices. As such, they suggest controlling for the joint accuracy of earnings forecasts and target prices. To proxy the level of private information that is included in the subjective adjustments, we compute the absolute EPS forecast error (EPS_ERROR).

We argue that the length of each report might be a proxy for the thoroughness of the analyst's valuation of a company. Hence, we create a variable called REPORT_LENGTH, which counts the number of pages in each report.

Finally, we introduce a set of standard control variables at the single report level. In particular, we compute a dummy variable that equals one if the analysts' recommendation for the company is upgraded (downgraded) from the previous published report, and zero otherwise [UP (DOWN)]. EPS_REV represents the percentage change of the current earnings per share forecast compared to the previous earnings per share forecast (published within the previous report); similarly, TP_REV is computed as the percentage change of the current target price forecast

[n] To extract this information from the analyst reports, we manually check all general disclosure sections and each section where the target price valuation is discussed in detail.

[o] Note that this logic is based on a positive target price forecast that is higher compared to the prevailing stock price at the date of the report issuance. In case of the target price being below the prevailing stock price (i.e. a negative forecast), the logic reverses and we code a stock price (after 12 months) that falls below the target price forecast as having overachieved the forecast.

compared to the previous target price forecast (published within the previous report).[p] If the information from the previous forecast is not included in the report at the publication day, we take the most recent report available in the *Investext* database on the specific firm (if released within 60 days prior to the publication day) to extract the previous earnings forecast or target price manually. We additionally split TP_REV into TP_REV_pos and TP_REV_neg. TP_REV_pos (TP_REV_neg) equals TP_REV for positive (negative) target price revisions, and zero otherwise. To account for the general type of recommendation, we include a dummy called BUY (SELL) that equals one if the analyst's report contains a buy or strong buy (sell or strong sell) recommendation.

3.2.2.3. Broker-specific characteristics

With respect to broker characteristics, the literature argues that the reputation of a bank plays an important role in terms of forecast accuracy. Clement (1999) and Jacob *et al.* (1999) show that analysts working for highly reputable banks issue more accurate earnings forecasts. Accordingly, we create a dummy variable TOPBANK that equals one for those reports published by one of the three banks that have employed the highest average number of top analysts in the three-year sample period. Top analysts are identified by the yearly *All Institutional Investors*' rankings issued by the *Institutional Investor* magazine.

Furthermore, we introduce a variable called EXPERIENCE that counts the number of reports that each specific analyst has issued previously. Following Jacob *et al.* (1999) and Emery & Li (2009), one might assume that this measure accounts for industry knowledge and general experience.

3.2.2.4. Company-specific characteristics

We use the market capitalization (MV) of each stock from *Datastream* on the day of the publication of the analyst's report. In the extant literature (e.g. Stickel 1995), company size is often used as a proxy for the information environment of the company. We accordingly build the variable LOG_MV as the natural logarithm of market capitalization. To control for growth and value stocks, we download the price-to-book value from *Datastream* on the day of the publication of the analyst's report. In addition, we compute the one-year performance prior to the publication day of the analysts' reports (1_YEAR_HISTORIC_RETURN). Next, we compute the standard deviation based on daily returns for the one-year period prior to the publication day of the analyst's report (VOLATILITY).

Finally, we include ANALYST, TIME, and INDUSTRY fixed effects that control for the specific analyst and year of each report and the specific industry in which a company operates.[q] We consider the INDUSTRY control to be important because

[p] In order to exclude potential outliers, we truncate the first and 99th percentiles of TP_REV and EPS_REV. We have also experimented winsorization and the results are qualitatively the same.

[q] For the TIME variable, the year 2002 is the base case. For the INDUSTRY variable, we take the largest group of companies as the base case, classified as companies belonging to the industrial sector.

various papers (e.g. Barker 1999b, Demirakos *et al.* 2004) have found that the selection of valuation models might depend on industry-specific characteristics.

3.3. *Sample summary statistics*

Table 3 presents the summary statistics for the full sample of 1000 reports.[r] Based on our sample, 949 reports contain target prices, 918 reports contain EPS forecasts, and 857 reports contain PE multiples, which are required to compute *pseudo*-target prices (see Panel A in Table 3). Panel B presents summary information for the dependent variables. *Ex-post* accuracy of issued target prices (TP_ACCURACY) is 67.32%. Furthermore, the summary statistics on CAR[−2, +2] show that cumulative abnormal returns are slightly negative on average (−0.61%). Panel C indicates that the average *pseudo*-target price (PSEUDO_TP) of €41.76 is slightly below the average target price (€44.49). This evidence suggests that analysts issue target prices that exceed simple multiple-based *pseudo*-target prices. The amount of deviation between target prices and *pseudo*-target prices (SUBJ_DEVIATION) ranges between no adjustment (0.01%) and very large ones (Max = 581.82%), with a sizeable mean value of 26.43%. A natural question that arises is why analysts release forecasts that are arguably similarly computed by the market participants (no adjustment forecasts) and therefore uninformative. However, as pointed by several contributions (e.g. Cheng *et al.* 2006, Hong & Kubik 2003, Jegadeesh *et al.* 2004), there are multiple reasons why analysts need to provide coverage of firms, even when forecasts do not convey substantial new information. For example, coverage and research are needed to confirm the existence of the viability of current price levels; research is part of a more general relationship between companies and financial institutions; investors use analysts' research to validate their own assessments; and analysts have career concerns that lead to the production of information to gain visibility.

With respect to the choice of valuation model, 31.93% of all reports state that additional models (ADD_MODEL), such as the DCF and EVA models, are used along with the basic multiples whereas the remaining reports refer to multiples as the only basis for the target price valuation.[s]

Figures in Panel D of Table 2 show that the average current stock price is €39.23, ranging from €1.17 to €566.49. At the same time, the target price has a (higher) mean of €44.49. Hence, analysts are on average optimistic about the future performance, which is consistent with the overall analyst optimism, as demonstrated by the

[r] Note that we truncate the first and 99th percentiles of TP_ACCURACY and VOLATILITY for the purpose of outlier elimination. Similarly, we truncate the 99th percentile of SUBJ_DEVIATION, which we also apply to PSEUDO_TP.

[s] It is not unsurprising that almost all reports mention the use of multiples. Asquith *et al.* (2005) have also reported that, for a sample of 1126 analyst reports, 99% mention the use of PE multiples whereas only 13% use DCF methods.

[t] Within the period from 2002 to 2004, there have been both bull and bear market phases. However, even in bear market phases, analysts are normally quite optimistic that markets will rebound.

Table 2. Summary statistics.

	N	Min	Mean	Median	Max	SD
Panel A: Total sample						
No. of reports with TP	949					
No. of reports with EPS (FY1)	918					
No. of reports with PE multiples	857					
Panel B: Dependent variables — target price accuracy/short-term market reaction/long-term performance						
TP_ACCURACY (%)	949	−44.70	67.32	73.48	99.63	26.19
CAR[−2, +2] (%)	949	−55.55	−0.61	−0.29	75.20	8.01
CAR[−5, +5] (%)	949	−61.28	−0.46	−0.52	72.75	9.95
Panel C: Explanatory variables - valuation model characteristics						
PSEUDO TP	810	−31.62	41.76	32.13	1060.40	60.06
SUBJ_DEVIATION (%)	810	0.01	26.43	17.18	581.82	41.26
ADD MODEL (%)			31.93			
Panel D: Explanatory variables - forecast-specific characteristics						
Current stock price	949	1.17	39.23	31.25	566.49	46.47
Target price	949	1.20	44.49	35.00	540.00	49.59
BOLDNESS (%)	949	0.00	23.75	15.74	350.00	31.46
OVERACHIEVEMENT (%)	946		36.89			
EPS_ERROR (%)	866	0.00	112.10	46.08	2264.55	256.82
REPORT LENGTH	949	3	6.42	5	20	3.86
TP_REV (%)	922	−89.09	−0.36	0.00	425.00	19.45
EPS_REV (%)	815	−71.15	−0.63	0.00	395.35	20.32
UP (%)	949		5.27			
DOWN (%)	949		6.74			
Panel E: Independent variables - broker-specific characteristics						
TOPBANK (%)			48.89			
EXPERIENCE	563	1	36.42	28	248	33.44
Panel F: Independent variables - company-specific characteristics						
MV (Market Capitalization)	949	26	12365	4627	72602	16355
PTBV (Price-to-book value)	948	0.35	2.29	1.71	21.43	2.06
1_YEAR_HISTORIC_RETURN (%)	946	−90.63	−2.49	−12.87	959.64	65.22
VOLATILITY	929	0.01	0.03	0.03	0.06	0.01

Notes: Panel A of this table displays information on the number of reports containing target prices, earnings forecasts, and PE multiples. The data are based on a panel of analyst reports on German companies over the period 2002–2004. Reports are received from the *Investext* database from *Thomson Research*. Panel B displays descriptive information on the dependent variables with regard to target price accuracy and the short-term market reaction. Panel C displays summary statistics for valuation model characteristics. Panel D shows descriptive information on forecast-specific characteristics. Panel E displays information on broker-specific characteristics whereas Panel F provides summary statistics on characteristics of the covered companies. For further details on the definitions of variables, see Table 1.

literature (e.g. Barber *et al.* 2006),[t] and more generally, they show a substantial degree of boldness with an average deviation from the current stock price at the forecast release date of 23.75%. Quite interestingly, the stock prices overshoot previously issued price targets in 36.89% of the cases. Furthermore, an average report contains 6.42 pages.

With respect to broker-specific characteristics, Panel E of Table 2 reveals that approximately 48.89% of the reports are issued by banks that we classify as top banks (TOPBANK). Additionally, we find that analysts have written an average of 36.42 reports (EXPERIENCE) prior to the report under consideration.

Panel F of Table 2 provides descriptive statistics on the covered companies. The market capitalization of companies is an average €12365 million, the price-to-book value is 2.29, and the one-year historic stock return (1_YEAR_HISTORIC_RETURN) is slightly negative (−2.49%).

Table 3 shows the Pearson correlation results for pairwise observations for all dependent and independent variables. The accuracy of price targets is positively correlated with a company's market capitalization (0.27) but is negatively correlated with a company's return volatility (−0.27). With respect to our key variable SUBJ_DEVIATION, our results reveal a positive correlation with the BOLDNESS of a price target (0.59). Although this level is not critical, we introduce interaction terms between these two variables for all accuracy models reported in Tables 5 and 6 to obtain clear inferences of the causal effect (if any) of our independent variable of interest (SUBJ_DEVIATION). Additionally, in all models we perform VIF tests to measure multicollinearity among variables.

3.4. *Accuracy and main explanatory variables' descriptive statistics*

Table 4 shows the descriptive statistics for the three key variables: TP_ACCURACY, BOLDNESS, and SUBJ_DEVIATION. Within all panels (A–I), we first show the results for all reports and, additionally, for (i) the sub-sample of reports that only use multiple valuation (ADD_MODEL $= 0$) and (ii) those reports that jointly use multiple-based models and additional methodologies (ADD_MODEL $= 1$). This table captures whether there are structural differences with respect to forecast accuracy, boldness, and deviation from simple models across the different valuation models that are used. In Panel A, which covers the total sample of all reports, the results show that neither TP_ACCURACY nor BOLDNESS generally differs significantly between both groups of analysts. The results indicate that the TP_ACCURACY is approximately 67%, whereas the average BOLDNESS is 24%. The only difference between both sub-groups of reports can be found with respect to the variable SUBJ_DEVIATION. Target prices most heavily deviate from the computed *pseudo*-target prices when analysts use more than just multiple-based models. In fact, target prices deviate from *pseudo*-target prices by 23.84% in the pure multiple valuation group, but this figure increases to 31.92% when analysts also jointly adopt the DCF or EVA models.

We then split the sample according to median market capitalization (high versus low: Panels B and C of Table 4), median price-to-book ratio (high versus low: Panels D and E of Table 4), median volatility (high versus low: Panels F and G of Table 4), and the dummy variable TOPBANK (Panels H and I of Table 4), and we obtain a number of relevant results. First, the results show that the relative use of additional valuation models is higher for small and growth stocks. For example, whereas the additional models are only used in 26.58% of large companies, they are used in 37.26% of small companies. This result is in line with the literature

Table 3. Correlation table.

	TP_ACCURACY	CAR[−2, +2]	CAR[−5, +5]	SUBJ_DEVIATION	BOLDNESS	EPS_ERROR	EPS_forecast	BUY	SELL	OVERACHIEVEMENT	LOG_MV	PTBV	VOLATILITY	ADD_MODEL	TOPBANK	REPORT_LENGTH	EXPERIENCE	TP_REV	EPS_REV
TP_ACCURACY	1																		
CAR[−2, +2]	0.05	1																	
CAR[−5, +5]	0.08	0.79*	1																
SUBJ_DEVIATION	−0.03	0.05	0.05	1															
BOLDNESS	−0.13*	−0.06	−0.01	0.59*	1														
EPS_ERROR	−0.10*	−0.07	−0.06	0.01	0.02	1													
EPS_forecast	−0.02	0.05	0.07	0.02	0.03	−0.03	1												
BUY	0.09	0.11*	0.11*	0.28*	0.41*	−0.05	0.05	1											
SELL	−0.20*	−0.06	−0.08	−0.05	−0.05	0.09	0.03	−0.32*	1										
OVERACHIEVEMENT	0.20*	0.05	0.06	−0.08	−0.14*	−0.03	0.03	−0.01	−0.08	1									
LOG_MV	0.27*	0.05	0.00	−0.08	−0.22*	−0.07	−0.05	−0.04	−0.07	−0.03	1								
PTBV	−0.06	0.04	0.02	0.08	−0.06	−0.07	0.01	0.08	−0.06	−0.03	0.11*	1							
VOLATILITY	−0.25*	−0.01	0.03	0.12*	0.20*	0.21*	−0.1	−0.01	0.12*	−0.03	−0.29*	0.15*	1						
ADD_MODEL	0.01	0.03	0.06	0.09	0.06	−0.06	0.00	0.08	0.02	0.04	−0.08	0.12*	0.03	1					
TOPBANK	0.02	0.05	0.03	0.02	−0.07	0.03	−0.01	−0.11*	−0.04	0.02	−0.17*	0.03	0.03	0.01	1				
REPORT_LENGTH	0.11*	0.03	0.02	0.03	0.04	−0.06	−0.02	0.07	−0.06	0.11*	0.06	0.01	0.03	0.30*	−0.07	1			
EXPERIENCE	0.00	−0.02	−0.01	−0.02	−0.07	0.01	0.02	0.06	−0.02	−0.02	0.01	−0.08	−0.10	−0.11	0.23*	−0.17*	1		
TP_REV	−0.01	0.23*	0.18*	0.08	0.07	−0.02	0.07	0.07	−0.01	0.06	0.01	0.03	0.06	0.06	0.01	0.01	−0.01	1	
EPS_REV	−0.02	0.22*	0.17*	0.05	0.07	−0.04	0.11*	0.07	−0.05	0.06	0.02	0.04	0.06	0.06	0.00	−0.01	−0.06	0.75*	1

Notes: This table displays Pearson's correlation results for pairwise observations. All variables are defined in Table 1. Whereas TP_ACCURACY, CAR[−2, +2], and CAR[−5, +5] serve as dependent variables within the analyses, all other variables are used as explanatory variables.

*denotes statistical significance at the 1% level.

(e.g. Demirakos *et al.* 2010), which has shown that analysts prefer DCF to PE multiple models when valuing small firms, high-risk firms, and firms with a limited number of industry peers. Second, comparing the *total* TP_ACCURACY figures from Panels B–I with Panel A of Table 4 reveals that analysts' forecasts are higher for large companies (73.27%) and low-volatility stocks (72.52%) compared to the total sample (67.32%). With respect to large companies, the literature refers to a more robust firm information environment (e.g. Stickel 1995), most likely due to better firm disclosure or higher analyst coverage. Focusing on the different levels of TP_ACCURACY within each panel, the results show that additional valuation models seem to be especially useful for valuing large, growth, and low-volatility stocks. Valuing large companies, for example, based on more sophisticated models leads to a significantly higher level of accuracy (76.82%) compared to using simple multiple models (72.18%). For the other groups of companies (small, value, and high volatility), similar results cannot be derived. Third, when comparing the *total* figures to forecast BOLDNESS, the results show that analysts are generally much bolder when dealing with small, value, and highly volatile stocks. However, when focusing on the different levels of BOLDNESS across the different valuation models within each panel, we cannot find any (significant) difference between both groups of valuation models. It seems that the amount of analyst boldness is independent of the selected model. Finally, comparing the *total* figures of SUBJ_DEVIATION shows that analyst deviation from *pseudo*-target prices is the highest within the groups of small (28.36%) and high-volatility stocks (31.80%) compared to the total sample in Panel A of Table 4 (26.43%). With respect to the different levels of SUBJ_DEVIATION across the different valuation models within each panel, the results show that analysts deviate the most within the sub-groups of large, growth, and low-volatility stocks. Hence, exactly in those cases where TP_ACCURACY is the highest, the issued target prices most heavily deviate from their *pseudo*-target prices within these groups of stocks.

4. Empirical Results

4.1. *Accuracy and subjective deviation*

The deviations from the simple naive baseline identified above could be either random or nonrandom. If adjustments were not information-driven they should also be nonsystematic, i.e. the cross-sectional predictive power of deviations should be zero and parameter estimates insignificant. Differently, if they contain valuable information, they should be significantly predicting future prices. We test this main conjecture by estimating the following equation:

$$\begin{aligned}\mathrm{ACCURACY}_i = {}& \beta_0 + \beta_1 \mathrm{SUB\_DEVIATION}_i + \beta_2 \mathrm{BOLDNESS}_i + \beta_3 \mathrm{EPS\_ERROR}_i \\ & + \beta_4 \mathrm{BUY}_i + \beta_5 \mathrm{SELL}_i + \beta_5 \mathrm{OVERACHIEVEMENT}_i + \beta_6 \mathrm{LOG\_MV}_i \\ & + \beta_8 \mathrm{PTBV}_i + \beta_9 \mathrm{VOLATILITY}_i + \beta_{10} \mathrm{ANALYST}_i + \beta_{11} \mathrm{TIME}_i \\ & + \beta_{12} \mathrm{INDUSTRY}_i + \varepsilon_i. \end{aligned} \tag{4.1}$$

OLS regressions are estimated with analysts fixed effects and White heteroscedasticity-consistent standard errors clustered at the analyst level to control for cross-sectional correlations as in Petersen (2009). VIF tests on all specifications do not provide evidence of meaningful multicollinearity issues. We repeat this important robustness control on all subsequent regressions with similar results.

Table 5 reports the results. Model 1 reports the estimated parameters for the baseline equation (3.1). In Models 2 and 4, we add an interaction term between BOLDNESS and SUBJ_DEVIATION to control for whether SUBJ_DEVIATION depends on the general level of BOLDNESS. Incidentally, the interaction term allows drawing clean inferences on the effects of deviation on accuracy controlling for the joint level of boldness. Models 1 and 2 show regression results without fixed effects, whereas Models 3 and 4 include controls for analyst-, time-, and industry-specific characteristics.

The results in Table 5 indicate a significantly positive coefficient of SUBJ_DEVIATION across all four different model specifications. Hence, target prices

Table 5. Summary statistics on target price accuracy, boldness and subjective deviation.

	TP_ACCURACY			BOLDNESS		SUBJ_DEVIATION	
	N	Fraction (%)	Mean	*N*	Mean	*N*	Mean
Panel A: Total sample							
Total	949		67.32	949	23.75	810	26.43
ADD_MODEL = 0	600	63.22	67.06	600	23.25	516	23.84
ADD_MODEL = 1	303	31.93	68.04	303	25.22	265	31.92
Diff.			−0.98		−1.97		−8.08**
Panel B: Large companies (>median)							
Total	474		73.27	474	18.86	391	24.37
ADD_MODEL = 0	320	67.51	72.18	320	18.20	266	20.69
ADD_MODEL = 1	126	26.58	76.82	126	20.17	108	33.63
Diff.			−4.64**		−1.97		−12.93**
Panel C: Small companies (<median)							
Total	475		61.39	475	28.62	419	28.36
ADD_MODEL = 0	280	58.95	61.21	280	29.01	250	27.19
ADD_MODEL = 1	177	37.26	61.79	177	28.81	157	30.75
Diff.			−0.58		0.20		−3.56
Panel D: High price-to-book companies (>median)							
Total	473		66.91	473	20.09	401	25.46
ADD_MODEL = 0	274	57.93	64.91	274	20.01	238	22.44
ADD_MODEL = 1	176	37.21	69.37	176	20.81	148	31.09
Diff.			−4.46*		−0.80		−8.65*
Panel E: Low price-to-book ratio companies (<median)							
Total	476		67.73	476	27.38	409	27.38
ADD_MODEL = 0	326	68.49	68.87	326	25.97	278	25.04
ADD_MODEL = 1	127	26.68	66.19	127	31.33	117	32.98
Diff.			2.68		−5.36		−7.94**
Panel F: High-volatility companies (>median)							
Total	465		62.39	465	28.84	394	31.80
ADD_MODEL = 0	296	63.66	63.00	296	29.12	250	30.18
ADD_MODEL = 1	148	31.83	61.30	148	29.05	130	36.00
Diff.			1.69		0.07		−5.82

Table 5. (*Continued*)

	TP_ACCURACY			BOLDNESS		SUBJ_DEVIATION	
	N	Fraction (%)	Mean	N	Mean	N	Mean
Panel G: Low-volatility companies (>median)							
Total	464		72.52	464	17.46	402	20.57
ADD_MODEL = 0	292	62.93	71.25	292	16.61	258	17.44
ADD_MODEL = 1	147	31.68	75.47	147	19.01	129	26.55
Diff.			−4.22**		−2.39		−9.11***
Panel H: TOPBANK							
Total	464		67.87	464	21.85	430	26.84
ADD_MODEL = 0	297	64.01	68.69	297	21.37	279	23.68
ADD_MODEL = 1	150	32.33	67.62	150	22.98	140	33.34
Diff.			1.07		−1.61		−9.66*
Panel I: No TOPBANK							
Total	485		66.80	485	25.56	380	25.98
ADD_MODEL = 0	303	62.47	65.46	303	25.09	237	24.02
ADD_MODEL = 1	153	31.55	68.45	153	27.41	125	30.33
Diff.			−2.98		−2.32		−6.31*

Notes: This table displays descriptive statistics across the three key measures TP_ACCURACY, BOLDNESS, and SUBJ_DEVIATION for the total sample (Panel A), for large versus small companies (Panels B and C), for growth versus value companies (Panels D and E), for High- versus low-volatility stocks (Panels F and G), and for TOPBANKS versus no TOPBANKS (Panels H and I). Within each panel, we display figures for all observations (total) and split the results into sub-groups where (i) analysts purely use multiple valuation (ADD_MODEL = 0) and (ii) those where they additionnaly use other valuation models such as DCF or EVA (ADD_MODEL = 1). For further details on the definitions of variables, see the Table 1.

that highly deviate from simple multiple-based *pseudo*-target prices are (*ex-post*) more accurate. Furthermore, the results suggest that all other variables are in line with the literature. We focus on Model 3 for the discussion of results since this model controls for analyst, time, and industry fixed effects. BOLDNESS is significantly negative at the 10% level, revealing that forecasts that are highly deviating from the current stock price are less often exactly reached after the 12-month period. Similar results have been obtained by Demirakos *et al.* (2010) and Bradshaw *et al.* (2013), who show that target price accuracy is reduced in the cases where forecasts highly deviate from the prevailing stock price. EPS_ERROR is insignificant but the positive and highly significant coefficient of LOG_MV indicates that analysts provide more accurate price forecasts of companies with a high level of informational disclosure (e.g. Stickel 1995). Unsurprisingly, negative coefficients of PTBV confirm previous findings in Gleason *et al.* (2012) and Bradshaw *et al.* (2013) on the lower ability of analysts to forecast prices of riskier stocks. With respect to the negative sign of SELL recommendations across all model specifications, Kerl (2011) has shown that analysts' forecasting abilities seem to be lower for negative forecasts. This might be associated with the fact that analysts' models work better for positive forecasts compared to negative developments, in which more unknown factors are important. Model 4 additionally includes the interaction term BOLDNESS ×

SUBJ_DEVIATION. The base coefficient of SUBJ_DEVIATION remains significant at the 1% level but the negative coefficient for the interaction term is insignificant suggesting that analyst deviations from the *pseudo*-target price are the main determinant of target price accuracy.[u] This result provides further support to the survey evidence on analysts' use of nonfinancial information in Orens & Lybaert (2010) and the analysts' use of nonaccounting information in Barker & Imam (2008).

4.1.1. *Robustness tests*

Our results show that subjective deviations consistently explain accuracy in the analyst forecast. However, a number of rival factors may lead to the observed results. In Table 6, we perform a number of robustness tests to control for potential confounding factors. All regressions are performed using the same set of control variables as in Table 5 (i.e. EPS_ERROR, EPS_forecast, BUY, SELL, OVERACHIEVEMENT, LOG_MV, PTBV, and VOLATILITY).

The extant literature shows that the valuation model plays an important role in determining the forecast quality (Liu *et al.* 2002, Gleason *et al.* 2012) and is likely to affect our estimates. Theoretically, our finding of more accurate target price forecasts in the case of high deviations between target prices and *pseudo*-target prices (high SUBJ_DEVIATION) could be due to the application of more sophisticated valuation models. In particular, the source of the deviation could be due to a point adjustment of one or more inputs of either a model similar to the benchmark or an altogether different model. While we cannot observe the actual source of the deviation, we can control for the use of multiple models by the analysts. We therefore re-estimate Table 5 controlling for the selection of sophisticated models (ADD_MODEL) by analysts. Models 1 and 2 in Table 6 show that all previous results robustly hold and in particular SUBJ_DEVIATION is unaltered in terms of magnitude, sign, and significance as a determinant of target price TP_ACCURACY. Differently, the control dummy ADD_MODEL is insignificant in both models, indicating that deviations do not systematically come from one single source of adjustment and the use of sophisticated models *per se* does not lead to more accurate target price forecasts.

Stickel (1992), Mikhail *et al.* (2004), Bonner *et al.* (2007), and Fang & Yasuda (2013) show that star analysts and those working for well-known and successful institutions have a stronger influence on capital markets and issue forecasts that are more accurate and profitable compared to their peers' forecasts. We therefore control for this possible effect on our results by including a dummy variable (TOPBANK) for the three banks that employ (on average) the highest number of top-rated analysts (following the yearly *All Institutional Investors*' rankings). The results reported in columns (3) and (4) of Table 6 show that forecasts from top banks are not

[u] We also checked for potential nonlinearities within the SUBJ_DEVIATION variable including a squared term of it. The results however are unchanged.

Table 6. Target price accuracy and forecasts characteristics.

	TP_ACCURACY			
	(1)	(2)	(3)	(4)
SUBJ_DEVIATION	0.043 ***	0.049 ***	0.042 ***	0.044 ***
	(2.93)	(3.30)	(2.95)	(2.98)
BOLDNESS	−0.112***	−0.033	−0.071*	−0.035
	(−2.89)	(−0.46)	(−1.78)	(−0.34)
BOLDNESS × SUBJ_DEVIATION		−0.048		−0.020
		(−1.55)		(−0.50)
EPS_ERROR	−0.005	−0.005	−0.002	−0.001
	(−0.84)	(−0.81)	(−0.26)	(−0.25)
EPS_forecast	−0.005**	−0.005**	0.000	−0.001
	(−2.01)	(−2.05)	(−0.10)	(−0.10)
BUY	0.043**	0.033	0.043	0.039
	(2.04)	(1.41)	(131)	(1.12)
SELL	−0.109***	−0.114***	−0.088	−0.090
	(−3.12)	(−3.25)	(−1.60)	(−1.64)
OVERACHIEVEMENT	0.096 ***	0.097 ***	0.060 **	0.060 **
	(4.95)	(5.01)	(2.35)	(2.38)
LOG_MV	0.031 ***	0.032 ***	0.047 ***	0.048 ***
	(5.14)	(5.18)	(3.33)	(3.36)
PTBV	−0.010**	−0.010**	−0.029***	−0.029***
	(−2.54)	(−2.46)	(−3.87)	(−3.77)
VOLATILITY	−0.038***	−0.039***	0.002	0.001
	(−3.17)	(−3.24)	(0.07)	(0.04)
ANALYST F.E.	No	No	Yes	Yes
TIME F.E.	No	No	Yes	Yes
INDUSTRY F.E.	No	No	Yes	Yes
Constant	0.518 ***	0.511 ***	0.251*	0.244*
	(8.69)	(8.53)	(1.97)	(189)
N	752	752	752	752
Adj.-R^2	0.176	0.177	0.362	0.361
F	12.604***	14.425***	5.249***	10.958***

Notes: This table displays regression results of target price accuracy on various analyst-specific and stock-specific measures. The target price accuracy measure equals one minus the absolute forecast error (i.e. the absolute difference between 12-month stock price and target price, scaled by target price). With regard to the analyst-specific information, SUBJ_DEVIATION measures the amount of deviation between the issued target price and the multiple-based *pseudo*-target price. We compute the *pseudo*-target price as the product of PE multiple and EPS forecast, as included within each report. BOLDNESS measures the analyst-specific optimism of each forecast. BOLDNESS × SUBJ_DEVIATION is the interaction term between the two variables BOLDNESS and SUBJ_DEVIATION. EPS_ERROR measures the absolute EPS forecast error. EPS_forecast represents the current earnings forecast. Whereas BUY (SELL) is a dummy variable for a buy (sell) recommendation as disclosed within each report, OVERACHIEVEMENT is a dummy variable that equals one in the case of the 12-month stock price being higher compared to the target price forecast (zero otherwise). With regard to the stock-specific measures, LOG_MVis the natural logarithmof the market capitalization of each stock at the publication day of the report. PTBV is the price-to-book value of each stock at the publication day of the report. VOLATILITY is the standard deviation based on daily returns for the one-year period prior to the publication day of a report. Models 3 and 4 control for analyst-, time-, and industry-specific effects. For further details on the definitions of variables, see Appendix. All regressions use White heteroscedasticity-consistent standard errors clustered at the analyst level, corresponding t-values are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% level, respectively.

significantly more accurate compared to those issued by other banks after controlling for the degree of subjective deviation.[v]

The thoroughness of the analysis can likely be an important factor in determining the quality of a forecast. We test this intuition using the length of a report as a proxy for its information content. Those analysts that provide more detail within their research publications (and hence publish longer reports) should arguably possess more information that is helpful for the valuation process. We proxy for the level of detail of the analysts' estimation exercise modeling a variable (REPORT_LENGTH) given by the page count of each report. Results reported in columns (5) and (6) of Table 6 do not provide additional explanatory power. The variable REPORT_LENGTH is slightly positive but insignificant and its introduction leaves the main result unchanged.

The significant effect of subjective adjustments to valuations emerging from a baseline model seems to be important determinant of forecast accuracy. However, adjustments may simply be the result of a stratified knowledge that builds over time and leads experienced analysts to capture unobservable factors affecting market prices. In such a case, we should observe deviations to be more common across experienced analysts. We address this important concern by measuring analyst-specific experience as the number of reports published by the same analyst from 1998 to the date of the report. We construct this variable (EXPERIENCE) by matching analyst names and institutions with the whole I/B/E/S set of analysts forecast from 1998 to the date of the last report. This variable can be computed for only 56% of our sample which introduces a potential sample size concern. Results presented in Models 7 and 8 of Table 6 show that experience is largely uncorrelated with subjective deviations and does not explain accuracy. Differently, the adjustments by analysts (SUBJ_DEVIATION) are significant at the 1% level and unchanged in the parameter sign and magnitude.

In Models 9 and 10 of Table 6, we jointly test these four controls. Results are unaffected with the exception of a mild positive significance of the REPORT_LENGTH variable that is qualitatively similar in magnitude to the estimates reported in Models 5 and 6 of Table 6.

4.2. *Short-term market reaction*

Brav & Lehavy (2003) have first shown that stock prices quickly adjust to the new information that is included in revised analyst forecasts. Accordingly, it could be argued that the stock market reaction should be more pronounced if the forecast changes are more valuable (i.e. those with a higher SUBJ_DEVIATION, as shown in Sec. 4.1). To address this question, we compute the cumulative abnormal returns (CAR[−2, +2] and CAR[−5, +5]) around the official publication date of each report

[v] Note that we only select banks to be included in our sample (see Sec. 3) that employed *All Institutional Investors*' star analysts. Because this was a strict selection criterion in the first place, it might explain why our results do not show any further impact of TOPBANK on the target price accuracy.

based on the event study methodology (MacKinlay 1997). The literature with respect to the market reaction based on analyst forecasts (e.g. Francis & Soffer 1997, Asquith *et al.* 2005) has shown that the stock reaction around the publication of an analyst's report is, to a large extent, driven by the "new" information it includes. Such information is generally measured in the literature by up- and down-grades of recommendation levels (UP and DOWN) and changes in EPS forecasts (EPS_REV) and target prices (TP_REV_pos and TP_REV_neg). In Model 1 of Table 7, we estimate the following standard OLS regressions with White heteroscedasticity-consistent standard errors clustered at the analyst level:

$$\begin{aligned}\mathrm{CAR}[-2,+2]_i = {} & \beta_0 + \beta_1\mathrm{SUBJ\_DEVIATION}_i + \beta_2\mathrm{TP\_REVpos}_i + \beta_3\mathrm{TP\_REVneg}_i \\ & + \beta_4\mathrm{EPS\_REV}_i + \beta_5\mathrm{UP}_i + \beta_6\mathrm{DOWN}_i + \beta_7\mathrm{LOG\_MV}_i + \beta_8\mathrm{PTBV}_i \\ & + \beta_9\mathrm{VOLATILITY}_i + \beta_{10}\mathrm{ANALYST}_i + \beta_{11}\mathrm{TIME}_i \\ & + \beta_{12}\mathrm{INDUSTRY}_i + \varepsilon_i. \end{aligned} \tag{4.2}$$

To analyze whether capital market participants can distinguish between the different levels of informativeness in analyst target prices, we additionally create interaction terms of each forecast revision (TP_REV_pos, TP_REV_neg, EPS_REV, UP, and DOWN) and SUBJ_DEVIATION. From these interaction terms, we can estimate the market reaction (if any) to analysts' departures from simple multiple-based valuation models.[w] Hence, we extend the basic model with respect to the inclusion of the interactions between SUBJ_DEVIATION and target price revision (Models 2 and 5 of Table 7) and the full set of interaction terms for all different forecast measures (Models 3 and 6 of Table 7). Columns (1)–(3) in Table 7 show the regression results based on CAR[−2, +2], whereas columns (4)–(6) report regressions based on CAR[−5, +5].

In line with the literature (e.g. Asquith *et al.* 2005), the results of Model 1 of Table 7 show that the market reacts positively if analysts increase their target price forecasts. The coefficient of TP_REV_pos is 0.076 although not significant. Not surprisingly, even if also insignificant, the coefficient of TP_REV_neg is larger (0.111), suggesting a stronger association between negative information (i.e. downgraded target price forecasts) and the resulting market reaction.[x] Based on interaction terms between the forecast variables and subjective deviation (Models 2 and 3 of Table 7), we analyze if markets are aware of different levels of informativeness in analysts' target prices. The coefficient for TP_REV_neg increases in magnitude and becomes significant supporting our previous interpretation. More importantly, the results reveal a positive and significant association between SUBJ_DEVATION and

[w] We argue that analysts who have additional information to justify their deviations from simple multiple-based *pseudo*-target prices are also likely to use this information to issue more valuable EPS forecasts or stock recommendations. Hence, Models 3 and 6 in Table 7 not only include the interaction term between SUBJ_DEVIATION and TP_REV but also interaction terms with the analysts' other forecasts.

[x] The coefficient of TP_REV_neg basically reveals a positive functional relation between the target price revision and market reaction. Hence, if the target prices are decreased, this consequently means that markets react in a negative way.

Table 7. Target price accuracy sophisticated valuation models, analysts ranking, report length and analyst experience.

	TP_ACCURACY									
	ADD_MODEL		TOPBANK		REPORT_LENGTH		EXPERIENCE		All variables	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SUBJ_DEVIATION	0.043***	0.045***	0.042***	0.044***	0.041***	0.042***	0.041***	0.043***	0.044***	0.046***
	(2.97)	(3.02)	(2.96)	(3.00)	(3.02)	(3.01)	(2.80)	(2.83)	(3.05)	(3.10)
BOLDNESS	−0.072*	−0.036	−0.071*	−0.036	−0.070*	−0.044	−0.057	−0.033	−0.055	−0.031
	(−1.80)	(−0.35)	(−1.79)	(−0.34)	(−1.81)	(−0.42)	(−0.79)	(−0.23)	(−0.78)	(−0.21)
BOLDNESS × SUBJ_DEVIATION		−0.020		−0.020		−0.015		−0.018		−0.019
		(−0.51)		(−0.50)		(−0.37)		(−0.25)		(−0.26)
ADD_MODEL	−0.018	−0.018							−0.043	−0.043
	(−0.60)	(−0.60)							(−1.06)	(−1.06)
TOPBANK			0.028	0.028					−0.047	−0.047
			(0.29)	(0.29)					(−0.36)	(−0.36)
REPORT_LENGTH					0.005	0.005			0.008*	0.008*
					(1.39)	(1.37)			(1.86)	(1.86)
EXPERIENCE							0.001	0.001	0.002	0.002
							(0.84)	(0.84)	(0.91)	(0.91)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ANALYST F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TIME F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
INDUSTRY F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. (*Continued*)

	TP_ACCURACY									
	ADD_MODEL		TOPBANK		REPORT_LENGTH		EXPERIENCE		All variables	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	0.261**	0.254*	0.235*	0.229	0.239*	0.234*	0.189	0.187	0.223	0.221
	(2.02)	(1.94)	(1.69)	(1.63)	(1.84)	(1.78)	(1.20)	(1.17)	1.246	1.221
N	752	752	752	752	752	752	464	464	464	464
Adj.-R^2	0.361	0.360	0.360	0.359	0.364	0.363	0.290	0.288	0.294	0.292
F	5.040***	9.992***	5.002***	10.593***	5.513***	11.387***	9.634***	9.257***	9.672***	9.645***

Notes: This table displays regression results of target price accuracy on various analyst-specific and stock-specific measures. The target price accuracy measure equals one minus the absolute forecast error(i.e. the absolute difference between 12-month stock price and target price, scaled by target price). With regard to the analyst-specific information, SUBJ_DEVIATION measures the amount of deviation between the issued target price and the multiple-based *pseudo*-target price. We compute the *pseudo*-target price as the product of PE multiple and EPS forecast, as included within each report. BOLDNESS measures the analyst-specific optimism of each forecast. BOLDNESS × SUBJ_DEVIATION is the interaction term between the two variables BOLDNESS and SUBJ_DEVIATION. Models 1 and 2 include the variable ADD_MODEL which equals one if the analyst computes his target price forecast based on additional, more sophisticated models such as DCF or EVA models in addition to purely using multiple-based models. Models 3 and 4 include the dummy variable TOPBANK that equals one for those reports written by one of the three banks that employ the highest average number of top analysts in the three-year sample period. Models 5 and 6 include the variable REPORT_LENGTH that displays the number of pages of each specific report. Models 7 and 8 include the variable EXPERIENCE that measures the total number of reports an analyst has written prior to the specific report. Models 9 and 10 include all four variables ADD_MODEL, TOPBANK, REPORT_LENGTH, and EXPERIENCE jointly. Within all models we use all control variables from Table 5 (EPS_ERROR, EPS_forecast, BUY, SELL, OVERACHIEVEMENT, LOG_MV, PTBV, and VOLATILITY) and control for analyst-, time-, and industry-specific effects. For further details on the definitions of variables, see Table 1. All regressions use White heteroscedasticity-consistent standard errors clustered at the analyst level, corresponding t-values are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

positive target price changes (TP_REV_pos, TP_REV_neg) suggesting that the market assigns a price-relevant information value to forecasts in which analysts deviate from simple multiple-based model outcomes, and consequently reacts in a marginally stronger way. Such a behavior seems rational as Table 5 has revealed that target price forecasts based on higher levels of SUBJ_DEVIATION are (*ex-post*) more accurate. The interaction between negative target price changes (TP_REV_neg) and SUBJ_DEVIATION is significantly negative. These results similarly hold for the longer event window (CAR[−5, +5]) where we also document significant market reaction levels for both positive and negative revisions associated with deviations from the simple valuation models.

As previously shown, the selection of more sophisticated models is associated with specific stock characteristics such as growth and size. Arguably, a more advanced valuation technique may lead to more credible estimates, causing stronger reactions from market participants. We test this hypothesis in a multivariate setting by introducing the dummy variable ADD_MODEL used for accuracy tests and an appropriate set of interaction terms with the relevant forecast measures (TP_REV_pos, TP_REV_neg, EPS_REV, UP, and DOWN). Results, omitted for brevity, do not

Table 8. Market reaction to analyst reports with respect to the deviation from multiple valuation.

	CAR[−2, +2]			CAR[−5, +5]		
	(1)	(2)	(3)	(4)	(5)	(6)
SUBJ_DEVIATION	0.012	0.008	0.015	0.012	0.007	0.020
	(1.29)	(114)	(1.29)	(0.83)	(0.64)	(1.26)
SUBJ_DEV × TP_REV_pos		0.365**	0.302*		0.380**	0.273
		(2.38)	(1.67)		(2.39)	(1.42)
SUBJ_DEV × TP_REV_neg		−0.220*	−0.312***		−0.404**	−0.563***
		(−191)	(−2.61)		(−1.97)	(−2.64)
SUBJ_DEV × EPS_REV			0.306			0.524*
			(1.43)			(1.66)
SUBJ_DEV × UP			−0.016			−0.032*
			(−113)			(−1.86)
SUBJ_DEV × DOWN			−0.030			−0.075
			(−0.20)			(−0.33)
BOLDNESS	−0.060	−0.063*	−0.067*	−0.046	−0.052	−0.060
	(−1.58)	(−1.66)	(−1.72)	(−1.00)	(−1.10)	(−1.23)
TP_REV_pos	0.076	−0.015	−0.006	0.122*	0.024	0.039
	(1.21)	(−0.22)	(−0.09)	(1.94)	(0.31)	(0.50)
TP_REV_neg	0.111	0.168*	0.187**	0.074	0.177	0.211*
	(1.40)	(1.77)	(2.04)	(0.70)	(1.36)	(1.67)
EPS_REV	0.042	0.040	−0.021	0.103*	0.099	−0.005
	(0.88)	(0.84)	(−0.33)	(1.66)	(1.58)	(−0.08)
UP	−0.024	−0.021	−0.016	−0.007	−0.003	0.007
	(−1.55)	(−1.37)	(−0.99)	(−0.37)	(−0.17)	(0.38)
DOWN	−0.031*	−0.029	−0.025	−0.015	−0.009	0.000
	(−1.76)	(−1.61)	(−1.35)	(−0.61)	(−0.39)	(−0.01)
LOG_MV	−0.003	−0.002	−0.003	−0.009*	−0.009*	−0.011**
	(−0.79)	(−0.70)	(−0.97)	(−1.78)	(−1.69)	(−2.07)

Table 8. (*Continued*)

	CAR[−2, +2]			CAR[−5, +5]		
	(1)	(2)	(3)	(4)	(5)	(6)
PTBV	−0.002	−0.002	−0.001	−0.006	−0.006	−0.005
	(−0.62)	(−0.63)	(−0.47)	(−1.09)	(−1.07)	(−0.91)
VOLATILITY	−0.008	−0.008	−0.010*	0.001	0.000	−0.003
	(−1.44)	(−1.60)	(−1.76)	(0.07)	(−0.04)	(−0.31)
ANALYST F.E.	Yes	Yes	Yes	Yes	Yes	Yes
TIME F.E.	Yes	Yes	Yes	Yes	Yes	Yes
INDUSTRY F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.079**	0.080**	0.089**	0.115*	0.118*	0.134**
	(2.22)	(2.12)	(2.31)	(1.95)	(1.90)	(2.15)
N	705	705	705	705	705	705
Adj.-R^2	0.049	0.064	0.066	0.014	0.033	0.038
F	3.093***	2.946***	2.614***	2.476***	**2.427*****	2.250***

Notes: This table displays regression results of cumulative abnormal returns around the publication date of analyst reports on various analyst measures. CAR[−2, +2] measures the five-day abnormal return around the report is suance whereas CAR[−5, +5] measures the 11-day abnormal return. SUBJ_DEVIATION measures the amount of deviation between the issued target price and the multiple-based *pseudo*-target price. We compute the *pseudo*-target price as the product of PE multiple and EPS forecast, as included within each report. BOLDNESS measures the analyst-specific optimism of each forecast. TP_REV_pos (TP_REV_neg) measures the percentage change of the current target price issued for a firm at the publication day compared to the previous target price of the firm if it is positive (negative), otherwise it is zero. EPS_REV measures the percentage change of the EPS forecast for the upcoming financial year issued for a firm at the publication day compared to the previous EPS forecast for the firm. UP (DOWN) is a dummy variable that equals one if the analyst's recommendation for the company is upgraded (downgraded) within the published report, zero otherwise. Additionally, we include interaction terms between SUBJ_DEVIATION and TP_REV_pos/TP_REV_neg within Models 2 and 5. Within Models 3 and 6, interaction terms between SUBJ_DEVIATION and all analyst forecast measures are included. LOG_MV is the natural logarithm of the market capitalization of each stock at the publication day of the report. PTBV is the price-to-book value of each stock at the publication day of the report. VOLATILITY is the standard deviation based on daily returns for the one-year period prior to the publication day of a report. Within all models we control for analyst-, time-, and industry-specific effects. For further details on the definitions of variables, see the Appendix. All regressions use White heteroscedasticity-consistent standard errors clustered at the analyst level, corresponding t-values are reported in parentheses. ***, ** and *denote statistical significance at the 1%, 5% and 10% levels, respectively.

support this notion and we find no evidence for a differential reaction by the market to the choice of valuation methodology.

5. Conclusions

Analysts serve an important function in capital markets. In this study, we provide previously unavailable evidence on target prices estimation characteristics and the related accuracy, and we investigate whether the choice of a specific valuation methodology is valuable to investors. Previous research (e.g. Liu *et al.* 2002, Gleason *et al.* 2012) shows that the adoption of certain valuation models (multiple versus residual income models) may result in more accurate forecasts. However, there is ample evidence showing that analysts hardly ever take the outcome of any valuation model at face value; rather, they adjust the models to account for factors such as the company's structure, relative market position, previous performance, or other firm and market characteristics. Analysts arguably possess additional information due to their experience or broad industry expertise that justifies these additional adjustments. Following this intuition, we investigate whether analyst forecasts that deviate from basic valuation model outcomes are more accurate predictions by computing a measure for such deviation as the difference between the actual forecast and multiple-based *pseudo*-target prices. We obtain several novel results: First, based on standard OLS regressions, we show that those forecasts in which analysts deviate from the simple *pseudo*-target prices are (*ex-post*) considerably more accurate. We argue that this increased accuracy can be attributed to additional information that analysts use to adjust their forecasts. Second, following the findings from Liu *et al.* (2002) and Gleason *et al.* (2012), we account for the potential influence of the selected valuation model. When controlling for the selected valuation model, our main finding that forecast accuracy and deviation from simple multiple-based models are positively associated is unchanged. In further robustness checks, we find no evidence for this result to change if we control for the status of the bank, the thoroughness of the evaluation, measured as the page count of a report, or the analyst-specific experience. Third, we test whether the market is aware of these differences in forecast accuracy when adjusting prices following the issuance of analysts' reports. We argue that investors should be able to capture the quality of a forecast and adjust their trading strategies accordingly. On a standard event-study setting, we find evidence for the market to react stronger to positive target price changes if analysts purposely deviate from simple *pseudo*-target prices when issuing their forecasts. Hence, it seems as if market participants are to some extent aware of the additional value of such forecasts. On the contrary, we find no difference in the short-term reaction to analyst reports with respect to the selection of DCF models for valuation purposes (relative to multiple valuation).

These results shed additional light on the role of analysts as information providers and the value of sell-side research for investors. In particular, we suggest that the nature of the forecasting task performed by analysts is an important source of information that is valuable to investors and that is still recognized by market participants only to a limited extent. A question that remains unanswered is on which grounds analysts perform their adjustments. Given that this is an entirely unobservable variable, a possible research approach could go in the direction of hand-collecting survey data from analysts in order to shed light on this important component of the forecasting process. We will address this task in future research.

Appendix A

Table A.1.

	SUBJ_DEVIATION			
Analyst	Standard deviation	Min	Max	Number of reports
Blum	1.0364	0.0059	4.4245	23
Siebrecht	0.1867	0.0065	0.8432	20
Annutsch	0.1092	0.0169	0.3730	16
Breitsprecher	0.0724	0.0003	0.1936	16
Geiger	0.3940	0.0160	1.4612	16
Benson	0.5711	0.0021	2.3019	15
Hofacker	0.2213	0.0111	0.8438	15
Hendricks	0.1339	0.0762	0.5179	12
Reilly	0.1671	0.0753	0.5658	12
Ashton	1.3419	0.0078	3.4073	10
Deimel	0.2005	0.0411	0.6874	10
Foessmeier	0.1151	0.0825	0.3871	10
Helmholz	0.1141	0.0305	0.3854	10
Danjou	0.1427	0.0209	0.3495	9
Faitz	0.2093	0.0928	0.7544	9
Pinatel	0.0907	0.0007	0.2755	9
Sigee	0.4926	0.0040	1.5693	9
Andreas	0.1566	0.0101	0.5069	8
Flurschuetz	0.3754	0.0079	1.1472	8
Geall	0.2086	0.0730	0.7363	8
Kraemling	0.0498	0.0499	0.1972	8
Oblinger	0.1496	0.0526	0.5320	8
Rans	0.6651	0.0008	1.9900	8
...	...	...	...	...

Notes: This table shows the analyst-specific standard deviation of SUBJ_DEVIATION alongside the analyst-specific minimum/maximum SUBJ_DEVIATION for the decile of most active analysts of our sample. Thereby, we measure the activity by the number of issued reports in the sample period from 2002 to 2004. SUBJ_DEVIATION measures the amount of deviation between the issued target price and the multiple-based *pseudo*-target price.

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