Do analysts' target prices stabilize the stock market?

Markus Buxbaum[1] · **Wolfgang Schultze**[1] · **Samuel L. Tiras**[2]

Abstract
If target prices reflect the true values of stocks, they should direct prices towards intrinsic values. But analysts' optimism and use of less sophisticated valuation methods have been found to impede target price informativeness. Contrary to conventional belief, we propose that, due to analysts' optimism, target prices are closer to intrinsic values, and hence more informative, when investor sentiment is low. Accordingly, we find that the association of target prices with future returns is highest when investor sentiment is low and target prices are inferred to be based on sophisticated valuation methods. When investor sentiment is high, however, we find that the association of target prices with future returns approaches zero, suggesting that analyst optimism drives target prices away from intrinsic values, irrespective of the implied valuation method. Further, investors' reactions to target price revisions are strongly positive and seemingly irrational with high investor sentiment—which potentially destabilizes markets.

Keywords Target prices · Sophisticated valuation models · Analyst optimism · Investor sentiment

JEL Classification M41

✉ Samuel L. Tiras
stiras@iu.edu

Markus Buxbaum
markus.buxbaum@wiwi.uni-augsburg.de

Wolfgang Schultze
wolfgang.schultze@wiwi.uni-augsburg.de

[1] University of Augsburg, Universitätsstraße 2, 86159 Augsburg, Germany

[2] Kelley School of Business, Indiana University, 801 W. Michigan Street, BS 4004, Indianapolis, IN 46202, USA

1 Introduction

This paper studies the extent that analysts' target prices have a stabilizing role in stock markets. Market participants are known to not always behave rationally by trading on "noise " rather than on "news " (i.e., information) (Black 1986). Psychology shows that investors are irrational in a predictable (correlated) way and that investor sentiment[1] drives stock prices away from fundamental values (e.g., Brown and Cliff 2005; Baker and Wurgler 2006). Analysts – as key capital market intermediaries – inform investors about firms' financial prospects (e.g., Bradshaw et al. 2017). Among analysts' key outputs (i.e., earnings forecasts, stock recommendations, and target prices), target prices have been found to be especially informative (e.g., Brav and Lehavy 2003; Asquith et al. 2005). Because target prices are presumed to convey analysts' opinions about what a stock is truly worth (e.g., Bandyopadhyay et al. 1995; Gleason et al. 2013), they should direct prices towards intrinsic values and counteract the influence of investor sentiment in order to have a stabilizing role in capital markets.

Prior literature finds that target prices are informative, but they are highly inaccurate and often too high (e.g., Bilinski et al. 2013; Bradshaw et al. 2013), thus of limited investment value. The literature provides evidence that this may be because target prices are: (1) optimistically biased due to analysts' job-related incentives (e.g., Bradshaw et al. 2006; Dechow and You 2020); and, (2) based on insufficient valuation assumptions and techniques that poorly reflect intrinsic values (Demirakos et al. 2010; Gleason et al. 2013). In this paper, we examine the extent to which the effects of both explanations depend on investor sentiment. In contrast to the conventional belief that target price optimism always weakens the informativeness of target prices, we expect that it has a positive effect on the investment value of target prices when investor sentiment is low, but not when it is high.

Brav and Lehavy (2003) show that target prices and share prices comove in optimistic relations and the long-term ratios of target prices and share prices (long-term BL-Ratios, henceforth) are stationary. Likewise, the evidence in Bradshaw et al. (2013) indicates that, while the degree of optimism varies across time, it is always positive, that is, target prices exceed concurrent share prices in all market phases. In addition, the literature finds that stock prices fluctuate strongly, but intrinsic values are rather stable over time (Shiller 1981). For target prices to be informative about business fundamentals and have a stabilizing role in the market, we would expect that they are close to intrinsic values and help align market prices to fundamentals.

Continuous target price optimism implies that target prices follow the fluctuations of stock prices through periods of low and high sentiment with a positive difference. In low sentiment, market prices tend to be lower compared to high sentiment, when market prices tend to be overvalued relative to intrinsic values (Baker and Wurgler 2007). Because target prices tend to be above market prices due to target price optimism, target prices will be even more strongly overvalued in high sentiment than market prices. In low sentiment, however, market prices tend to be lower and less overvalued than in high sentiment, or even undervalued. Consequently, target prices will be less overvalued in low sentiment than in high sentiment. The difference between target prices and intrinsic values, which we term target price excess, will hence be smaller in low sentiment than in high sentiment. We depict the expected joint effect of investor sentiment and

[1] Investor sentiment can be defined as: "…a belief about future cash flows and investment risks that is not justified by the facts at hand." (Baker and Wurgler 2007, 129). For brevity, we interchangeably use the terms "investor sentiment" and "sentiment".

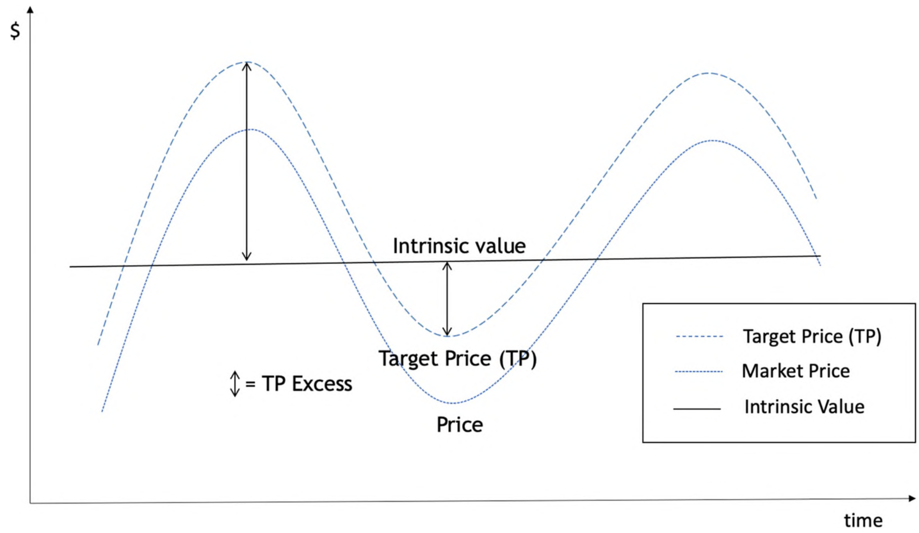

Fig. 1 Target price optimism, market sentiment and stock's intrinsic value (Prediction)

target price optimism on the relation between concurrent market prices, target prices, and intrinsic values in Fig. 1.

Figure 1 illustrates how the implications of target price optimism depend on investor sentiment. Because target prices tend to be above market prices, they will, on average, be closer to intrinsic values in periods of low sentiment. In periods of high investor sentiment, however, target prices will on average be even higher than market prices, such that target prices are far above intrinsic values and even less reflective of fundamentals. Based on this expected joint effect of investor sentiment and target price optimism on target price informativeness, we hypothesize that target price excess (the difference between target prices and intrinsic values) is greater in periods of high sentiment than in low sentiment. Because of these effects, we expect that target prices are more reflective of intrinsic values in periods of low sentiment. It follows that we also hypothesize that return predictability is higher in periods of low sentiment and target price errors (the difference between one-year-ahead target price and the actual realized price one year later) are higher in periods of high sentiment.

Prior literature finds that analysts' inferred use of sophisticated valuation methods is negatively associated with market sentiment (Clarkson et al. 2020). This result implies that analysts use sophisticated valuation methods more often when investor sentiment is low. Moreover, interviews with analysts indicate that analysts switch from sophisticated to heuristic valuation methods in periods of high sentiment to attain higher valuations (e.g., Glaum and Friedrich 2006; Imam et al. 2008). We know from prior evidence that sophisticated valuation methods are more informative (Gleason et al. 2013). It hence follows that the investment value of target prices will be higher in low sentiment, consistent with findings in Clarkson et al. (2020). These findings would imply that the superior investment value in low investor sentiment arises from analysts' use of more sophisticated valuation. However, we predict that target price optimism has an additional, potentially stronger, effect beyond sophisticated valuation, not yet considered in the literature.

Using a large dataset of 254,263 U.S. target prices from 1999 to 2014, we find evidence consistent with these expectations. We begin our analyses by examining how continuous target price optimism and valuation method choice are related. Survey evidence suggests that analysts use different valuation techniques depending on investor sentiment in order to maintain a continuous level of optimism (e.g., Glaum and Friedrich 2006; Imam et al. 2008), indicating that valuation method choice and target price optimism are correlated. Empirically, analysts' use of more or less sophisticated valuation techniques in target prices cannot be observed directly, but the literature typically infers their use from pseudo-target prices (e.g., Gleason et al. 2013).[2] Analysts may hence appear to be using less sophisticated methods, such as heuristics, when they are optimistic. We find that the inferred use of sophisticated valuation is positively associated with the proximity of the resulting target price to the intended long-term level of target price optimism as measured by the long-term BL-ratios, indicating that analysts' valuation method choice and target price optimism are linked.

If target price optimism drives analysts' valuation method choice, conditional on the level of investor sentiment, it likely also affects the informativeness of target prices. Hence, we next analyze the informativeness of target prices, conditional on sentiment, target price optimism, and inferred valuation method use. We first examine target price excess (the difference between target prices and *ex post* intrinsic values) in order to reveal the extent to which target prices differ from fundamentals in different market phases. We find that target price excess is positively associated with sentiment, consistent with the depiction in Fig. 1 and the notion that target price optimism biases target prices away from intrinsic values in high sentiment while the opposite is true for low sentiment.

When we estimate the investment value of target prices using return predictability as our proxy, following prior research, to investigate the extent to which target price information can help investors to predictably make valuable investment decisions, we find that the association of return predictability and analysts' inferred use of more sophisticated valuation methods is largely moderated by sentiment.[3] In low sentiment, return predictability is considerably higher and is highest for target prices based on sophisticated valuation. In high sentiment, however, the investment value of target prices is close to zero, irrespective of the valuation methods used. We also examine target price errors (target price minus actual price one year ahead) to study the extent to which target prices are predictive of future stock prices; we find equivalent results as for return predictability.

Finally, we analyze whether investors understand the dynamics that we document. Prior literature finds that investors react positively to target price revisions (e.g., Asquith et al. 2005) and understand the long-term dynamics of target price optimism (Brav and Lehavy 2003). Consequently, we would expect that investors rationally react more strongly to target price revisions when target prices are expected to have higher investment value, that is, when target prices reflect fundamental values more strongly in low sentiment. In contrast to this expectation, we find that investors irrationally react more strongly to target price

[2] Valuation methods can be observed in analysts' reports, but these reports are not available for all target prices. Also, analysts often use different methods in parallel, so that the reported target price is not based on a single valuation model but several (e.g., Imam et al. 2008; Imam, Chan, and Shah 2013). It is hence difficult to determine what valuation method was used from analysts' reports where several methods are reported. Literature hence infers the method that most closely approximates the reported target price.

[3] Prior literature that has analyzed the influence of more sophisticated valuation method use (Gleason et al. 2013) and sentiment (Clarkson et al. 2020) has not investigated the interrelation between these factors. To maintain a continuous level of target price optimism, however, the influence of valuation method use would depend on the level of sentiment.

revisions in high sentiment. Investors appear to not comprehend the differential informativeness of target prices with respect to sentiment and sophisticated valuation. This is consistent with Bradshaw et al. (2013) who find that market participants appear to not understand the differential informativeness of individual analysts' forecasting performance.[4]

The results of our study contribute to literature on the informativeness of analysts' target prices by providing evidence that the implications of target price optimism on target price informativeness vary with investor sentiment. Contrary to conventional belief, target price optimism is not generally detrimental to the informativeness of target prices. Our results document that target prices have higher investment value in periods of low sentiment, not only because analysts' greater use of sophisticated valuation methods, but due to optimism biasing target prices towards intrinsic values by pushing target prices closer to intrinsic values. In contrast, target price optimism biases target prices away from intrinsic values in high sentiment resulting in the investment value of target prices being close to zero, irrespective of the valuation methods used. Our results are robust to endogeneity concerns that arise from factors that influence both investor sentiment and analysts' target prices, which has not been considered in prior studies.

Furthermore, we provide evidence that the market does not understand the differential informativeness of target prices across high and low sentiment. Our findings indicate that the lower investment value of target prices in periods of high sentiment combined with even higher market reactions to these overly optimistic target prices potentially fuels the build-up of new bubbles. Our study also contributes to a growing literature on the determinants of analysts' target prices (e.g., Bradshaw et al. 2013; Clarkson et al. 2020; Dechow and You 2020) by documenting that the influence of analysts' continuous target price optimism on target prices varies based on sentiment.

Finally, we show that target price optimism decreased after the regulatory reforms in 2000–2003, which contributes to the literature on the consequences of stock market regulations affecting analysts (e.g., Barber et al. 2006; Dong and Hu 2016).[5]

In Sect. 2, we review the related literature and develop our hypotheses. We describe in Sect. 3 our research methodology and approach to inferring analysts' valuation method use. In Sect. 4, we discuss our sample and we present our findings in Sect. 5. Section 6 concludes.

2 Related literature and hypotheses

2.1 Target price informativeness and optimism

Prior literature shows that analysts' target prices are highly informative to investors, beyond the information found in analysts' summary earnings forecasts, stock recommendations

[4] Our results are robust to a battery of sensitivity tests and different specifications such as different deflators. All tests control for analysts' earnings forecasts, stock recommendations, firm, and analyst characteristics.

[5] This paper is also related to Loh and Stulz (2018) finding that analysts' output is more useful for investors in periods of high macro uncertainty, such as crises. While related, macro uncertainty refers to the fundamental business- and information-environment, where sentiment refers to investors' opinions driven by factors other than fundamentals (Baker and Wurgler 2007). The Baker and Wurgler (2006, 2007) investor sentiment index (*SENT*) is orthogonalized to the NBER recession indicator. Also, the economic policy uncertainty index (Baker, Bloom, and Davis 2016) used in Loh and Stulz (2018) is uncorrelated with *SENT* over our sample period (-0.02, $p > 0.10$).

and analyst reports (e.g., Huang et al. 2009; Da and Schaumburg 2011; Da et al. 2016). However, the literature also finds that target prices are highly inaccurate and often too high (e.g., Bonini et al. 2010; Bradshaw et al. 2013).

One explanation for why target prices are of limited investment value is that target prices may be based on insufficient valuation assumptions and techniques leading to forecasts that poorly reflect intrinsic values. Gleason et al. (2013) find that the predictability of analysts' target prices for one-year-ahead abnormal stock returns is substantially improved when target prices appear to be based on more sophisticated valuation. Also, Huang et al (2022) show that market reactions are stronger for target prices accompanied by sophisticated valuation methods discussed in their reports. However, small sample evidence of Asquith et al. (2005) and Bonini and Kerl (2014) find no evidence that market reactions to target price revisions are stronger when analysts refer to the use of sophisticated valuation in their reports.

An alternative explanation for the limited investment value of target prices is that target prices are optimistically biased as a result of analysts' job-related incentives (e.g., Bradshaw et al. 2006; Dechow and You 2020). Brav and Lehavy (2003) show that analysts' target prices and share prices comove and that their ratio is stationary around a common value of 1.28. They find that the reversion of the ratio of target-to-share price to its long-term value (BL-ratio) is largely attributable to revisions in target prices rather than market prices. Their finding of continuous target price optimism is confirmed by several studies (e.g., Bilinski et al. 2013; Bradshaw et al. 2013, 2019; Dechow and You 2020).

This optimism is explained by conflicts of interest resulting from the analysts' employment by investment banks and brokerage houses (Bradshaw 2011; Bradshaw et al. 2016). While these organizations benefit from deals and commissions, they also compensate their analysts. For example, Bradshaw (2011, 27) notes that: "*…it is easier to convince an investor to buy a stock that they do not own rather than convincing them to sell a stock they must already own.*" Accordingly, prior literature shows that analysts more often issue buy than sell recommendations. The former are regularly accompanied by optimistic target prices (e.g., Bradshaw 2002). Several studies confirm that analysts' job incentives are related to the optimistic bias in target prices (e.g., Bradshaw et al. 2006; Bilinski et al. 2019; Dechow and You 2020). Also, Allee et al. (2021) find that independent analysts' target prices are more likely to be met within 12 months after their issuance than those issued by investment-bank analysts.

2.2 Target prices and investor sentiment

Generally, target prices are determined by several fundamental factors, such as analysts' earnings forecasts or firm risk (e.g., Da et al. 2016; Dechow and You 2020). Moreover, behavioral factors such as the stocks' 52-week-high prices, investor sentiment and other stock market anomalies play a role (Roger et al. 2018; Clarkson et al. 2020; Engelberg et al. 2020). Earnings forecasts, as important valuation inputs, are themselves positively related to investor sentiment (e.g., Bergman and Roychowdhury 2008; Qian 2009; Hribar and McInnis 2012; Walther and Willis 2013). Several studies show that analysts issue more favorable stock recommendations in periods of high sentiment (Bagnoli, Clement, Crawley, and Watts 2014; Miwa and Ueda 2016; Cornell et al. 2017). Bagnoli et al. (2014) attribute this to analysts' riding waves of sentiment, that is, benefitting from further appreciations of stock value.

Clarkson et al. (2020) find evidence that sentiment is a determinant of target prices. In particular, they find that ratios of target-to-share prices are positively related to sentiment and return predictability. They also find that target price errors (actuals minus forecasts) are negatively associated with investor sentiment and that the ratios of target-to-share prices and target price errors are, on average, higher when analysts use less sophisticated valuation (approximated by the VMR measure of Gleason et al. 2013). Clarkson et al. (2020) do not consider optimism in their analysis, and do not examine the interrelation of investor sentiment with analysts' use of sophisticated valuation and analysts' continual optimism, which is what we propose determines whether target prices serve to stabilize the stock market. The evidence from their study, therefore, examines only one side of the triangle that we propose. Further, their investigation does not consider the association of investor sentiment (nor the use of sophisticated valuation models or analyst optimism) with the predictability of target prices nor the market's reactions to revisions of target prices—key metrics that are informative on whether investors act rationally when reacting to these revisions.

2.3 Analysts' valuation method choice and investor sentiment

Analysts build target prices using their short-term earnings forecasts and their assessment of a firm's long-term prospects using available fundamental and private information (Brown et al. 2015; Buxbaum et al. 2022; Da et al. 2016). Prior evidence suggests that analysts use different valuation methods when combining this information to derive a target price, depending on analyst and firm characteristics, client preferences, market prices, and more (e.g., Glaum and Friedrich 2006; Imam et al. 2008, 2013; Demirakos et al. 2010). Interviews with analysts indicate that analysts switch from sophisticated to heuristic valuation methods in periods of high sentiment to achieve higher valuations (e.g., Glaum and Friedrich 2006; Imam et al. 2008).[6]

Imam et al. (2008) conclude that when the market does well and prices are on an upward trend, analysts assume a growth focus, as captured by the price-earnings-growth (PEG) ratio. However, when the market falls and the investors shift to a more defensive focus on yield, then dividend yield becomes important. Demirakos et al. (2010) find, based on a content analysis of analysts' reports, that analysts' use of discounted cash flow (DCF) models is higher in low sentiment. Huang et al. (2022) confirm this in a large sample of analysts' reports.

2.4 Hypotheses development

We begin our analyses by verifying our assumptions underlying Fig. 1 and test our expectation that continuous target price optimism affects the association of investor sentiment and analysts' valuation method choice. Our expectations rest on the assumption that target price optimism persists through all market phases. Empirical findings in prior

[6] For example, an analyst commented: "*4–5 years ago, the DCF method was practicably useless, because the resulting values were much lower than the companies' market prices at that time.*" (Glaum and Friedrich 2006, 170). Similarly, another analyst stated: "*We try to guess what the share price would be, not try to guess what the value of the company would be. Share price is a factor of two things: one is the stock market sentiment towards earnings and other is the earnings … it is tough to guess what the sentiment would be towards the earnings and what the earnings is going to be. Multiples are basically a guess of that. It is about what it should be if you feel confident and what it should be if you are not feeling confident. You try to guess what the market will do in 12 months' time.*" (Imam et al. 2008, 522).

studies confirm this assumption but for earlier periods (Brav and Lehavy 2003; Bradshaw et al. 2013). To validate this assumption, we begin by analyzing the pattern of target price optimism for our sample period.

Continuous target price optimism implies that analysts' target prices exceed the concurrent share prices in periods of low as well as in periods of high investor sentiment. Brav and Lehavy's (2003) finding that the reversion of the ratio of target-to-share-price back to the long-term BL-ratio is largely attributable to revisions in target prices indicates that analysts adapt their forecasts to attain a continuous level of optimism. Heuristic valuation methods are market-based and hence translate current market prices to target prices. Sophisticated valuation methods are less sensitive to market fluctuations (e.g., Block 1999; Glaum and Friedrich 2006; Imam et al. 2008) and better reflect intrinsic values. Heuristic and sophisticated valuation methods result in different target prices and may be useful for maintaining target price optimism to a different extent. If analysts maintain a continuous level of target price optimism, we expect that analysts will use the valuation method that helps them to better rationalize their target price optimism, consistent with survey evidence (Glaum and Friedrich 2006; Imam et al. 2008). We hence expect that analysts' valuation method choice is associated with the proximity of a target price inferred from a particular valuation method to the firm's long-term BL-Ratio. We hypothesize:

H1 Analysts' inferred use of sophisticated valuation methods is positively associated with its proximity to the firm's long run level of target price optimism.

If H1 holds, such that target price optimism and analysts' inferred use of sophisticated valuation methods are positively associated, the underlying reason for the prior literature's conclusion that analysts' inferred use of sophisticated valuation methods explain the variation in accuracy of target prices may be driven by target price optimism. The prior literature's finding that return predictability is higher in low sentiment (Clarkson et al. 2020) may arise because sophisticated valuation methods are more informative (Gleason et al. 2013) and analysts choose those more often in periods of low sentiment (Glaum and Friedrich 2006; Imam et al. 2008). An alternative explanation is that continuous target price optimism biases target prices toward intrinsic values in low investor sentiment, which makes them more informative in low relative to high investor sentiment. Since both explanations are conceptually linked, it is an empirical question which of the effects dominates.

Target price optimism biases target prices toward the higher intrinsic values in periods of low sentiment, when concurrent market prices are below intrinsic values and target prices are above market prices due to analysts' optimism (Fig. 1). We hence expect that target price excess, that is, the difference between target prices and intrinsic values, is greater in high sentiment. Thus, target prices are less informative in high sentiment. In turn, they are more reflective of intrinsic values in low sentiment, not only when sophisticated valuation methods are used, but also because of the effects of target price optimism. Consequently, we expect that sentiment negatively moderates the association of return predictability and analysts' inferred use of sophisticated valuation, i.e., that the investment value of target prices is higher in low sentiment when sophisticated valuation methods are used. Since target prices are less justified by fundamentals in high sentiment, we also expect that target price errors, i.e., the difference between target prices and one-year ahead market prices, are higher in periods of high sentiment. We hypothesize:

H2 Sentiment negatively moderates the association of analysts' inferred use of sophisticated valuation methods with return predictability of target prices and positively moderates the association of analysts' inferred use of sophisticated valuation methods with target price errors.

In our third hypothesis, we examine the market reactions to target price revisions. Prior literature shows that investors react to target price revisions (e.g., Brav and Lehavy 2003; Asquith et al. 2005). Positive (negative) target price revisions are related to positive (negative) abnormal returns around the target price release date. Brav and Lehavy (2003) find that investors understand the long-term dynamics of analysts' target price optimism. Accordingly, we expect that investors understand the differential investment value of target prices in high or low sentiment. If investors react efficiently to target price revisions, they should react more strongly when target prices are expected to have higher investment value, that is, when target prices are based on sophisticated valuation and/or in periods of low sentiment. We hypothesize:

H3 The associations of short-term abnormal returns to target price revisions are higher when analysts' target prices are based on sophisticated valuation methods, lower in periods of high market sentiment, and negatively moderated by sentiment.

3 Research method

3.1 Inferred valuation method use

Analysts typically transform valuation inputs into target prices by using different valuation models (e.g., Imam et al. 2008, 2013; Demirakos et al. 2010). Both sophisticated and heuristic valuation models are based on fundamental information (e.g., book values of equity, actual earnings and earnings forecasts), but to different extents (e.g., Gleason et al. 2013). Analysts often use multiple methods in parallel, so that the reported target price is not based on a single valuation model but several (e.g., Imam et al. 2008, 2013). Thus, we cannot clearly infer what valuation method an analyst may have used from the analyst's report. We follow Gleason et al. (2013) and infer valuation method use based on pseudo-target prices derived from sophisticated and heuristic valuation models. We use a broad set of valuation models to infer the method that is closest to the target price released by the analyst and hence likely represents the valuation method employed.

Studies based on content analyses of analyst reports and interviews with analysts find that the five most often used valuation models are discounted cash flows (DCF), Price-Earnings (PE) ratio, Enterprise Value/EBITDA ratio, Price-Book (PB) ratio, and Dividend Discount Model (DDM), among which the PE ratio is found the most popular (e.g., Imam et al. 2008, 2013; Brown et al. 2015). Gleason et al. (2013) use the price-earnings-to-growth (PEG) ratio and the residual income model (RIM) with fade rates as a DCF model substitute (Lundholm and O'Keefe 2001). The latter leads to very conservative values, while DCF valuation in practice is often applied with optimistic terminal value assumptions that do not imply mean reversion in expected industry returns (e.g., Bradshaw 2004).

Therefore, we use two different RIM specifications, one with fade rates V_{RIF}, and one without fade rates V_{RIP} as well as the DDM in the specification of Gordon and Gordon (1997). For valuation heuristics, we use the PE-Ratio V_{PE}, the PEG-Ratio V_{PEG} as well as the PB-Ratio V_{PB}. These valuation methods are described in Appendix 1.

To infer the valuation model that was likely used to determine a target price, we compare the analyst's target price (*TP)* with the six pseudo-target prices (V_{RIP}, V_{RIF}, V_{DDM}, V_{PE}, V_{PEG} *and* V_{PB}). We select the pseudo-target price based on sophisticated valuation (V_{SOPH}) or valuation heuristics (V_{HEUR}) that is closest to the actual target price (analyst *j*, firm *i*, time *t*)[7]:

$$SOPH_{jit} = 1 \text{ if } \left|TP_{jit} - V_{SOPH_{jit}}\right| < \left|TP_{jit} - V_{HEUR_{jit}}\right|, 0 \text{ otherwise} \tag{1}$$

where *SOPH* is set equal to 1 if the absolute difference between analyst's target price *TP* and the pseudo-target price based on sophisticated valuation V_{SOPH} is smaller than the absolute difference between the target price *TP* and the pseudo-target price based on heuristic valuation V_{HEUR}, and 0 otherwise. Using a dichotomous specification of the valuation variable simplifies the interpretation of the results of the three-way interactions we employ to test our expectations. The related approach of Gleason et al. (2013) compares the regression residuals between target prices and pseudo-target prices of different valuation techniques. While we include this approach for robustness, we directly compare the target price with the pseudo-target prices because of recent literature that finds using residuals as a dependent variable may lead to biased inferences (Chen et al. 2018).

We construct the variable *BLFIT* to test whether analysts use valuation methods such that the ratios of target-to-share prices are as close as possible to BL-Ratios *BLR*:

$$BLFIT_{jit} = 1 \text{ if } \left|\frac{V_{SOPH_{jit}}}{P_{it}} - BLR_{jit}\right| < \left|\frac{V_{HEUR_{jit}}}{P_{it}} - BLR_{jit}\right|, 0 \text{ otherwise} \tag{2}$$

where *BLFIT* is set equal to 1 if the pseudo-target price based on sophisticated valuation V_{SOPH} deflated by the closing price *P* is closer to the long-term BL-Ratio *BLR* than the pseudo-target price based on the heuristic valuation V_{HEUR} deflated by *P*, and 0 otherwise. The long-term BL-Ratio *BLR* is calculated as the 36-months moving average of the ratios of available target prices relative to share prices (Brav and Lehavy 2003). In first 36 months of data, we use the average of these data.

Moreover, we construct a variable *TPEXC* measuring the difference between a target price and the stock's intrinsic value, where the latter is proxied by the *ex-post* intrinsic value (Shiller 1981; Lee et al. 1999; Subramanyam and Venkatachalam 2007), based on V_{int} using three-years of actual future data (see Appendix 1 for a detailed description of V_{int}):

$$TPEXC_{jit} = \frac{\left(TP_{jit} - V_{int_{it}}\right)}{P_{it}} \tag{3}$$

where *TPEXC* is target price excess as the difference between analysts' target price *TP* minus the stock's ex-post intrinsic value V_{int} deflated by the closing price *P*.

[7] V_{SOPH} is the pseudo-target price V_{RIP}, V_{RIF}, or V_{DDM} that is closest to the actual target price *TP*, measured by the absolute difference. Analogously, V_{HEUR} is the pseudo-target price V_{PE}, V_{PEG}, or V_{PB} which is closest to the actual target price *TP*.

3.2 Regression models

To analyze the relationship between target prices and sentiment for comparability with prior research, we estimate the following equation:

$$TP_{jit} = \beta_0 + \beta_1 SENT_t + \beta_2 (SENT_t * SOPH_{jit}) + \beta_3 SOPH_{jit} + \gamma_1 CONTROL^{TP} + \gamma_2 (CONTROL^{TP} * SOPH_{jit}) + \gamma_3 IND + \gamma_4 (IND * SOPH_{jit}) + \varepsilon_{jit} \tag{4}$$

where *TP* is analyst's target price scaled by the firm's total assets per share, *SENT* is the monthly Baker and Wurgler (2006, 2007) investor sentiment index[8] in the target price release month, *SOPH* is a categorical variable set equal to 1 if analyst's target price is inferred to be based on a sophisticated valuation model, and 0 otherwise (see Appendix 1), and $CONTROL^{TP}$ is a vector of control variables discussed in the next section. *IND* is a vector of dummy variables indicating in which of the 12 Fama and French industries the firm was operating on the target price release date (also discussed in the next section). We expect a positive coefficient on *SENT*, indicating that target prices are higher when sentiment is high. We expect a negative coefficient on *SENT*SOPH*, indicating that target prices are lower in high sentiment when analysts use sophisticated valuation, and a positive coefficient on *SOPH*, indicating that target prices are higher when analysts use sophisticated valuation. To test if analysts' inferred use of sophisticated valuation is negatively associated with investor sentiment ($\beta_1 < 0$), we estimate the following equation:

$$SOPH_{jit} = \beta_0 + \beta_1 SENT_t + \gamma_1 CONTROL^{TP} + \gamma_2 IND + \varepsilon_{jit} \tag{5}$$

To test H1 that analysts' use of sophisticated valuation is positively associated with its contribution to target price optimism ($\beta_2 > 0$), we estimate the following equation:

$$SOPH_{jit} = \beta_0 + \beta_1 SENT_t + \beta_2 BLFIT_{jit} + \gamma_1 CONTROL^{TP} + \gamma_2 IND + \varepsilon_{jit} \tag{6}$$

where *BLFIT* is a categorical variable is set equal to 1 if one of the sophisticated valuation models results in a pseudo-target-to-share price closer to the firm's long-term BL ratio than the heuristic valuation models, and 0 otherwise (see Appendix 1). To test if target price excess is stronger in periods of high sentiment ($\beta_1 > 0$), we estimate the following equation:

$$TPEXC_{jit} = \beta_0 + \beta_1 SENT_t + \gamma_1 CONTROL^{TP} + \gamma_2 IND + \varepsilon_{jit} \tag{7}$$

where *TPEXC* is target price excess as defined in Eq. (3). To test H2 that the association of return predictability of target prices and analysts' inferred use of sophisticated valuation methods is negatively moderated by sentiment ($[\beta_3 + \beta_4] < 0$), we estimate the following equation:

$$\begin{aligned} FRET_{jit} = {} & \beta_0 + \beta_1 TPP_{jit} + \beta_2 (TPP_{jit} * SOPH_{jit}) + \beta_3 (TPP_{jit} * SENT_t) \\ & + \beta_4 (TPP_{jit} * SENT_t * SOPH_{jit}) + \beta_5 SENT_t + \beta_6 (SENT_t * SOPH_{jit}) + \beta_7 SOPH_{jit} \\ & + \gamma_1 CONTROL^{TP} + \gamma_2 (CONTROL^{TP} * SOPH_{jit}) + \gamma_3 IND + \gamma_4 (IND * SOPH_{jit}) + \varepsilon_{jit} \end{aligned} \tag{8}$$

[8] The monthly investor sentiment index is a composite index originally based on six variables and defined using annual data in Baker and Wurgler (2006), now the index is only based on five variables and it is also calculated using monthly data (http://people.stern.nyu.edu/jwurgler/). We employ the version orthogonalized to several macroeconomic conditions. Kaplanski and Levy (2017) conclude that sentiment is exogenous to the work of financial analysts, where analysts do not initiate sentiment.

where *FRET* is the firm's one-year future return, calculated as the cumulative 250-days ex-dividend stock return following the target price release date and *TPP* is the ratio of analyst's target price relative to share price. We expect the coefficient on *TPP*SOPH* to be positive and the coefficient on *TPP*SENT* to be negative (Gleason et al. 2013; Clarkson et al. 2020). Based on H2, we expect a negative sign on *TPP*SENT*SOPH*, indicating that return predictability is lower when analysts use sophisticated valuation when investor sentiment is high. We expect a positive association of target-to-share prices *TPP* and *FRET* (Gleason et al. 2013) and a negative association of *FRET* with *SENT* indicating that future returns are more difficult to predict in high sentiment (Clarkson et al. 2020). Since analysts are more likely to use sophisticated methods in low sentiment, we expect a positive sign on *SENT*SOPH*, indicating that the negative effect of sentiment on return predictability is reduced by more sophisticated valuation. We expect a negative sign on *SOPH* indicating that sophisticated valuation has lower return predictability in high sentiment.

To test whether the association of target price errors and analysts' inferred use of sophisticated valuation methods is moderated by sentiment ($\beta_2 > 0$), we estimate:

$$\begin{aligned} TPERR_{jit} = {} & \beta_0 + \beta_1 SENT_t + \beta_2 (SENT_t * SOPH_{jit}) + \beta_3 SOPH_{jit} \\ & + \gamma_1 CONTROL^{TP} + \gamma_2 (CONTROL^{TP} * SOPH_{jit}) + \gamma_3 IND + \gamma_4 (IND * SOPH_{jit}) + \varepsilon_{jit} \end{aligned} \tag{9}$$

where *TPERR* is the target price error calculated as the difference between the analyst's target price minus the one-year-ahead share price scaled by the closing price on the trading day before the target price release date. We expect a positive sign on *SENT* implying that target prices exceed future stock prices in periods of high market sentiment. Based on H2 we expect a positive sign on *SENT*SOPH*.

To test H3, we estimate the following equation:

$$\begin{aligned} ARET_{jit} = {} & \beta_0 + \beta_1 TPREV_{jit} + \beta_2 (TPREV_{jit} * SOPH_{jit}) + \beta_3 (TPREV_{jit} * SENT_t) \\ & + \beta_4 (TPREV_{jit} * SENT_t * SOPH_{jit}) + \beta_5 SENT_t + \beta_6 (SENT_t * SOPH_{jit}) + \beta_7 SOPH_{jit} \\ & + \gamma_1 CONTROL^{REV} + \gamma_2 (CONTROL^{REV} * SOPH_{jit}) + \gamma_3 IND + \gamma_4 (IND * SOPH_{jit}) + \varepsilon_{jit} \end{aligned} \tag{10}$$

where *ARET* is a firm's short-term abnormal return, calculated as the difference between the buy-and-hold returns of the firm and the NYSE/AMEX/Nasdaq value-weighted market index from the target price release date until two days later, *TPREV* is the analyst's target price revision, calculated as analyst's target price divided by analyst's previous target price minus 1.

Based on H3, we expect that short-term abnormal returns to target price revisions are higher if target prices are based on sophisticated valuation, that is, a positive sign on *SOPH* and on *TPREV*SOPH*. We also expect that short-term abnormal returns to target price revisions are higher for low market sentiment, that is, a negative sign on *SENT* and on *TPREV*SENT*. Further, we expect a negative sign on *TPREV*SENT*SOPH*, indicating that market reactions to target price revisions are higher in periods of low market sentiment when analysts use sophisticated valuation methods. Prior literature predicts that abnormal returns to target price revisions *ARET* are positively associated with *TPREV* (Brav and Lehavy 2003) and that *ARET* are negatively associated with *SENT* because future returns are more difficult to predict in high sentiment (Baker and Wurgler 2007). We expect a positive sign on *SENT*SOPH*, indicating that the negative effect of sentiment on return predictability is reduced by more sophisticated valuation method use.

Equations (4), (7), (8–10) are run as OLS regressions and (5) and (6) as pooled logit regressions each with corrections for clustering of standard errors by firm, analyst and month (Petersen 2009; Gow et al. 2010; Cameron et al. 2011).

3.3 Endogeneity

To address concerns that the results may be biased by endogeneity regarding investor sentiment *SENT*, we adopt a Two Stages Least Squares (2SLS) approach. We estimate the following first stage regression model of the endogenous variable *SENT:*

$$SENT_t = \beta_0 + \beta_1 MICH_t + \beta_2 EMV_t + \gamma_1 OTHER + \varepsilon_t \tag{11}$$

where *MICH* is the 12-month lagged Index of Consumer Sentiment of the University of Michigan, *EMV* is the 6-month lagged Baker et al.'s (2019) newspaper-based U.S. Equity Market Volatility tracker, *OTHER* is a vector of main and control variables used in the second stage regressions of Eqs. (4) to (7) and (9), and *IND* are industry dummies (see above).

The variables *MICH* and *EMV* are our instrumental variables (IV). For an IV estimation to be consistent, the IVs need to be relevant and exogenous (Stock and Watson 2012). That is, they need to correlate with the endogenous regressor (i.e., investor sentiment) but not with the error term of the second stage (Larcker and Rusticus 2010). Consumer confidence *MICH* is a proxy for investor sentiment (e.g., Qiu and Welch 2004). While the Baker and Wurgler (2006, 2007) investor sentiment index *SENT* is based on financial variables such as the average first-day IPO returns, the monthly Michigan consumer confidence index *MICH* is based on survey questions conducted by telephone containing approximately 50 core questions, each of which tracks a different aspect of consumer attitudes and expectations.[9] *MICH* does not rely on financial measures (Qiu and Welch 2004) and hence is largely independent of (unobserved) capital market effects that potentially influence analysts' target prices. In addition, we use the *EMV* tracker as a second IV because prior literature finds that the stock market volatility is negatively associated with investor sentiment (e.g., Lee et al. 2002; Smales 2017), because expected stock market volatility is a proxy for investors' fear (e.g., Whaley 2000). The U.S. equity market volatility *EMV* could be correlated with the return volatilities of the individual stocks which are known to affect target prices (e.g., Dechow and You 2020). However, because we control for the individual stock return volatilities in all regressions, we expect no endogeneity regarding *EMV*. Moreover, we use a time lag for *MICH* and *EMV* since a time lag of the endogenous regressor can control for some forms of endogeneity (Harjoto and Jo 2015). Various tests substantiate the validity of our IVs (see section Regression results). We also use time lags of *SENT* in robustness analyses (Sect. 5.).

We test for endogeneity in all regressions and present 2SLS results in all cases where the test is significant, which are regression models (4), (5), (6), (7) and (9). For model (8) and (10), the test is insignificant, thus we only present OLS results, but 2SLS results are consistent.

[9] The detailed survey description is available at: https://data.sca.isr.umich.edu/fetchdoc.php?docid=24774 (Surveys of Consumers, University of Michigan).

3.4 Control variables

Control variables are described in detail in Appendix 2. Based on prior literature (e.g., Womack 1996; Demirakos et al. 2004; Clarkson et al. 2020), we include analysts' earnings and earnings growth forecasts (*FEPS*, *FEPSA*, *FDIFF*, *FDIFFA* and *FLTG*) and stock recommendations (*REC*IncREC*). We expect a positive relation with *SOPH*, *TP* and *TPP, TPERR, TPEXC* and *FRET*. For market reaction tests in Eq. (10), we include analysts' earnings forecast and stock recommendation revisions (*EPSREV* and *RECREV*) instead and expect a positive sign on these variables (e.g., Brav and Lehavy 2003; Asquith et al. 2005). Otherwise, we use the same control variables in Eq. (10) as described below and expect the same signs on the coefficients as for model (8) with *FRET* as dependent variable.

Based on prior literature (e.g., Demirakos et al. 2004, 2010; Imam et al. 2008; Bradshaw et al. 2013; Clarkson et al. 2020; Dechow and You 2020), we include the return volatility of stocks (*CSD*), CAPM betas (*CBETA*), firm's book-to-market ratios (*CBM*) and firm size (*CSIZE*). We expect a positive (negative) association of *CSD* with *TP, TPP*, and *TPERR* (*TPEXC* and *FRET*) and a positive (negative) association between *CBETA* and *TP* as well as *TPP* (*SOPH*). Firms with high *CBM* could be difficult to value with conservative DCF methods indicating a positive relation between *CBM* and *SOPH.* Otherwise, we expect that firms with low *CBM* have on average higher *TP* (*TPP*), *TPERR* and *TPEXC* and lower *FRET*. We expect a positive (negative) relation between *CSIZE* and *SOPH* (*TPP* and *FRET*). Given the co-movement of target prices and share prices (Brav and Lehavy 2003), we expect that *TP* is positively related to *CSIZE*.

We include a firm's external finance (*CEXF*) as a proxy for analysts' incentives to inflate their forecasts due to investment banking conflicts (Bradshaw et al. 2006). We expect that higher *CEXF* reduces (increases) *SOPH* and *FRET* (*TP*, *TPP*, *TPERR* and *TPEXC)*. Additionally, we control for the firm's past stock returns (*CPRET*) and expect a negative relation between *CPRET* and *SOPH* and a positive relation between *CPRET* and *TP*, *TPP*, *TPERR*, *TPEXC* and *FRET* (e.g., Jegadeesh and Titman 1993; Bradshaw et al. 2013). Moreover, we include the 52-week high prices relative to share prices (*CWH*) (Clarkson et al. 2020) and expect a positive (negative) relation between *CWH* and *SOPH*, *TPP* and *FRET* (*TP*, *TPERR* and *TPEXC*).

We control for several variables reflecting analyst characteristics (e.g., Mikhail et al. 1997; Clement 1999; Jacob et al. 1999; Clarkson et al. 2020). We expect that analyst's firm experience (*AFEXP)* and broker size (*ABSIZ)* positively affect *SOPH* and *FRET* and negatively affect *TPERR* and *TPEXC*. We include the number of firms (*ANFIR*) and industries (*ANIND*) followed by the analyst. Analysts' workload could reduce but spillover effects could increase the forecast quality. Thus, we do not predict the signs on these variables. We include *AROUND* indicating if a target price was rounded. We expect that *AROUND* is positively (negatively) related to *TP*, *TPP*, *TPERR* and *TPEXC* (*SOPH* and *FRET*). We also include a variable to correct for possible structural changes caused by regulatory reforms after April 2003 (*PostREG*). Based on prior literature (Barniv et al. 2009; Chen and Chen 2009; Dong and Hu 2016), we expect that regulations increase *SOPH* and *FRET* and decrease *TP, TPP*, *TPERR* and *TPEXC*. Additionally, we include industry-fixed effects *IND* in every regression (e.g., Bradshaw et al. 2013).

Table 1 Sample selection procedure

	Sample	No. of target prices
1	U.S. firm target prices from April 1999 to December 2014	1,270,662
2	Target prices with 12-month forecast horizon and not null	1,243,892
3	EPS forecasts and long-term EPS growth forecasts are available	517,181
4	Pseudo-target prices are computable and positive	439,761
5	Non-missing variables	254,344
6	Stock prices are at least one dollar	**254,263**

This table reports the sample sizes after important steps of data preparation

4 Sample data and descriptive statistics

We obtain analysts' target prices, stock recommendations, earnings forecasts, and share prices to compute the price-earnings ratios from the I/B/E/S database. Firms' fundamental data are retrieved from Compustat; stock returns and market prices are from CRSP. The monthly Baker and Wurgler (2006, 2007) investor sentiment index is from Jeffrey Wurgler's Homepage,[10] the monthly U.S. Equity Market Volatility tracker (Baker et al. 2019) is from the Economic Policy Uncertainty homepage[11] and the Index of Consumer Sentiment is from the University of Michigan Surveys of Consumers.[12] The Fama and French (1993) three factors, the 30-day U.S. treasury bill yields and the Fama and French (1997) industry classifications and returns are downloaded from the Kenneth R. French—Data Library.[13] The sample selection process is reported in Table 1.

The raw dataset comprises all U.S. firm target prices in the I/B/E/S database from April 1999 to December 2014.[14] We include all positive U.S. firm target prices with a 12-month forecast horizon, where multiple intraday forecasts are eliminated, and the latest forecasts are kept (Ho et al. 2018). We require that analysts' one- and two-year-ahead EPS forecasts are issued on the target price release date. Missing long-term EPS growth forecasts are replaced by the median consensus long-term growth forecasts to avoid a selection bias. We lose observations due to missing data to compute all pseudo-target prices. The constraint that pseudo-target prices must be positive ensures that the valuation methods are practically useful to derive a target price. Moreover, we lose target prices due to missing or not computable variables for our analysis. Finally, we exclude target prices if concurrent share prices are less than one dollar (e.g., Bradshaw et al. 2013). The final sample comprises 254,263 target prices for 3,976 U.S. firms issued by 6,615 analysts.

Table 2 presents the descriptive statistics. All variables, except for *SENT* and *REC*, are winsorized at the top and bottom 0.5% levels to mitigate the effect of outliers. The mean value of *SOPH* indicates that target prices are based on sophisticated valuation in 25.4% of cases. The monthly Baker and Wurgler (2006, 2007) investor sentiment index *SENT* is

[10] http://pages.stern.nyu.edu/~jwurgler/main.htm.

[11] https://www.policyuncertainty.com/.

[12] http://www.sca.isr.umich.edu/.

[13] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[14] The sample period refers to the target price release dates. Data to calculate other variables deviates in part from this period (e.g., daily stock returns to compute the firms' one-year future returns *FRET*).

Table 2 Distribution statistics

Variable	Full Sample (N = 254,263)					Sample SOPH = 0 (N = 189,789)			Sample SOPH = 1 (N = 64,474)		
	Mean	Median	Std. dev	Min	Max	Mean	Median	Std. dev	Mean	Median	Std. dev
Main variables											
SOPH	0.254	0.000	0.435	0.000	1.000	0.000	0.000	0.000	1.000	1.000	0.000
SENT	0.006	0.010	0.516	−0.890	3.200	0.055	0.050	0.541	−0.139	−0.070	0.397
BLFIT	0.270	0.000	0.444	0.000	1.000	0.101	0.000	0.301	0.767	1.000	0.423
TP	1.984	1.396	2.080	0.047	14.151	2.036	1.464	2.104	1.833	1.165	2.002
TPP	1.175	1.148	0.211	0.688	2.238	1.176	1.149	0.206	1.170	1.145	0.225
TPEXC	0.181	0.466	1.130	−8.223	1.599	0.252	0.530	1.092	−0.028	0.215	1.212
TPERR	0.065	0.055	0.452	−1.591	1.474	0.081	0.069	0.447	0.018	0.013	0.464
TPREV	0.014	0.029	0.178	−0.542	0.750	0.019	0.031	0.173	0.001	0.020	0.191
FRET	0.110	0.089	0.410	−0.862	1.841	0.095	0.075	0.403	0.154	0.132	0.426
ARET	−0.001	0.001	0.073	−0.299	0.259	0.000	0.001	0.071	−0.003	0.000	0.076
PostREG	0.920	1.000	0.272	0.000	1.000	0.905	1.000	0.293	0.963	1.000	0.189
Control variables											
FEPS	0.061	0.058	0.040	−0.101	0.250	0.059	0.057	0.035	0.066	0.060	0.051
FEPSA	0.082	0.070	0.068	−0.056	0.367	0.083	0.071	0.068	0.078	0.065	0.067
EPSREV	−0.019	0.004	0.343	−2.583	2.000	−0.013	0.006	0.318	−0.034	−0.003	0.406
FDIFF	0.013	0.009	0.024	−0.067	0.184	0.012	0.009	0.021	0.015	0.009	0.030
FDIFFA	0.017	0.012	0.024	−0.052	0.162	0.017	0.012	0.024	0.016	0.011	0.026
IncFLTG	0.075	0.000	0.264	0.000	1.000	0.077	0.000	0.266	0.071	0.000	0.257
FLTG	0.151	0.140	0.082	0.018	0.596	0.151	0.140	0.078	0.152	0.135	0.092
IncREC	0.111	0.000	0.314	0.000	1.000	0.112	0.000	0.315	0.110	0.000	0.313
REC	3.598	4.000	0.635	1.000	5.000	3.615	4.000	0.637	3.549	3.500	0.624
RECREV	0.000	0.000	0.106	−0.500	0.500	0.001	0.000	0.105	−0.003	0.000	0.106
CSD	0.026	0.023	0.012	0.008	0.079	0.025	0.022	0.012	0.028	0.025	0.013
CBETA	1.285	1.178	0.739	−0.101	4.266	1.277	1.164	0.759	1.308	1.215	0.676

Table 2 (continued)

	Full Sample (N = 254,263)					Sample SOPH = 0 (N = 189,789)			Sample SOPH = 1 (N = 64,474)		
Variable	Mean	Median	Std. dev	Min	Max	Mean	Median	Std. dev	Mean	Median	Std. dev
CBM	0.478	0.398	0.345	−0.026	2.247	0.452	0.384	0.313	0.552	0.442	0.419
CSIZE	22.113	22.045	1.638	18.261	26.243	22.113	22.038	1.629	22.113	22.063	1.665
CEXF	0.124	0.044	0.331	−0.300	2.769	0.125	0.045	0.333	0.122	0.042	0.326
CPRET	0.177	0.117	0.518	−0.787	3.014	0.195	0.131	0.513	0.122	0.071	0.529
CWH	1.366	1.148	0.619	1.000	5.625	1.332	1.137	0.567	1.466	1.185	0.741
AFEXP	0.030	0.020	0.026	0.000	0.120	0.029	0.020	0.026	0.032	0.020	0.028
ANFIR	0.176	0.170	0.071	0.020	0.450	0.175	0.170	0.070	0.177	0.170	0.072
ANIND	0.031	0.020	0.021	0.010	0.120	0.031	0.030	0.022	0.031	0.020	0.021
ABSIZ	0.759	0.570	0.627	0.010	2.880	0.761	0.570	0.628	0.753	0.570	0.625
AROUND	0.945	1.000	0.228	0.000	1.000	0.947	1.000	0.224	0.939	1.000	0.239

This table reports the mean, median, standard deviation, minimum and maximum for all variables based on a sample of 254,263 target prices for U.S. firms over the period from April 1999 to December 2014. Except for the *SENT* and the *REC* variable, all variables are winsorized at 99.5 and 0.5%. In addition, this table reports the mean, median and standard deviation for the variables of the subsamples of target prices which are inferred to be based on heuristic ($SOPH = 0$) and sophisticated valuation models ($SOPH = 1$). Variable definitions can be found in the Appendix 2

Table 3 Annual means of main variables and valuation variables

Year	SOPH	SENT	V_{SOPH}/P	V_{HEUR}/P	BLFIT	BLR	TP	TPP	TPEXC	TPERR	TPREV	FRET	ARET	N
1999	0.059	−0.033	0.520	1.092	0.059	1.321	3.533	1.294	0.800	0.100	0.018	0.195	−0.003	1,987
2000	0.047	1.124	0.461	1.123	0.066	1.320	4.122	1.346	0.903	0.355	0.051	−0.010	0.002	4,473
2001	0.063	2.192	0.587	1.121	0.079	1.303	2.646	1.281	0.737	0.381	−0.078	−0.100	−0.007	4,772
2002	0.156	−0.008	0.751	1.144	0.163	1.301	1.931	1.257	0.459	0.142	−0.062	0.134	−0.010	7,010
2003	0.229	−0.553	0.834	1.036	0.231	1.272	2.032	1.147	0.180	−0.100	0.079	0.242	0.006	10,409
2004	0.118	−0.010	0.702	1.070	0.121	1.220	2.260	1.164	0.431	−0.001	0.017	0.169	−0.003	13,639
2005	0.079	0.224	0.620	1.080	0.084	1.183	2.118	1.152	0.539	0.021	0.033	0.132	0.001	14,278
2006	0.066	0.364	0.562	1.092	0.071	1.157	2.209	1.151	0.638	0.043	0.015	0.111	−0.002	14,787
2007	0.078	0.538	0.581	1.090	0.087	1.153	2.129	1.145	0.615	0.366	0.008	−0.219	−0.004	16,948
2008	0.327	−0.167	1.053	1.225	0.376	1.168	1.529	1.263	0.076	0.268	−0.106	0.007	−0.009	23,975
2009	0.368	−0.635	1.080	1.049	0.404	1.199	1.521	1.153	−0.634	−0.168	0.100	0.309	0.007	20,963
2010	0.339	−0.562	1.008	1.066	0.356	1.198	1.884	1.171	−0.127	−0.009	0.048	0.174	0.004	23,481
2011	0.350	0.196	1.058	1.119	0.373	1.192	1.928	1.195	−0.057	0.143	−0.005	0.051	−0.002	25,893
2012	0.378	−0.055	1.055	1.088	0.391	1.173	1.782	1.167	−0.094	−0.084	0.003	0.254	−0.003	23,674
2013	0.329	0.062	0.929	1.017	0.335	1.164	1.941	1.109	0.451	−0.058	0.059	0.162	0.003	23,954
2014	0.248	−0.013	0.860	1.045	0.252	1.154	2.107	1.141	0.583	0.117	0.010	0.024	−0.003	24,020
Total	0.254	0.006	0.878	1.088	0.270	1.191	1.984	1.175	0.181	0.065	0.014	0.110	−0.001	254,263

This table reports annual means of main variables and further valuation variables based on a sample of 254,263 target prices for U.S. firms over the period from April 1999 to December 2014. Except for the *SENT* and the *REC* variable, all variables are winsorized at 99.5% and 0.5%. V_{SOPH}/P (V_{HEUR}/P) is the pseudo-target price based on the sophisticated (heuristic) valuation models divided by the firm's share price one day prior to the target price release date and *BLR* is the firm's BR-Ratio on the target price release date. Variables *BLR*, V_{SOPH} and V_{HEUR} are described in detail in Sect. 3. All other variable definitions can be found in the Appendix 2

Table 4 Correlations of main variables

Variable	SOPH	SENT	BLFIT	TP	TPP	TPEXC	TPERR	TPREV	FRET	ARET	PostREG
Full sample (N = 254,263)											
SOPH	–	−0.175***	0.653***	−0.072***	−0.018***	−0.173***	−0.064***	−0.039***	0.069***	−0.017***	0.093***
SENT	−0.164***	–	−0.180***	0.091***	0.005**	0.323***	0.234***	−0.060***	−0.259***	−0.013***	−0.170***
BLFIT	0.653***	−0.167***	–	−0.063***	0.044***	−0.145***	−0.034***	−0.046***	0.068***	−0.010***	0.094***
TP	−0.042***	0.115***	−0.042***	–	0.136***	0.378***	0.080***	0.166***	−0.043***	0.065***	−0.041***
TPP	−0.012***	0.048***	0.074***	0.102***	–	0.284***	0.362***	−0.023***	0.016***	0.192***	−0.132***
TPEXC	−0.108***	0.280***	−0.099***	0.177***	0.124***	–	0.365***	0.053***	−0.269***	0.028***	−0.157***
TPERR	−0.060***	0.249***	−0.022***	0.082***	0.401***	0.304***	–	−0.097***	−0.867***	−0.093***	−0.080***
TPREV	−0.042***	−0.090***	−0.044***	0.161***	−0.043***	0.028***	−0.073***	–	0.021***	0.322***	0.069***
FRET	0.063***	−0.247***	0.062***	−0.050***	0.041***	−0.266***	−0.869***	−0.002	–	0.068***	0.025***
ARET	−0.018***	−0.026***	−0.006***	0.060***	0.186***	−0.006***	−0.096***	0.326***	0.057***	–	0.005***
PostREG	0.093***	−0.398***	0.094***	−0.104***	−0.147***	−0.111***	−0.081***	0.068***	0.009***	0.016***	–
Subsample SOPH = 0 (N = 189,789)											
SENT	–	–	−0.126***	0.106***	0.019***	0.340***	0.234***	−0.057***	−0.253***	−0.009***	−0.203***
BLFIT	–	−0.108***	–	−0.085***	0.090***	−0.075***	0.026***	−0.086***	0.041***	−0.010***	0.054***
TP	–	0.133***	−0.079***	–	0.143***	0.364***	0.089***	0.139***	−0.049***	0.061***	−0.056***
TPP	–	0.069***	0.177***	0.116***	–	0.319***	0.366***	−0.027***	0.006***	0.190***	−0.154***
TPEXC	–	0.295***	−0.058***	0.152***	0.137***	–	0.383***	0.035***	−0.275***	0.030***	−0.187***
TPERR	–	0.246***	0.046***	0.092***	0.410***	0.312***	–	−0.097***	−0.871***	−0.089***	−0.098***
TPREV	–	−0.087***	−0.077***	0.147***	−0.047***	0.017***	−0.072***	–	0.021***	0.322***	0.065***
FRET	–	−0.236***	0.042***	−0.053***	0.025***	−0.271***	−0.873***	−0.002	–	0.064***	0.033***
ARET	–	−0.021***	−0.006**	0.057***	0.180***	−0.006**	−0.092***	0.325***	0.052***	–	0.006**
PostREG	–	−0.431***	0.054***	−0.130***	−0.173***	−0.132***	−0.101***	0.062***	0.019***	0.017***	–
Subsample SOPH = 1 (N = 64,474)											
SENT	–	–	−0.007*	0.008*	−0.044***	0.179***	0.212***	−0.102***	−0.253***	−0.036***	0.006
BLFIT	–	−0.011***	–	0.101***	0.042***	0.028***	−0.014***	0.091***	0.004	0.025***	0.025***
TP	–	0.016***	0.112***	–	0.112***	0.429***	0.045***	0.233***	−0.015***	0.074***	0.053***

Table 4 (continued)

Variable	SOPH	SENT	BLFIT	TP	TPP	TPEXC	TPERR	TPREV	FRET	ARET	PostREG
TPP	–	−0.032***	−0.020***	0.060***	–	0.201***	0.350***	−0.014***	0.044***	0.198***	−0.040***
TPEXC	–	0.189***	0.001	0.235***	0.089***	–	0.298***	0.077***	−0.227***	0.012***	0.025***
TPERR	–	0.239***	−0.021***	0.045***	0.378***	0.269***	–	−0.103***	−0.853***	−0.107***	0.019***
TPREV	–	−0.144***	0.086***	0.196***	−0.036***	0.040***	−0.084***	–	0.028***	0.319***	0.111***
FRET	–	−0.272***	0.002	−0.032***	0.086***	−0.238***	−0.857***	0.009**	–	0.083***	−0.043***
ARET	–	−0.059***	0.034***	0.069***	0.200***	−0.012***	−0.112***	0.327***	0.075***	–	0.012***
PostREG	–	−0.139***	0.025***	0.030***	−0.053***	0.009**	0.028***	0.123***	−0.064***	0.022***	–

This table reports Pearson correlations of the main variables below the diagonal and Spearman rank correlations above the diagonal. Correlations are based on a sample of 254,263 target prices for U.S. firms over the period from April 1999 to December 2014. In addition, this table reports Pearson correlations and Spearman rank correlations of the main variables for the subsample of target prices which are inferred to be based on heuristic (*SOPH* = 0) and sophisticated valuation models (*SOPH* = 1). Variable definitions can be found in the Appendix 2

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively standardized such that the mean (median) value of 0.006 (0.010) represents nearly neutral market sentiment. The mean value of *BLFIT* implies that sophisticated valuation methods are used in 27.0% of cases to be closer to the BL-Ratios. The mean value of the firms' BL-Ratios is 1.191 (not tabulated). The mean (median) of target prices *TP* of 1.984 (1.396) implies that target prices exceed firms' total assets per share by 98.4%. Accordingly, the mean (median) of *TPP* of 1.175 (1.148) shows that target prices are on average 17.5% higher than their concurrent share prices.

The mean (median) of *TPEXC* of 0.181 (0.466) indicates that target prices are on average 18.1% higher than estimates of intrinsic values. The mean (median) of *TPERR* of 0.065 (0.055) shows that target prices exceed share prices at the end of the 12-month forecast horizon by on average 6.5%. The mean (median) of *TPREV* of 0.014 (0.029) reveals that positive exceed negative target price revisions. In turn, the mean (median) of *ARET* of -0.001 (0.001) indicates that negative and positive short-term abnormal stock returns to target price revisions are well balanced. The mean (median) value of *FRET* of 0.110 (0.089) shows that the firms' future returns are on average 11.0% implying that target prices are on average 6.5% too high (17.5%-11.0%).

Table 3 presents annual statistics for the main variables. The mean values of target-to-share prices *TPP* fell strongly after 2002 to 2003 from 1.257 to 1.147 indicating that regulatory reforms were successful in reducing target price optimism, but optimism persists in all market phases. *BLR* also decreased, where the effect is smoother since BL-Ratios are moving averages. *SENT* reached peaks in 2001 and in 2007, where analysts' use of sophisticated valuation was low. *SENT* was lowest in 2003, 2009 and 2010, where analysts' use of sophisticated valuation was high. *BLFIT* and *SOPH* seem to comove, indicating that both are linked. This is also supported by the movements of V_{SOPH}/P and V_{HEUR}/P.

Analysts' target prices *TP* were high during the Dot.com bubble in 2000 and low during the credit crisis in 2008 and 2009. *TPEXC* was very high in 2000, where the mean value of 0.903 implies that target prices exceed estimates of intrinsic values by 90.3% (stock price as basis). *TPEXC* was lowest after the credit crisis in 2009. When observing both *TPEXC* and *SENT* it appears that both variables are closely related and follow the pattern depicted in Fig. 1. *TPERR* were highest in 2001 and lowest in 2009. Negative *FRET* in 2000, 2001 and 2007 suggest that market prices were corrected when the Dot.com burst and at the beginning of the credit crisis. *ARET* are most negative in 2002 and 2008, coinciding with the breakdown of the Dot.com bubble and the credit crisis.

5 Main results

5.1 Univariate correlation results

Pearson (Spearman rank) correlations among the main variables are presented in Table 4. The negative correlation of –0.147 (–0.132) between *TPP* and *PostREG* supports that target price optimism decreased after regulatory reforms. The positive correlation of 0.653 (0.653) between *SOPH* and *BLFIT* supports H1 that the use of sophisticated valuation is

Table 5 Determinants of analysts' target prices and analysts' valuation model choice (Regression results)

Model		(4) (OLS)		(4) (2SLS) First Stage		(4) (2SLS) Second Stage			Additional test (OLS)	
Variable	Pred	TP		SENT		TP		Pred	TPP	
	Sign	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Sign	Coeff	[*t*-stat.]
Panel A: Determinants of analysts' target prices										
SENT	(+)	0.174***	[4.77]	–	–	–	–	(+)	0.002	[0.35]
SENT*SOPH	(−)	−0.222***	[−3.72]	–	–	–	–		–	–
SENT (Instr.)	(+)	–	–	–	–	0.662***	[7.52]		–	–
SENT (Instr.)*SOPH	(−)	–	–	–	–	−0.836***	[−7.03]		–	–
SOPH	(+)	0.895	[1.37]	–	–	1.730***	[2.62]		–	–
MICH (IV)	(+)	–	–	0.018***	[5.92]	–	–		–	–
EMV (IV)	(−)	–	–	−0.013***	[−4.00]	–	–		–	–
PostREG	(−)	−0.327***	[−4.11]	−0.504***	[−2.55]	0.084	[0.93]	(−)	−0.055***	[−5.90]
FEPSA (FEPS)	(+)	16.005***	[30.17]	0.299***	[3.91]	15.953***	[30.23]	(+)	1.428***	[13.82]
FDIFFA (FDIFF)	(+)	25.315***	[24.24]	0.312	[0.98]	25.014***	[24.35]	(+)	2.333***	[19.66]
IncFLTG	(?)	0.017	[0.89]	−0.021**	[−2.33]	0.016	[0.82]	(?)	0.005*	[1.77]
FLTG	(+)	4.438***	[11.19]	0.233***	[5.00]	4.197***	[10.61]	(+)	0.187***	[8.32]
IncREC	(?)	−0.620***	[−8.19]	0.088***	[2.73]	−0.644***	[−8.51]	(?)	−0.199***	[−21.05]
REC	(?)	−0.070***	[−3.24]	0.038***	[2.82]	−0.082***	[−3.81]	(?)	0.084***	[30.46]
REC*IncREC	(+)	0.167***	[7.78]	−0.031***	[−3.35]	0.173***	[8.08]	(+)	0.047***	[19.39]
CSD	(+)	14.143***	[7.34]	−4.067*	[−1.95]	22.231***	[9.17]	(+)	0.331	[1.16]
CBETA	(+)	−0.012	[−0.45]	0.034***	[2.84]	−0.050*	[−1.88]	(+)	0.016***	[7.00]
CBM	(−)	−0.646***	[−8.79]	0.026	[1.56]	−0.604***	[−8.33]	(−)	−0.047***	[−8.01]
CSIZE	(+)	0.063***	[4.15]	0.004	[0.85]	0.074***	[4.85]	(−)	−0.007***	[−6.29]
CEXF	(+)	0.287***	[5.42]	0.073***	[4.56]	0.224***	[4.13]	(+)	0.007**	[1.98]
CPRET	(+)	0.538***	[8.51]	−0.075***	[−2.70]	0.546***	[8.76]	(+)	−0.002	[−0.57]
CWH	(−)	−0.063**	[−1.97]	−0.027	[−0.83]	−0.082**	[−2.56]	(+)	0.074***	[11.18]
AFEXP	(?)	−1.710***	[−5.75]	0.686***	[3.29]	−1.599***	[−5.63]	(?)	0.134***	[3.28]
ANFIR	(?)	0.543***	[3.54]	0.061	[1.25]	0.530***	[3.43]	(?)	0.005	[0.23]

Table 5 (continued)

Model		(4) (OLS)		(4) (2SLS) First Stage		(4) (2SLS) Second Stage			Additional test (OLS)	
Variable	Pred	TP		SENT		TP		Pred	TPP	
	Sign	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Sign	Coeff	[*t*-stat.]
ANIND	(?)	−1.891***	[−3.21]	0.020	[0.13]	−1.634***	[−2.75]	(?)	0.116	[1.40]
ABSIZ	(?)	−0.034***	[−2.85]	0.005	[0.73]	−0.038***	[−3.21]	(?)	−0.022***	[−9.48]
AROUND	(+)	0.070***	[2.98]	−0.011	[−1.39]	0.079***	[3.34]	(+)	0.030***	[6.65]
Constant	(?)	−1.105***	[−2.95]	−0.939*	[−1.84]	−1.813***	[−4.52]	(?)	0.806***	[21.78]
CONTROL^{TP}*SOPH		YES		NO		YES			NO	
IND		YES		YES		YES			YES	
IND*SOPH		YES		NO		YES			NO	
No. of Obs		254,263		254,263		254,263			254,263	
Adj. R^2		0.741		0.431		0.743			0.322	
Endogeneity test of endogenous regressor						25.234***			2.397 (No endogeneity)	
Hansen J statistic (Overidentification test of all instruments)						0.044				
Kleibergen-Paap rk Wald F statistic (Weak identification test)						43.000 (> 19.93)				

Model		(5) (Logit)		(5) (2SLS) First Stage		(5) (2SLS) Second Stage		(6) (Logit)		(6) (2SLS) First Stage		(6) (2SLS) Second Stage	
Variable	Pred	SOPH		SENT		SOPH		SOPH		SENT		SOPH	
	Sign	Coeff	[z-stat.]	Coeff	[z-stat.]	Coeff	[z-stat.]	Coeff	[z-stat.]	Coeff	[z-stat.]	Coeff	[z-stat.]
Panel B: Determinants of analysts' valuation model choice													
SENT	(−)	−0.704***	[−6.87]	–	–	–	–	−0.479***	[−7.23]	–	–	–	–
SENT (Instr.)	(−)	–	–	–	–	−1.056***	[−28.06]	–	–	–	–	−0.649***	[−20.86]
BLFIT	(+)	–	–	–	–	–	–	3.239***	[37.15]	−0.025***	[−6.88]	1.827***	[84.35]
MICH (IV)	(+)	–	–	0.018***	[91.97]	–	–	–	–	0.018***	[89.00]	–	–
EMV (IV)	(−)	–	–	−0.012***	[−45.78]	–	–	–	–	−0.012***	[−51.02]	–	–
PostREG	(+)	0.742***	[5.84]	−0.489***	[−40.32]	−0.223***	[−5.99]	0.422***	[4.34]	−0.496***	[−40.79]	−0.132***	[−4.04]
FEPS	(+)	5.111***	[4.88]	−0.112	[−1.62]	2.739***	[7.29]	1.657***	[2.63]	−0.079	[−1.14]	1.341***	[5.26]

Table 5 (continued)

Model		(5) (Logit)		(5) (2SLS) First Stage		(5) (2SLS) Second Stage		(6) (Logit)		(6) (2SLS) First Stage		(6) (2SLS) Second Stage	
Variable	Pred	SOPH		SENT		SOPH		SOPH		SENT		SOPH	
	Sign	Coeff	[z-stat.]	Coeff	[z-stat.]	Coeff	[z-stat.]	Coeff	[z-stat.]	Coeff	[z-stat.]	Coeff	[z-stat.]
FDIFF	(+)	5.654***	[4.38]	0.071	[0.67]	3.155***	[6.68]	1.661**	[2.11]	0.106	[0.99]	1.393***	[4.01]
IncFLTG	(?)	−0.044	[−1.31]	−0.020***	[−5.13]	−0.025*	[-1.87]	−0.026	[−0.80]	−0.020***	[−5.08]	−0.015	[−1.03]
FLTG	(+)	1.825***	[6.10]	0.248***	[8.25]	1.361***	[9.88]	1.148***	[4.87]	0.256***	[8.54]	0.845***	[7.97]
IncREC	(?)	0.193	[1.62]	0.094***	[6.01]	0.166***	[2.74]	0.520***	[3.73]	0.092***	[5.90]	0.315***	[5.25]
REC	(?)	−0.126***	[−4.25]	0.041***	[9.58]	−0.048***	[−2.91]	−0.122***	[−4.77]	0.041***	[9.45]	−0.055***	[−4.25]
REC*IncREC	(?)	−0.057*	[−1.73]	−0.033***	[−7.47]	−0.048***	[−2.81]	−0.127***	[−3.37]	−0.033***	[−7.38]	−0.079***	[−4.77]
CSD	(+)	5.902**	[2.35]	−4.202***	[−13.27]	−7.163***	[−7.05]	0.539	[0.30]	−3.994***	[−12.69]	−5.649***	[−6.78]
CBETA	(−)	−0.081**	[−2.34]	0.034***	[9.33]	0.006	[0.35]	−0.062**	[−2.12]	0.032***	[8.99]	0.003	[0.25]
CBM	(+)	0.708***	[8.21]	0.000	[0.01]	0.361***	[10.25]	0.535***	[6.93]	0.002	[0.30]	0.275***	[9.10]
CSIZE	(+)	0.057***	[2.82]	0.006***	[3.49]	0.021**	[2.10]	0.039***	[2.70]	0.006***	[3.70]	0.012*	[1.78]
CEXF	(−)	0.064	[1.33]	0.067***	[5.70]	0.120***	[4.53]	0.051	[1.06]	0.067***	[5.73]	0.077***	[3.28]
CPRET	(−)	−0.101**	[−2.00]	−0.066***	[−11.35]	−0.068***	[−3.87]	−0.023	[−0.67]	−0.068***	[−11.76]	−0.034**	[−2.32]
CWH	(+)	0.172***	[3.21]	−0.026***	[−3.73]	0.134***	[7.90]	0.075**	[2.38]	−0.026***	[−3.59]	0.065***	[4.78]
AFEXP	(+)	2.950***	[5.16]	0.683***	[16.90]	1.649***	[8.07]	2.100***	[4.91]	0.681***	[16.85]	1.225***	[6.58]
ANFIR	(?)	0.459**	[2.05]	0.057***	[3.19]	0.251***	[2.77]	0.301	[1.63]	0.057***	[3.17]	0.160**	[2.01]
ANIND	(?)	−1.393	[−1.52]	0.024	[0.31]	−0.912**	[−2.02]	−1.261*	[−1.77]	0.019	[0.24]	−0.769**	[−2.24]
ABSIZ	(+)	0.024	[1.21]	0.005**	[2.36]	0.024***	[3.26]	0.038**	[2.05]	0.005**	[2.48]	0.026***	[3.62]
AROUND	(−)	−0.015	[−0.37]	−0.008*	[−1.88]	−0.022	[−1.14]	−0.046	[−1.10]	−0.008*	[−1.75]	−0.031	[−1.59]
Constant	(?)	−3.810***	[−6.82]	−1.000***	[−17.13]	−1.277***	[−5.16]	−3.755***	[−9.32]	−0.953***	[−16.33]	−1.590***	[−8.84]
IND		YES		YES		YES		YES		YES		YES	
No. of Obs		254,263		254,263		254,263		254,263		254,263		254,263	
Pseudo R^2		0.067		–		–		0.370		–		–	
Wald test of exogeneity						363.96***						203.66***	

Table 5 (continued)

Model		(5) (Logit)		(5) (2SLS) First Stage		(5) (2SLS) Second Stage		(6) (Logit)		(6) (2SLS) First Stage		(6) (2SLS) Second Stage	
Variable	Pred	SOPH		SENT		SOPH		SOPH		SENT		SOPH	
	Sign	Coeff	[z-stat.]	Coeff	[z-stat.]	Coeff	[z-stat.]	Coeff	[z-stat.]	Coeff	[z-stat.]	Coeff	[z-stat.]
Hansen J statistic (Overidentification test of all instruments)						5.258**						6.089**	
Kleibergen-Paap rk Wald F statistic (Weak identification test)						42.819 (> 19.93)						42.925(> 19.93)	

Panel A of this table presents the results of Equation (4) and Panel B presents the results of equation (5) and (6) based on a sample of 254,263 target prices for U.S. firms over the period from April 1999 to December 2014. Equation (4) examines the relation between target prices *TP* and investor sentiment *SENT* dependent upon analysts' valuation model choice *SOPH*. The additional test shown in the last column of Panel A examines the relation between the ratios of target-to-share prices *TPP* and regulatory reforms *PostREG*. The results of the additional test are discussed in the additional analyses. Equation (5) examines the relation between analysts' use of sophisticated valuation models *SOPH* and investor sentiment *SENT*. Equation (6) examines the relation between analysts' use of sophisticated valuation models *SOPH* and the proximity of the resulting pseudo-target-to-share prices to the firms' long-term BL-Ratios *BLFIT*. Equation (4) and the additional test are run as pooled OLS regressions and equations(5) and (6) are run as pooled logit regressions. Adj. R2s (Pseudo R2s) are mentioned for equation (4) and the additional test (equations (5) and (6)). Variables *FEPSA* and *FDIFFA* are replaced by *FEPS* and *FDIFF* in equation (5), (6), and the additional test. To address endogeneity concerns, Panel A and B of this table additionally present the first stage and second stage coefficients of 2SLS regressions of model (4), (5), and (6)

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. Significance tests are based on a two-tailed t-test (Equ. 4 and the additional test) or on a two-tailed z-test (Equ. 5 and 6) corrected for clustering of standard errors by firm, analyst, and month (Petersen 2009; Gow et al. 2010; Cameron et al. 2011). The 2SLS models of equation (5) and (6) are run as probit 2SLS regressions corrected for clustering of standard errors by firm

Table 6 Target price excess/errors and return predictability of analysts' target prices (Regression results)

Panel A: Target price excess and return predictability of analysts' target prices

Model		(7) (OLS)		(7) (2SLS) First Stage		(7) (2SLS) Second Stage			(8excl.SENT) (OLS)		($8_{excl.SOPH}$) (OLS)		(8) (OLS)	
Variable	Pred	TPEXC		SENT		TPEXC		Pred	FRET		FRET		FRET	
	Sign	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Sign	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]
SENT	(+)	0.422***	[7.61]	–	–	–	–	(−)	–	–	−0.106***	[−2.71]	−0.114***	[−2.98]
SENT (Instr.)	(+)	–	–	–	–	1.250***	[10.90]		–	–	–	–	–	–
MICH (IV)	(+)	–	–	0.018***	[5.90]	–	–		–	–	–	–	–	–
EMV (IV)	(−)	–	–	−0.013***	[−3.98]	–	–		–	–	–	–	–	–
TPP		–	–	–	–	–	–	(+)	−0.026	[−1.03]	0.024	[1.14]	−0.014	[−0.59]
TPP*SOPH		–	–	–	–	–	–	(+)	0.161***	[5.17]	–	–	0.090***	[3.08]
TPP*SENT		–	–	–	–	–	–	(−)	–	–	−0.087***	[−2.92]	−0.065**	[−2.19]
TPP*SENT*SOPH		–	–	–	–	–	–	(−)	–	–	–	–	−0.102**	[−2.52]
SENT*SOPH		–	–	–	–	–	–	(+)	–	–	–	–	0.024	[0.45]
SOPH		–	–	–	–	–	–	(−)	−0.151	[−1.21]	–	–	−0.148	[−1.34]
PostREG	(−)	−0.182***	[−2.73]	−0.500**	[−2.52]	0.538***	[5.44]	(+)	0.058	[1.16]	−0.128***	[−3.00]	−0.118***	[−2.81]
FEPS	(?)	−4.614***	[−6.87]	−0.112	[−0.53]	−4.305***	[−6.77]	(?)	1.121***	[5.15]	0.563***	[3.25]	0.923***	[4.75]
FDIFF	(?)	−4.174***	[−5.84]	0.068	[0.21]	−4.085***	[−5.54]	(?)	0.158	[0.50]	−0.337	[−1.21]	−0.082	[−0.28]
IncFLTG	(?)	−0.016	[−0.66]	−0.020**	[−2.23]	−0.017	[−0.75]	(?)	0.001	[0.21]	0.003	[0.56]	0.001	[0.16]
FLTG	(?)	0.761***	[4.26]	0.246***	[5.12]	0.352*	[1.96]	(?)	−0.091	[−1.45]	−0.027	[−0.46]	0.003	[0.05]
IncREC	(?)	−0.257***	[−3.96]	0.094***	[2.93]	−0.316***	[−4.81]	(?)	0.012	[0.41]	−0.006	[−0.23]	0.021	[0.79]
REC	(?)	0.053***	[2.68]	0.041***	[3.08]	0.027	[1.29]	(?)	0.007	[0.88]	0.008	[1.31]	0.012*	[1.86]
REC*IncREC	(+)	0.068***	[3.76]	−0.033***	[−3.58]	0.084***	[4.55]	(+)	−0.006	[−0.75]	−0.001	[−0.18]	−0.008	[−1.20]
CSD	(−)	−12.029***	[−6.01]	−3.945*	[−1.90]	1.669	[0.74]	(−)	2.516**	[2.34]	−0.158	[−0.19]	−0.444	[−0.55]
CBETA	(?)	0.165***	[8.76]	0.032***	[2.72]	0.098***	[5.71]	(?)	−0.039***	[−3.88]	−0.023**	[−2.51]	−0.024***	[−2.74]
CBM	(−)	−0.733***	[−13.24]	−0.001	[−0.03]	−0.680***	[−12.78]	(+)	0.057***	[2.92]	0.038**	[2.21]	0.040**	[2.12]
CSIZE	(?)	−0.105***	[−6.75]	0.006	[1.25]	−0.089***	[−6.20]	(−)	−0.005	[−1.27]	−0.007*	[−1.77]	−0.009**	[−2.36]
CEXF	(+)	0.142***	[5.37]	0.067***	[4.28]	0.036	[1.22]	(−)	−0.084***	[−5.73]	−0.064***	[−4.89]	−0.057***	[−4.40]
CPRET	(+)	0.094***	[2.91]	−0.069**	[−2.46]	0.106***	[3.72]	(+)	0.011	[0.68]	0.014	[0.98]	0.008	[0.55]

Table 6 (continued)

Panel A: Target price excess and return predictability of analysts' target prices														
Model		(7) (OLS)		(7) (2SLS) First Stage		(7) (2SLS) Second Stage			(8excl.SENT) (OLS)		($8_{excl.SOPH}$) (OLS)		(8) (OLS)	
Variable	Pred	TPEXC		SENT		TPEXC		Pred	FRET		FRET		FRET	
	Sign	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Sign	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]
CWH	(−)	−0.124***	[−3.41]	−0.027	[−0.85]	−0.168***	[−4.74]	(+)	0.060*	[1.88]	0.077***	[2.79]	0.074***	[2.73]
AFEXP	(−)	−0.390	[−1.31]	0.672***	[3.22]	−0.262	[−0.99]	(+)	0.084	[0.59]	0.142	[1.14]	0.063	[0.47]
ANFIR	(?)	0.396***	[3.61]	0.055	[1.11]	0.383***	[3.43]	(?)	−0.065	[−1.51]	−0.065	[−1.55]	−0.063	[−1.52]
ANIND	(?)	0.180	[0.39]	0.025	[0.16]	0.469	[1.02]	(?)	0.038	[0.22]	−0.031	[−0.19]	−0.036	[−0.22]
ABSIZ	(−)	−0.030***	[−2.70]	0.005	[0.65]	−0.038***	[−3.50]	(+)	0.006	[1.32]	0.010***	[2.78]	0.009**	[2.23]
AROUND	(+)	0.068***	[3.31]	−0.008	[−1.03]	0.082***	[3.91]	(−)	−0.013	[−1.41]	−0.015*	[−1.85]	−0.016*	[−1.91]
constant	(?)	3.102***	[8.17]	−0.950*	[−1.86]	1.986***	[5.89]	(?)	0.041	[0.29]	0.248**	[2.14]	0.301**	[2.59]
$CONTROL^{TP}$*SOPH		NO		NO		NO			YES		NO		YES	
IND		YES		YES		YES			YES		YES		YES	
IND*SOPH		NO		NO		NO			YES		NO		YES	
No. of Obs		254,263		254,263		254,263			254,263		254,263		254,263	
Adj. R^2		0.249		0.430		0.275			0.050		0.097		0.102	
Endogeneity test of endogenous regressor						36.866***								1.662 (No endogeneity)
Hansen J statistic (Overidentification test of all instruments)						1.261								
Kleibergen-Paap rk Wald F statistic (Weak identification test)						42.819 (> 19.93)								

Table 6 (continued)

Panel B: Results of equation (8) (OLS) partitioned for the subsamples SOPH = 0 and SOPH = 1

Model/Sample		(8) (OLS) / SOPH = 0		(8) (OLS) / SOPH = 1			
Variable	Pred	FRET		FRET		Diff. (SOPH = 1 − SOPH = 0)	
	Sign	Coeff	[t-stat.]	Coeff	[t-stat.]	Coeff	[t-stat.]
TPP	(+)	−0.014	[−0.59]	0.076**	[2.58]	0.090***	[3.08]
TPP*SENT	(−)	−0.065**	[−2.19]	−0.167***	[−3.77]	−0.102**	[−2.52]
SENT	(−)	−0.114***	[−2.98]	−0.090	[−1.41]	0.024	[0.45]
PostREG	(+)	−0.118***	[−2.81]	−0.185***	[−3.60]	−0.067**	[−2.06]
FEPS	(?)	0.923***	[4.75]	0.209	[0.97]	−0.714***	[−3.32]
FDIFF	(?)	−0.082	[−0.28]	−0.439	[−1.36]	−0.357	[−1.32]
IncFLTG	(?)	0.001	[0.16]	0.011	[1.23]	0.010	[1.26]
FLTG	(?)	0.003	[0.05]	−0.029	[−0.36]	−0.032	[−0.41]
IncREC	(?)	0.021*	[0.79]	−0.067	[−1.72]	−0.088**	[−2.48]
REC	(?)	0.012*	[1.86]	−0.002	[−0.21]	−0.014	[−1.57]
REC*IncREC	(+)	−0.008	[−1.20]	0.016	[1.53]	0.024**	[2.51]
CSD	(−)	−0.444	[−0.55]	−0.458	[−0.45]	−0.013	[−0.02]
CBETA	(?)	−0.024***	[−2.74]	−0.008	[−0.57]	0.017	[1.57]
CBM	(+)	0.040**	[2.12]	0.036**	[2.10]	−0.004	[−0.25]
CSIZE	(−)	−0.009**	[−2.36]	−0.001	[−0.26]	0.008*	[1.92]
CEXF	(−)	−0.057***	[−4.40]	−0.077***	[−4.13]	−0.019	[−1.18]
CPRET	(+)	0.008	[0.55]	0.033*	[1.83]	0.025	[1.53]
CWH	(+)	0.074***	[2.73]	0.081***	[2.70]	0.008	[0.47]

Table 6 (continued)

Panel B: Results of equation (8) (OLS) partitioned for the subsamples SOPH = 0 and SOPH = 1

Model/Sample		(8) (OLS) / SOPH = 0		(8) (OLS) / SOPH = 1			
Variable	Pred	FRET		FRET		Diff. (SOPH = 1 − SOPH = 0)	
	Sign	Coeff	[t-stat.]	Coeff	[t-stat.]	Coeff	[t-stat.]
AFEXP	(+)	0.063	[0.47]	0.269^{**}	[2.16]	0.205^{*}	[1.70]
ANFIR	(?)	−0.063	[−1.52]	−0.065	[−1.16]	−0.002	[−0.04]
ANIND	(?)	−0.036	[−0.22]	−0.029	[−0.13]	0.007	[0.03]
ABSIZ	(+)	0.009^{**}	[2.23]	0.014^{***}	[2.92]	0.005	[1.22]
AROUND	(−)	-0.016^{*}	[−1.91]	−0.013	[−1.05]	0.003	[0.30]
constant	(?)	0.301^{**}	[2.59]	0.153	[1.08]	−0.148	[−1.34]
IND		YES		YES			
No. of Obs		189,789		64,474			
Adj. R^2		0.090		0.120			

Panel C: Sum of interaction coefficients: Simple intercepts and simple slopes of FRET with respect to SENT based on the results of Eq. (8) (OLS)

	Simple intercept with respect to SENT	[z-stat.]	Simple slope with respect to SENT	[z-stat.]
SOPH = 0	0.109^{***}	[7.13]	-0.191^{***}	[−9.16]
SOPH = 1	0.114^{***}	[6.71]	-0.286^{***}	[−9.14]

Table 6 (continued)

Panel D: Target price errors

Model		(9) (OLS)		(9) (2SLS) First Stage		(9) (2SLS) Second Stage	
Variable	Pred	TPERR		SENT		TPERR	
	Sign	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]
SENT	(+)	0.198***	[8.94]	–	–	–	–
SENT*SOPH	(+)	0.067***	[3.07]	–	–	–	–
SENT (Instr.)	(+)	–	–	–	–	0.394***	[5.78]
SENT (Instr.)*SOPH	(+)	–	–	–	–	0.022	[0.48]
SOPH	(?)	0.009	[0.08]	–	–	0.097	[0.82]
MICH (IV)	(+)	–	–	0.018***	[5.90]	–	–
EMV (IV)	(−)	–	–	−0.013***	[−3.98]	–	–
PostREG	(−)	0.041	[0.96]	−0.500**	[−2.52]	0.199**	[2.42]
FEPS	(?)	0.804***	[3.69]	−0.112	[−0.53]	0.959***	[3.99]
FDIFF	(?)	2.870***	[8.94]	0.068	[0.21]	2.899***	[8.85]
IncFLTG	(?)	0.007	[1.08]	−0.020**	[−2.23]	0.005	[0.85]
FLTG	(?)	0.227***	[3.37]	0.246***	[5.12]	0.138*	[1.89]
IncREC	(?)	−0.126***	[−4.28]	0.094***	[2.93]	−0.140***	[−4.66]
REC	(?)	0.064***	[8.96]	0.041***	[3.08]	0.057***	[7.03]
REC*IncREC	(+)	0.031***	[4.11]	−0.033***	[−3.58]	0.035***	[4.43]
CSD	(+)	0.268	[0.27]	−3.945*	[−1.90]	3.593***	[3.01]
CBETA	(?)	0.045***	[4.77]	0.032***	[2.72]	0.030***	[2.96]
CBM	(−)	−0.086***	[−4.28]	−0.001	[−0.03]	−0.072***	[−3.94]
CSIZE	(?)	0.002	[0.48]	0.006	[1.25]	0.006	[1.59]
CEXF	(+)	0.070***	[5.11]	0.067***	[4.28]	0.047***	[3.14]
CPRET	(+)	−0.018	[−1.02]	−0.069**	[−2.46]	−0.015	[−0.89]

Table 6 (continued)

Panel D: Target price errors

Model		(9) (OLS)		(9) (2SLS) First Stage		(9) (2SLS) Second Stage	
Variable	Pred	TPERR		SENT		TPERR	
	Sign	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]
CWH	(−)	0.016	[0.59]	−0.027	[−0.85]	0.009	[0.28]
AFEXP	(−)	0.027	[0.18]	0.672^{***}	[3.22]	0.078	[0.50]
ANFIR	(?)	0.055	[1.13]	0.055	[1.11]	0.052	[1.02]
ANIND	(?)	0.195	[1.08]	0.025	[0.16]	0.303^{*}	[1.71]
ABSIZ	(−)	-0.030^{***}	[−6.37]	0.005	[0.65]	-0.031^{***}	[−6.41]
AROUND	(+)	0.044^{***}	[4.08]	−0.008	[−1.03]	0.046^{***}	[4.23]
constant	(?)	-0.454^{***}	[−3.51]	-0.950^{*}	[−1.86]	-0.735^{***}	[−5.03]
$\text{CONTROL}^{\text{TP}}$*SOPH		YES		NO		YES	
IND		YES		YES		YES	
IND*SOPH		YES		NO		YES	
No. of Obs		254,263		254,263		254,263	
Adj. R^2		0.124		0.430		0.115	
Endogeneity test of endogenous regressor						8.329^{***}	
Hansen J statistic (Overidentification test of all instruments)						0.390	
Kleibergen-Paap rk Wald F statistic (Weak identification test)						42.819 (> 19.93)	

Panel A of this table presents the results of the equation (7) and (8) based on a sample of 254,263 target prices for U.S. firms over the period from April 1999 to December 2014. Equation (7) examines the relation between the target price excess *TPEXC* and investor sentiment *SENT*. Equation (8) examines the relation between the firms' one-year future returns *FRET* and the ratios of target-to-share prices *TPP* dependent upon analysts' valuation model choice *SOPH* and investor sentiment *SENT*. Panel B presents the results of the equation (8) for the subsamples $SOPH = 0$ and $SOPH = 1$. Panel C presents the simple intercepts and simple slopes with respect to *SENT* based on the results of equation (8) (i.e., $\beta_0 + \beta_1{*}TPP + \gamma_1{*}CONTROL = 0.109$; $\beta_3{*}TPP + \beta_5 = -0.191$; $\beta_0 + \beta_7 + (\beta_1 + \beta_2){*}TPP + (\gamma_1 + \gamma_2){*}CONTROL = 0.114$; and $(\beta_3 + \beta_4){*}TPP + \beta_5 + \beta_6 = -0.286$; with *TPP* at the mean). Panel D presents the results of equation (9). Equation (9) examines the relation between the target price errors *TPERR* and investor sentiment *SENT* dependent upon analysts' valuation model choice *SOPH*. Equations (7), (8), and (9) are run as pooled OLS regressions. To address endogeneity concerns, Panel A and D of this table additionally present the first stage and second stage coefficients of 2SLS regressions of model (7) and (9). Variable definitions can be found in the Appendix 2.

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. Significance tests are based on a two-tailed *t(z)*-test corrected for clustering of standard errors by firm, analyst, and month (Petersen 2009; Gow et al. 2010; Cameron et al. 2011).

positively associated with its contribution to target price optimism. The positive correlation of 0.280 (0.323) between *TPEXC* and *SENT* implies that target prices are closer to intrinsic values in low sentiment (Fig. 1). Consistent with H2, the correlation between *TPERR* and *SENT* is 0.249 (0.234).

The correlation between *TP* based on heuristic valuation (*SOPH*=0) and *SENT* is 0.133 (0.106), whereas it is only 0.016 (0.008) for *SOPH*=1 and *SENT*. The correlation between *FRET* and *TPP* based on heuristic valuation models (*SOPH*=0) is 0.025 (0.006). The higher correlation between *FRET* and *TPP* based on sophisticated valuation (*SOPH*=1) with 0.086 (0.044) indicates that target prices based on sophisticated valuation are of higher investment value. The correlation between *ARET* and *TPREV* based on heuristic (sophisticated) valuation (*SOPH*=*0*) (*SOPH*=1) are very similar at 0.325 (0.322) and 0.327 (0.319).

5.2 Regression results

Table 5 presents the results regarding Hypothesis 1. Panels A and B contain the results from regressing Eqs. (4) and (5) that examine the relations between *TP* with *SENT* and *SOPH*, as well as *TP*'s relation with the interaction of *SOPH* and *SENT* as a baseline for our main analysis (6). The first column of Panel A presents the OLS regression results of Eq. (4). The significantly positive coefficient on *SENT* of 0.174 ($p<0.01$) indicates that target prices based on heuristics are higher in high sentiment. The coefficient on *SOPH* is not significantly different from zero. Further, the coefficient on *SENT*SOPH* is significantly negative (–0.222, $p<0.01$), indicating that target prices based on sophisticated valuation are lower (higher) than heuristics in high (low) sentiment.

The test of endogeneity is significant (25.234, $p<0.01$) and we present 2SLS regression results in the second and third column of Panel A of Table 5. First stage results show that both IVs are significantly associated with *SENT* (0.018 and -0.013, $p<0.01$). Overidentification (0.044, $p>0.1$) and weak identification (43 is above the critical value of 19.93) can be rejected, confirming the IVs' validity (Stock and Yogo 2002; Bascle 2008). The second stage results in the third column show a significantly positive coefficient on *SENT (Instr.)* (0.662, $p<0.01$) and a negative coefficient on the interaction *SENT (Instr.)*SOPH* (-0.836, $p<0.01$), confirming the OLS regression results that target prices based on sophisticated valuation are lower (higher) than heuristics in high (low) sentiment. In an additional test shown in the fourth column, we find that regulatory reforms *PostREG* reduce the ratios of target-to-share prices *TPP* (discussed in more detail in the additional analyses section).

Panel B of Table 5 presents the logit regression results from Eqs. (5) and (6). The negative and highly significant coefficient on *SENT* of -0.704 ($p<0.01$) in the first column (Eq. 5) supports the expectation that analysts' inferred use of sophisticated valuation methods is negatively associated with market sentiment, consistent with Clarkson et al. (2020). An increase in sentiment from neutral (*SENT*=0) to very high such as during the Dot.com bubble (*SENT*=3.20) corresponds to a decrease of analysts' use of sophisticated valuation by -20.3 percentage points. The fourth column presents the results for testing H1 based on Eq. (6) that examines the relation between *SOPH* and the proximity of the resulting pseudo-target-to-share prices to the long-term BL-Ratios *BLFIT*. The inclusion of *BLFIT* increases the pseudo *R*-squared to 37.0% (Chi-square test, $p<0.01$). The coefficient on *BLFIT* of 3.239 ($p<0.01$) is positive and highly significant, which supports H1 that analysts use sophisticated valuation when their use attains target prices that are closer to their long-run target price optimism. The effect is large since the predicted probability that an analyst uses sophisticated valuation is 68.9% when the

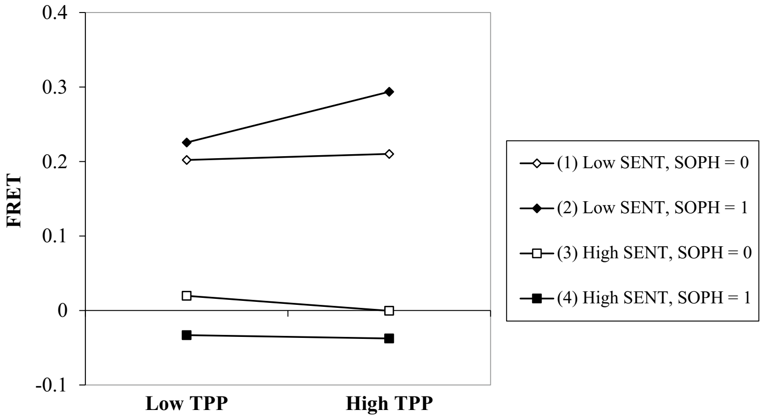

Fig. 2 Return predictability of target prices and the influence of analysts' valuation model choice and sentiment (Eq. (8))

pseudo-target price based on sophisticated valuation is closer to the BL-Ratio (i.e., if *BLFIT* = 1 vs. 8.0% if *BLFIT* = 0). The coefficient on *SENT* of -0.479 ($p < 0.01$) is highly significant.

The Wald test of exogeneity indicates endogeneity related to *SENT* for Eqs. (5) and (6) (363.96 and 203.66, $p < 0.01$). The third and sixth column of Panel B of Table 6 show the 2SLS second stage results of Eq. (5) and (6). Weak identification of the IVs can be rejected (42.819 and 42.925 > 19.93). Overidentification of the IVs cannot be rejected (5.258 and 6.089, $p < 0.05$), but overidentification disappears and the results remain inferentially equivalent when we only use one of the IVs (not tabulated). Overall, the second stage results show a negative coefficient on *SENT (Instr.)* (-1.056, $p < 0.01$) and a positive coefficient on *BLFIT* (1.827, $p < 0.01$) and confirm that analysts' inferred use of sophisticated methods is negatively associated with investor sentiment and that analysts use sophisticated methods when their use attains target prices that are closer to their long-run target price optimism, consistent with H1.

Table 6 presents the results for testing Hypothesis 2. The first column of Panel A of Table 6 presents the OLS regression results for testing Eq. (7) that examines the relation between *TPEXC* and *SENT*. The adjusted R-squared is high at 24.9% (F-test, $p < 0.01$). The coefficient on *SENT* is positive and highly significant (0.422, $p < 0.01$), consistent with our expectation that target price excess is stronger in periods of high sentiment. The coefficient of 0.422 implies that when sentiment increases by one standard deviation, target price excess increases by 21.8 percentage points (0.422*0.516). Control variables carry the expected signs. The endogeneity test is significant (36.866, $p < 0.01$). In the third column, 2SLS second stage results confirm the OLS regression results. Overidentification (1.261, $p < 0.01$) and weak identification (42.819 > 19.93) can be rejected and the coefficient on *SENT (Instr.)* is positive and highly significant (1.250, $p < 0.01$). These results are in line with our observation in Table 3 that the amounts of *TPEXC* follow the same pattern as sentiment and are consistent with our underlying assumptions depicted in Fig. 1 that target prices will be more informative in low sentiment.

The sixth column of Panel A of Table 6 presents the OLS regression results[15] for Eq. (8) that examines the relation between *FRET* and *TPP* dependent upon *SOPH* and *SENT*, based on H2 that the investment value of target prices is higher in low sentiment when

[15] As shown in the third column of Panel B of Table 6, the endogeneity test is statistically insignificant indicating no endogeneity related to *SENT* in regression Eq. (8) (1.662, $p > 0.1$) and hence we only present OLS regression results, but 2SLS results would not be conflicting.

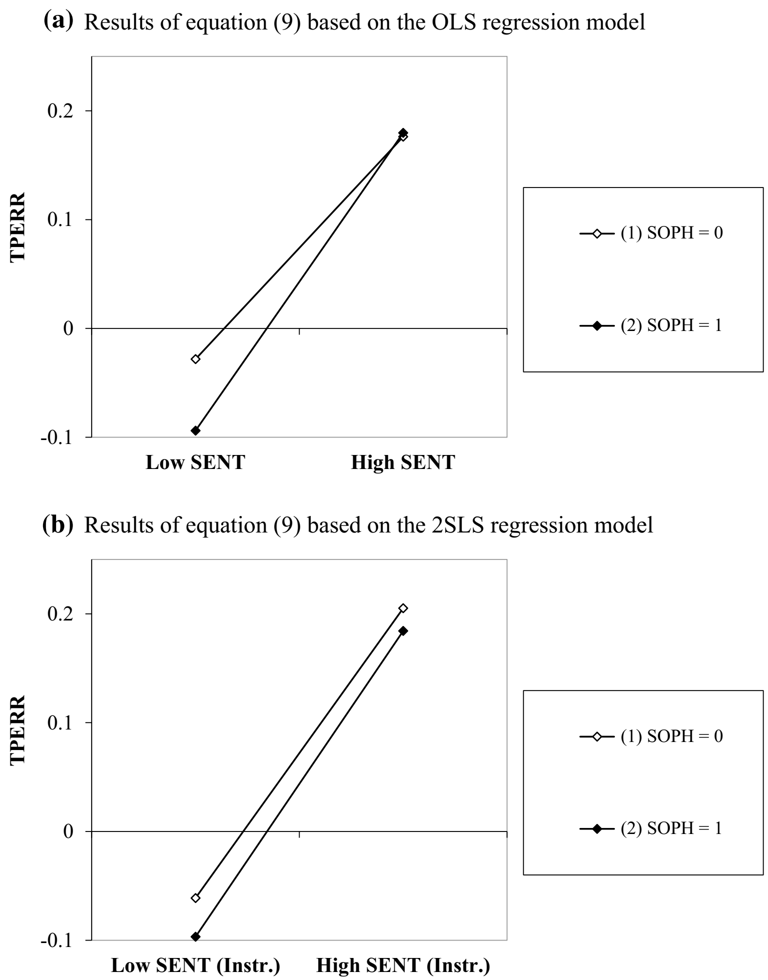

Fig. 3 Target price errors and the influence of analysts' valuation model choice and sentiment (Eq. 9) **a** Results of Eq. (9) based on the OLS regression model. **b** Results of Eq. (9) based on the 2SLS regression model

sophisticated valuation methods are used. The fourth column presents results excluding *SENT* to replicate the analysis in Gleason et al. (2013) as a baseline. The insignificant coefficient on *TPP* and the sum of the coefficients on *TPP* and *TPP*SOPH* being significantly positive at 0.135 ($p<0.01$) confirm the findings of Gleason et al. (2013) that target prices based on sophisticated valuation are of higher investment value. The fifth column presents results for Eq. (8) excluding *SOPH* to replicate the analysis in Clarkson et al. (2020). The negative and highly significant coefficient on *TPP*SENT* of -0.087 ($p<0.01$) confirms their findings that the return predictability of target prices decreases with higher market sentiment for our sample.

The analysis in the sixth column of Panel A of Table 6 tests our proposed relation in H2 by jointly examining *SENT* and *SOPH*. The overall model shows high statistical validity with an adjusted R-squared of 10.2% (F-test, $p<0.01$) which is higher than in the other specifications. Coefficients on control variables carry the expected signs. *PostREG* is significantly positive in the first column excluding sentiment. The inclusion of sentiment turns the sign negative, indicating that some of the effect of *PostREG* is captured by *SENT*, which is strongly negatively correlated.[16] The variables of interest show the expected signs. *SENT* is negatively associated with *FRET* and highly significant (-0.114, $p<0.01$). The coefficient on *TPP*SOPH* is significantly positive (0.09, $p<0.01$) and *TPP*SENT* is significantly negative (-0.065, $p<0.01$), as expected. Both coefficients decrease when *TPP*SENT*SOPH* is included in the regression, indicating that the relationship of return predictability of target prices and analysts' use of sophisticated valuation is largely moderated by sentiment, as expected in H2. The coefficient on *TPP*SENT*SOPH* is significantly negative (-0.102, $p<0.01$), implying that return predictability of target prices based on sophisticated valuation is higher in low sentiment, supporting H2.

To simplify the interpretation of the three-way interactions, we present the OLS regression results of Eq. (8) for the subsamples $SOPH=0$ and $SOPH=1$ in Panel B of Table 6. The coefficient on *TPP* is significantly higher for $SOPH=1$ than for $SOPH=0$ (0.09, $p<0.01$). The coefficients on *TPP*SENT* are significantly negative for both subsamples, but significantly more negative by -0.102 ($p<0.01$) for $SOPH=1$, which equals the coefficient on *TPP*SENT*SOPH* in Panel A of Table 6.

To fully interpret the results of the three-way interaction, the coefficients need to be interpreted in conjunction with each other (Hayes 2013). The joint effect of *SENT* on *FRET* via *SOPH* is presented in Panel C of Table 6. For target prices based on heuristic valuation ($SOPH=0$), the simple intercept and simple slope of *FRET* with respect to *SENT* (indicating the overall effect of *SENT* on *FRET*) are 0.109 ($p<0.01$) and -0.191 ($p<0.01$), respectively (*TPP* at the mean). For sophisticated valuation ($SOPH=1$), the simple intercept is 0.114 ($p<0.01$) and the simple slope is –0.286 ($p<0.01$), indicating that the overall effect of *SENT* on *FRET* is significantly negative. We graph the OLS regression results in Fig. 2. To do so, we predict *FRET* based on the regression results for different combinations of *SOPH, SENT,* and *TPP.* We set low (high) values of *SENT* and *TPP* at one standard deviation below (above) their mean values (Aiken and West 1991); all other variables are held at their mean values.

The results displayed in Fig. 2 show that return predictability is considerably higher for low sentiment compared to high sentiment. Return predictability is highest for target prices based on sophisticated valuation in low sentiment (2), but only slightly higher than for target prices based on heuristics in low sentiment (1). Return predictability is significantly different from zero ($p<0.01$) in both cases. The difference in predicted returns *FRET* between (2) and (1) is on average 5.3 percentage points (significant at $p<0.01$) and the difference between (3) and (4) is 4.5 percentage points (significant at $p<0.05$). Return predictability is lowest for sophisticated valuation used in high sentiment (4). The difference in predicted returns *FRET* between (2) and (4) is 29.5 percentage points and (1) and (3) is 19.7 percentage points on average (each significant at $p<0.01$). Hence, the magnitude of the effect of *SENT* on *FRET* is about 6 times as strong as that of *SOPH*. In fact, return predictability in high sentiment ((3) and (4)) is not significantly different from zero for both heuristic and sophisticated valuation methods, indicating that target prices have poor investment value in high sentiment irrespective of the valuation method used. Overall, the evidence strongly supports H2. These findings are consistent with the interpretation that

[16] There are, however, no multicollinearity problems in our regressions, the highest VIF is 1.5. We also perform additional tests that include the interactions *TPP*PostREG* and *TPP*PostREG*SOPH* in Eq. (8). Our main conclusions are robust when adding these interactions.

Table 7 Market reactions to target price revisions (Regression results)

Panel A: Market reactions to target price revisions (Primary model results)

Model		$(10_{excl.SENT})$ (OLS)		$(10_{excl.SOPH})$ (OLS)		(10) (OLS)		$(10_{excl.Dot.com + 2008crisis})$ (OLS)	
Variable	Pred	ARET		ARET		ARET		ARET	
	Sign	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]
TPREV	(+)	0.145***	[22.02]	0.144***	[21.35]	0.145	[21.95]	0.165***	[27.53]
TPREV*SOPH	(+)	−0.004	[−0.59]	–	–	0.004	[0.61]	0.002	[0.31]
TPREV*SENT	(−)	–	–	0.006	[0.79]	−0.000	[−0.01]	0.075***	[8.18]
TPREV*SENT*SOPH	(−)	–	–	–	–	0.039***	[4.49]	0.009	[0.74]
SENT	(−)	–	–	0.000	[0.47]	0.001	[0.85]	−0.003***	[−2.85]
SENT*SOPH	(+)	–	–	–	–	−0.002	[−1.29]	−0.001	[−0.51]
SOPH	(+)	−0.021*	[−1.82]	–	–	−0.017	[−1.54]	−0.024**	[−2.10]
PostREG	(+)	−0.001	[−0.31]	−0.001	[−0.51]	0.000	[0.15]	–	–
EPSREV	(+)	0.021***	[13.38]	0.019***	[14.11]	0.021***	[13.41]	0.019***	[12.41]
RECREV	(+)	0.047***	[13.90]	0.049***	[12.94]	0.047***	[13.92]	0.033***	[10.75]
CSD	(−)	−0.381***	[−7.63]	−0.363***	[−7.33]	−0.369***	[−7.47]	−0.401***	[−7.78]
CBETA	(?)	−0.001	[−1.41]	−0.001	[−1.19]	−0.001	[−1.53]	−0.001*	[−1.96]
CBM	(+)	−0.001	[−1.29]	−0.001	[−0.94]	−0.001	[−1.17]	−0.001	[−0.63]
CSIZE	(−)	−0.001***	[−3.06]	−0.001**	[−2.10]	−0.001***	[−3.01]	−0.001***	[−3.48]
CEXF	(−)	−0.001	[−1.17]	−0.003**	[−2.48]	−0.002	[−1.29]	−0.002	[−1.11]
CPRET	(+)	−0.004***	[−3.20]	−0.003***	[−2.76]	−0.004***	[−3.26]	−0.003**	[−2.50]
CWH	(+)	0.016***	[9.43]	0.015***	[10.20]	0.016***	[9.45]	0.022***	[8.64]
AFEXP	(+)	−0.013	[−1.53]	−0.011	[−1.51]	−0.013	[−1.50]	−0.010	[−1.14]
ANFIR	(?)	−0.004	[−1.33]	−0.004	[−1.39]	−0.004	[−1.33]	−0.005	[−1.44]
ANIND	(?)	−0.011	[−0.81]	−0.010	[−0.84]	−0.010	[−0.79]	−0.014	[−0.97]
ABSIZ	(+)	0.000	[0.63]	0.000	[0.78]	0.000	[0.61]	0.000	[0.31]
AROUND	(−)	0.002**	[2.31]	0.003***	[2.91]	0.002**	[2.33]	0.002**	[2.00]
constant	(?)	0.005	[0.67]	−0.002	[−0.22]	0.003	[0.48]	0.003	[0.36]
$CONTROL^{REV}$*SOPH		YES		NO		YES		YES	

Table 7 (continued)

Panel A: Market reactions to target price revisions (Primary model results)

Model		$(10_{excl.SENT})$ (OLS)		$(10_{excl.SOPH})$ (OLS)		(10) (OLS)		$(10_{excl.Dot.com + 2008crisis})$ (OLS)	
Variable	Pred	ARET		ARET		ARET		ARET	
	Sign	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]
IND		YES		YES		YES		YES	
IND*SOPH		YES		NO		YES		YES	
No. of Obs		254,263		254,263		254,263		201,714	
Adj. R^2		0.131		0.130		0.131		0.153	
Endogeneity test of endogenous regressor						0.238 (No endogeneity)			

Panel B: Results of Eq. (10) (OLS) partitioned for the subsamples SOPH = 0 and SOPH = 1

Model / Sample		(10) (OLS) / SOPH = 0		(10) (OLS) / SOPH = 1			
Variable	Pred	ARET		ARET		Diff. (SOPH = 1−SOPH = 0)	
	Sign	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]
TPREV	(+)	0.145***	[21.95]	0.148***	[17.56]	0.004	[0.61]
TPREV*SENT	(−)	0.000	[−0.01]	0.039***	[3.28]	0.039***	[4.49]
SENT	(−)	0.001	[0.85]	−0.001	[−0.71]	−0.002	[−1.29]
PostREG	(+)	0.000	[0.15]	−0.006	[−1.51]	−0.006	[−1.50]
EPSREV	(+)	0.021***	[13.41]	0.015***	[10.66]	−0.006***	[−3.78]
RECREV	(+)	0.047***	[13.92]	0.052***	[8.03]	0.005	[1.01]
CSD	(−)	−0.369***	[−7.47]	−0.345***	[−4.51]	0.024	[0.33]
CBETA	(?)	−0.001	[−1.53]	0.000	[0.18]	0.001	[1.15]
CBM	(+)	−0.001	[−1.17]	0.000	[−0.10]	0.001	[0.70]
CSIZE	(−)	−0.001***	[−3.01]	0.000	[0.27]	0.001**	[2.27]
CEXF	(−)	−0.002	[−1.29]	−0.006***	[−4.25]	−0.004***	[−2.78]
CPRET	(+)	−0.004***	[−3.26]	0.000	[−0.19]	0.004**	[2.16]
CWH	(+)	0.016***	[9.45]	0.015***	[8.62]	−0.001	[−0.62]

Table 7 (continued)

Panel B: Results of Eq. (10) (OLS) partitioned for the subsamples SOPH = 0 and SOPH = 1

Model / Sample		(10) (OLS) / SOPH = 0		(10) (OLS) / SOPH = 1			
Variable	Pred	ARET		ARET		Diff. (SOPH = 1−SOPH = 0)	
	Sign	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]	Coeff	[*t*-stat.]
AFEXP	(+)	−0.013	[−1.50]	−0.005	[−0.58]	0.008	[0.73]
ANFIR	(?)	−0.004	[−1.33]	−0.002	[−0.30]	0.002	[0.38]
ANIND	(?)	−0.010	[−0.79]	−0.016	[−0.77]	−0.006	[−0.27]
ABSIZ	(+)	0.000	[0.61]	0.000	[0.72]	0.000	[0.36]
AROUND	(−)	0.002**	[2.33]	0.003*	[1.91]	0.001	[0.61]
constant	(?)	0.003	[0.48]	−0.014	[−1.13]	−0.017	[−1.54]
IND			YES		YES		
No. of Obs			189,789		64,474		
Adj. R^2			0.130		0.134		

Panel C: Sum of interaction coefficients: Simple intercepts and simple slopes of ARET with respect to SENT based on the results of Eq. (10) (OLS)

	Simple intercept with respect to SENT	[z-stat.]	Simple slope with respect to SENT	[z-stat.]
SOPH = 0	0.025***	[20.82]	0.001	[0.52]
SOPH = 1	0.025***	[16.06]	0.006**	[2.11]

Panel A of this table presents the results of the Eq. (10) based on a sample of 254,263 target prices for U.S. firms over the period from April 1999 to December 2014. Equation (10) examines the relation between the firms' short-term abnormal returns *ARET* and target price revisions dependent upon analysts' valuation model choice *SOPH* and investor sentiment *SENT*. The results shown in the last column are discussed in the additional analyses (i.e., results for a subsample excluding the Dot.com period and the 2008 financial crisis). Panel B presents the results of the Eq. (10) for the subsamples *SOPH* = 0 and *SOPH* = 1. Panel B presents the simple intercepts and simple slopes with respect to *SENT* based on the results of Eq. (10) (i.e., $\beta_0 + \beta{*}TPREV + \gamma_1{*}CONTROL = 0.025$; $\beta_3{*}TPREV + \beta_5 = 0.001$; $\beta_0 + \beta_7 + (\beta_1 + \beta_2){*}TPREV + (\gamma_1 + \gamma_2){*}CONTROL = 0.025$; and $(\beta_3 + \beta_4){*}TPREV + \beta_5 + \beta_6 = 0.006$; with *TPREV* at one standard deviation above the mean). Equation (10) is run as a pooled OLS regression. Variable definitions can be found in the Appendix 2

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. Significance tests are based on a two-tailed *t(z)*-test corrected for clustering of standard errors by firm, analyst, and month (Petersen 2009; Gow et al. 2010; Cameron et al. 2011)

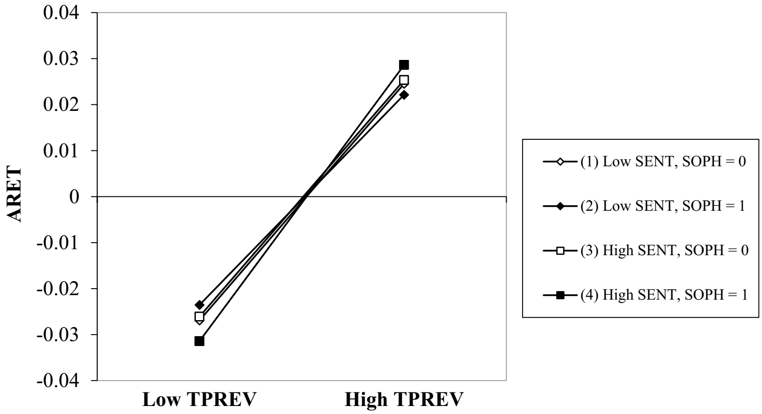

Fig. 4 Market reaction to target price revisions and the influence of analysts' valuation model choice and sentiment (Eq. (10))

target prices have higher investment value in low sentiment not only because of sophisticated valuation method use, but also because optimism biases target prices toward the higher intrinsic values.

The first column of Panel D of Table 6 presents the OLS results for testing Eq. (9) that examines the relation between *TPERR* and *SENT* dependent upon *SOPH*. The overall model shows high statistical validity with an adjusted R-squared of 12.4% (F-test, $p<0.01$). The positive coefficient on *SENT* of 0.198 ($p<0.01$) confirms that target price errors are higher in periods of high market sentiment, the positive coefficient on *SENT*SOPH* of 0.067 ($p<0.01$) indicates that errors are highest for sophisticated valuation models used in high sentiment, consistent with H2. For illustration, OLS regression results are graphed in Fig. 3a.

Figure 3a highlights that *TPERR* are higher in high sentiment. Target price errors are not significantly different depending on valuation method use in high sentiment. Compared to low sentiment, *TPERR* are significantly higher in high sentiment by 27.4 percentage points ($p<0.01$) for sophisticated valuation (*SOPH*=1) and by 20.4 ($p<0.01$) for heuristic valuation (*SOPH*=0). In low sentiment, errors are lower for sophisticated compared to heuristic valuation by 6.6 percentage points ($p<0.01$). Target price errors are hence largely explained by investor sentiment, consistent with H2.

The endogeneity test is significant (8.329, $p<0.01$) in regression Eq. (9). The second stage 2SLS regression results are shown in the third column of Panel D of Table 6. Overidentification (0.390, $p<0.01$) and weak identification ($42.819>19.93$) can be rejected. The coefficient on *SENT (Instr.)* (0.394, $p<0.01$) is positive, and the coefficient on the interaction *SENT (Instr.)*SOPH* is positive but insignificant. The sum of the coefficients of *SENT (Instr.)* and *SENT (Instr.)*SOPH* is significantly positive ($0.394+0.022=0.416$, $p<0.01$), indicating that the moderating effect of sentiment significantly affects *TPERR*. Figure 3b graphs the results. Similar to the OLS regression results, *TPERR* is significantly higher in high relative to low sentiment by 28.1 percentage points ($p<0.01$) for sophisticated valuation (*SOPH*=1) and by 26.6 ($p<0.01$) for heuristic valuation (*SOPH*=0), *TPERR* is not significantly different depending on valuation method use in high sentiment, and *TPERR* is lower for sophisticated compared to heuristic valuation by 3.56 percentage points in low sentiment ($p < 0.01$), consistent with H2.

Panel A of Table 7 presents the OLS regression[17] results of Eq. (10) for testing Hypothesis 3, examining the relation between the firms' short-term abnormal returns *ARET* and analysts' target price revisions *TPREV* dependent upon *SOPH* and *SENT*. The adjusted R-squared is 13.1% (F-test, $p < 0.01$). The coefficient on the interaction *TPREV*SENT*SOPH* is positive and highly significant (0.039, $p < 0.01$), indicating that market reactions to target price revisions are higher in periods of high sentiment when analysts use sophisticated valuation, which contradicts H3. The coefficients on *TPREV*SOPH*, *TPREV*SENT*, and *SOPH* are insignificant. Control variables carry the expected signs, except for the positive (negative) coefficient on *AROUND* (*CPRET*).

Panel B of Table 7 presents the OLS regression results of Eq. (10) for the subsamples *SOPH* = 0 and *SOPH* = 1. The coefficients on *TPREV* show that investors react to target price revisions independently of valuation method use in low sentiment (Diff. = 0.004, $p > 0.1$), but react significantly more strongly to sophisticated valuation in high sentiment (Diff. on *TPREV*SENT* = 0.039; $p < 0.01$). Panel C of Table 7 presents the simple slopes and intercepts with respect to *SENT* based on the regression results of Eq. (10). Even though our analyses reveal that target prices are more meaningful in low sentiment, investor reactions are significantly stronger in high sentiment ($p < 0.01$), indicating that investors do not comprehend the differential informativeness of target prices and react irrationally to target price revisions in high sentiment. We plot the results in Fig. 4 as described above.

5.3 Additional analyses

In our main analyses, we control for important regulatory reforms introduced between 2000 and 2003 that affected analysts' conflicts of interest, we expect that they also affect target price optimism. These include Regulation Fair Disclosure (Reg FD), NASD Rule 2711, an amendment to NYSE Rule 472, Regulation AC and the Global Research Analyst Settlement in 2003. These regulations were, among other things, intended to reduce analysts' conflicts of interest and to enhance the independence of analysts' research (see e.g., Bradshaw 2009 for details). Prior literature finds that analysts' use of sophisticated valuation increased (e.g., Barniv et al. 2009; Chen and Chen 2009) and analysts' optimism in setting stock recommendations decreased after these regulations (e.g., Barber et al. 2006; Dong and Hu 2016). In an additional test, we examine whether analysts' target price optimism (i.e., the ratios of target-to-share prices *TPP*) decreased subsequent to the implementation of analysts' regulatory reforms after April 2003. We include the results in the fourth column of Table 5. The negative and highly significant coefficient on *PostREG* (-0.055; $p < 0.01$) supports our expectation that target price optimism is reduced after the regulatory reforms. Moreover, the relation between *TPP* and *SENT* is statistically insignificant, indicating that target price optimism is stable and not related to investor sentiment, consistent with our underlying assumptions.

[17] As shown in the last row of Panel A of Table 7, the endogeneity test is statistically insignificant indicating no endogeneity related to *SENT* in regression Eq. (10) (0.238, $p > 0.01$) and hence we only present OLS regression results, but 2SLS results would not be conflicting.

Table 8 Main analyses based on investor sentiment with a one-month time lag SENTl1 (Regression results)

Panel A: Regression results of Eq. (4) to (10) (OLS) using investor sentiment with a one-month time lag SENTl1

Model		(4) (OLS)			(5) (Logit)		(6) (Logit)			(7) (OLS)	
Variable		TP			SOPH		SOPH			TPEXC	
		Coeff	[*t*-stat.]		Coeff	[*t*-stat.]	Coeff	[*t*-stat.]		Coeff	[*t*-stat.]
SENTl1	(+)	0.156***	[4.31]	(−)	−0.636***	[−6.20]	−0.430***	[−6.38]	(+)	0.414***	[7.08]
SENTl1*SOPH	(−)	−0.197***	[−3.27]		–	–	–	–		–	–
SOPH	(+)	0.870	[1.32]		–	–	–	–		–	–
BLFIT		–	–	(+)	–	–	3.243***	[37.18]		–	–
TPP (TPR.)		–	–		–	–	–	–		–	–
TPP (TPR.)*SOPH		–	–		–	–	–	–		–	–
TPP (TPR.)*SENTl1		–	–		–	–	–	–		–	–
TPP (TPR.)*SENTl1*SOPH		–	–		–	–	–	–		–	–
Constant	(?)	−1.084***	[−2.87]	(?)	−3.891***	[−6.82]	−3.807***	[−9.28]	(?)	3.102***	[8.11]
CONTR/IND		YES			YES		YES			YES	
CONTR.*SOPH/ IND*SOPH		YES			NO		NO			NO	
No. of Obs		254,263			254,263		254,263			254,263	
Adj. R^2 (Pseudo R^2)		0.741			0.066		0.370			0.249	

Model		(8) (OLS)			(9) (OLS)			(10) (OLS)	
Variable		FRET			TPERR			ARET	
		Coeff	[*t*-stat.]		Coeff	[*t*-stat.]		Coeff	[*t*-stat.]
SENTl1	(−)	−0.109***	[−2.76]	(+)	0.195***	[8.71]	(−)	0.001	[1.55]
SENTl1*SOPH	(+)	0.011	[0.21]	(+)	0.055**	[2.50]	(+)	−0.003	[−1.61]

Table 8 (continued)

Model		(8) (OLS)			(9) (OLS)			(10) (OLS)	
Variable		FRET			TPERR			ARET	
		Coeff	[*t*-stat.]		Coeff	[*t*-stat.]		Coeff	[*t*-stat.]
SOPH	(−)	−0.190*	[−1.66]	(?)	0.024	[0.20]	(+)	−0.017	[−1.52]
BLFIT		–	–		–	–		–	–
TPP (TPR.)	(+)	−0.011	[−0.48]		–	–	(+)	0.145***	[22.01]
TPP (TPR.)*SOPH	(+)	0.110***	[3.83]		–	–	(+)	0.002	[0.33]
TPP (TPR.)*SENTl1	(−)	−0.068**	[−2.16]		–	–	(−)	0.000	[0.03]
TPP (TPR.)*SENTl1*SOPH	(−)	−0.071*	[−1.79]		–	–	(−)	0.034***	[3.86]
Constant	(?)	0.303**	[2.54]	(?)	−0.459***	[−3.50]	(?)	0.002	[0.31]
CONTR/IND		YES			YES			YES	
CONTR.*SOPH/ IND*SOPH		YES			YES			YES	
No. of Obs		254,263			254,263			254,263	
Adj. R^2 (Pseudo R^2)		0.100			0.123			0.131	

	Simple intercept with respect to SENTl1	[z-stat.]	Simple slope with respect to SENTl1	[z-stat.]
Panel B: Sum of interaction coefficients: Simple intercepts and simple slopes of FRET with respect to SENTl1 based on the results of Eq. (8) (OLS)				
SOPH = 0	0.110***	[7.14]	−0.189***	[−9.12]
SOPH = 1	0.120***	[7.19]	−0.261***	[−8.58]

Table 8 (continued)

	Simple intercept with respect to SENTI1	[z-stat.]	Simple slope with respect to SENTI1	[z-stat.]
Panel C: Sum of interaction coefficients: Simple intercepts and simple slopes of ARET with respect to SENTI1 based on the results of Eq. (10) (OLS)				
SOPH = 0	0.025***	[21.03]	0.002	[1.03]
SOPH = 1	0.025***	[15.65]	0.006*	[1.91]

Panel A of this table presents the results of the Eq. (4) to (10) based on a sample of 254,263 target prices for U.S. firms over the period from April 1999 to December 2014 based on investor sentiment with a one-month time lag *SENTI1* (i.e., *SENTI1* is investor sentiment in the month prior to the target price release month). Equation (4) examines the relation between target prices *TP* and lagged investor sentiment *SENTI1* dependent upon analysts' valuation model choice *SOPH*. Equation (5) examines the relation between analysts' use of sophisticated valuation models *SOPH* and lagged investor sentiment *SENTI1*. Equation (6) examines the relation between analysts' use of sophisticated valuation models *SOPH* and the proximity of the resulting pseudo-target-to-share prices to the firms' long-term BL-Ratios *BLFIT*. Equation (7) examines the relation between the target price excess *TPEXC* and lagged investor sentiment *SENTI1*. Equation (8) examines the relation between the firms' one-year future returns *FRET* and the ratios of target-to-share prices *TPP* dependent upon analysts' valuation model choice *SOPH* and lagged investor sentiment *SENTI1*. Equation (9) examines the relation between the target price errors *TPERR* and lagged investor sentiment *SENTI1* dependent upon analysts' valuation model choice *SOPH*. Equation (10) examines the relation between the firms' short-term abnormal returns *ARET* and target price revisions *TPREV* dependent upon analysts' valuation model choice *SOPH* and lagged investor sentiment *SENTI1*. Panel B presentsthe simple intercepts and simple slopes with respect to lagged investor sentiment *SENTI1* based on the results of Eq. (8) (i.e., $\beta_0 + \beta_1{*}TPP + \gamma_1 CONTROL = 0.110$; $\beta_3{*}TPP + \beta_5 = -0.189$; $\beta_0 + \beta_7 + (\beta_1 + \beta_2){*}\mathrm{TPP} + (\gamma_1 + \gamma_2){*}CONTROL = 0.120$; and $(\beta_3 + \beta_4)TPP + \beta_5 + \beta_6 = -0.261$; with *TPP* at the mean). Panel C presents the simple intercepts and simple slopes with respect to lagged investor sentiment SENTI1 based on the results of Eq. (10) (i.e., $\beta_0 + \beta_1{*}TPREV + \gamma_1 CONTROL = 0.025$; $\beta_3{*}TPREV + \beta_5 = 0.002$; $\beta_0 + \beta_7 + (\beta_1 + \beta_2){*}TPREV + (\gamma_1 + \gamma_2){*}CONTROL = 0.025$; and $(\beta_3 + \beta_4){*}TPREV + \beta_5 + \beta_6 = 0.006$; with *TPREV* at one standard deviation abovethe mean). Equation (4), (7), (8), (9) and (10) are run as pooled OLS regressions and Eqs. (5) and (6) are run as pooled logit regressions. Adj. R2s (Pseudo R2s) are mentioned for Eqs. (4), (7), (8), (9) and (10) (Eqs. (5) and (6)). Variable definitions can be found in the Appendix 2

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. Significance tests are based on a two-tailed *t(z)*-test corrected for clustering of standard errors by firm, analyst, and month (Petersen 2009; Gow et al. 2010; Cameron et al. 2011)

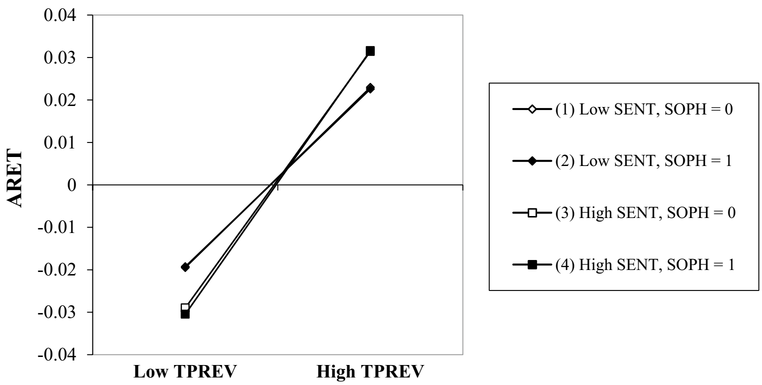

Fig. 5 Market reaction to target price revisions excluding the Dot.com and 2008 financial crisis periods (Eq. (10))

Moreover, we perform several sensitivity tests to examine the robustness of our results. First, we re-run our main analyses based on investor sentiment with a one-month time lag *SENTl1* considering the possibility that analysts process prior (not current) investor sentiment when they derive target prices. Using a time-lag also provides for more causal inferences of the results.

Panel A of Table 8 presents the regression results of Eq. (4) to (10) based on *SENTl1*. Panel B and C present the corresponding simple intercepts and simple slopes of *FRET* and *ARET* with respect to *SENTl1* based on the results of Eqs. (8) and (10). The results are very similar to the main results shown in Table 5, 6 and 7 and confirm that the investment value of target prices is highest when sentiment is low and target prices are based on sophisticated valuation. In high sentiment, the investment value of target prices is close to zero independently of the valuation method used. Similarly, the results show that investors react irrationally to target price revisions in high sentiment. In not tabulated tests, we additionally re-run the analyses based on two- and three-month lagged investor sentiment. Overall, the results are robust when using one-, two- or three-months lags of investor sentiment but become weaker with longer time-lags, indicating that analysts' valuation procedures are more strongly affected by recent investor sentiment.

Second, Barber et al. (2003) highlight that excluding crises can significantly impact inferences regarding analysts. Hence, we build three subsamples (1) excluding the Dot.com period and the period of important regulations (i.e., before May 2003, see e.g., Dong and Hu 2016), (2) excluding the credit crisis (i.e., the period from October 2007 to March 2009, see Arand and Kerl 2012) and (3) excluding both periods. The inferences from these additional tests are qualitatively equivalent to our main analyses except for the market reactions to target price revisions. For subsamples 1 and 3, we find evidence that investors react more strongly to target price revisions in high sentiment, independent of the valuation method used (see the last column in Panel A of Table 7 and Fig. 5). Hence, target price revisions do not differ depending on valuation method use, contradicting H3, indicating that investors do not appreciate the differential investment value of target prices based on sophisticated valuation. This evidence is similar to Asquith et al. (2005) and Bonini and Kerl (2014) finding no evidence for stronger market reactions to target price revisions when analysts refer to the use of sophisticated valuation methods in their reports.

Third, we separately include the stocks' trading volume (Dechow and You 2020), fixed effects for every firm/analyst combination (since our panel-dataset has three dimensions: firms, analysts and time) instead of industry fixed effects and a time trend in every equation. Trading volume appears to contain very similar information as firm size in our regressions. Our main inferences remain unaffected throughout all variations. Fourth, we re-test all equations based on a subsample of high volatility stocks. Baker and Wurgler (2006) show that especially hard-to-value firms are affected by the level of investor sentiment. We sort the monthly target prices in quintiles, based on the stocks' return volatility (a proxy for hard-to-value stocks), and re-test our analyses for target prices of the highest quintile. In brief, our results are robust for the subsample.

Fifth, we repeat our analyses using Campbell and Shiller's Cyclically-Adjusted Price to Earnings (CAPE) ratio (Campbell and Shiller 1988; 1998; 2001) instead of the Baker and Wurgler (2006, 2007) investor sentiment index. We find that the CAPE ratio is highly correlated with the investor sentiment index (by 63% in our panel dataset). Our conclusions are also robust in this setting. Finally, we repeat all analyses based on the VMR measure of Gleason et al. (2013) rather than our *SOPH* measure. Since this measure is continuous, the results of the three-way interaction are harder to interpret, but they are inferentially equivalent to our main results.

6 Conclusion

This study examines whether analysts' target prices stabilize the stock market. Target prices closer to the firms' fundamental values should be more informative to investors and hence have a stabilizing effect. We expect that target price optimism has a positive effect when investor sentiment is low, but not when sentiment is high. Our evidence provides support for this expectation.

Our findings thus add to literature on the informativeness of analysts' target prices by showing that target price optimism and valuation method use have different implications for target price informativeness depending on investor sentiment. We also contribute to the literature on the consequences of stock market regulations for analysts (e.g., Barber et al. 2006; Dong and Hu 2016) by showing that analysts' target price optimism decreased significantly subsequently to the release of regulations affecting analysts' behavior (Regulation Fair Disclosure, NASD Rule 2711, an amendment to NYSE Rule 472, Regulation AC and the Global Research Analyst Settlement in 2003). Finally, we add to literature on analysts' valuation method choice (e.g., Glaum and Friedrich 2006; Imam et al. 2008; Demirakos et al. 2010). Based on a statistical inference procedure, we confirm that analysts' valuation method use depends on the level of investor sentiment whereas related studies are based on interviews with analysts or the information in analyst reports (e.g., Glaum and Friedrich 2006; Imam et al. 2008; Demirakos et al. 2010; Huang et al. 2022). While an advantage of such a statistical approach is that the results do not depend on analysts' subjective statements, a limitation of our study is the ability of this statistical approach to capture the actual behavior of analysts.

Appendix 1

Valuation model description

Models classified as sophisticated valuation methods (V_{RIP}, V_{RIF} and V_{DDM})

Residual Income Valuation with Perpetuity Assumption V_{RIP}:

$$V_{RIP,t} = BVPS_t + \sum_{\tau=1}^{5} \frac{E_t\left[RI_{t+\tau}\right]}{(1+r)^{\tau}} + \frac{E_t\left[RI_{t+5}\right]}{r(1+r)^5}$$

where $V_{RIP,t}$ is the pseudo-target price at time t, $BVPS$ is the equity book value per share, $E[RI]$ is residual income ($EPS_{t+\tau}$-r*$BVPS_{t+\tau-1}$), EPS is analyst's earnings per share forecast, r is the equity cost of capital, and τ is a time index (Bradshaw 2004). The time index is simplified for illustration. In fact, the residual income is discounted to the first day of the target price release month. Analyst and firm subscripts are omitted for brevity. Contemporaneously issued one- and two-year-ahead EPS forecasts are required to be available. Unavailable EPS forecasts from three up to five years are extrapolated by analyst's long-term EPS growth forecast (Bradshaw 2004). Missing long-term EPS growth forecasts are replaced by the median consensus long-term EPS growth forecasts. In the first three months of a fiscal year, the equity book value per share is approximated by the clean surplus relation ($BVPS_t = BVPS_{t-1} + EPS_t - DPS_t$ where DPS is the dividend per share, we require that the EPS forecasts are not older than 90 days on the fiscal year end), afterwards the most recent equity book value per share (COMPUSTAT item #60 divided by item #25) is used. Future equity book values per share are also determined by the clean surplus relation. It is assumed that firms maintain their historical dividend payout ratio (Bradshaw 2004). The dividend payout ratio to compute the dividends per share is defined as the payout ratio of the most recent fiscal year (item #21 divided by item #237) or the mean payout ratio over the previous three years if the prior year payout ratio is less than zero or greater than one (Bradshaw 2004). For loss-making firms, the payout ratio is computed as the most recent dividends divided by 6% (Frankel and Lee 1998) of firm's total assets (item #6). Further, unreasonable payout ratios of less than zero or greater than one are set to zero or to one, respectively (Lee et al. 1999). The industry discount rate r is the 48 industry-specific risk premiums (Fama and French 1997) plus the risk-free rate (30-day U.S. treasury bill yield) using twenty-year rolling regressions in effect for the month prior to the target price release date (Bradshaw 2004). We apply twenty-year rolling regressions since five-year rolling regressions generate in part negative industry discount rates after the subprime crisis. Monthly industry discount rates are annualized by multiplying with 12.

Residual Income Valuation with a Fade-Rate Assumption V_{RIF}:

$$V_{RIF,t} = BVPS_t + \sum_{\tau=1}^{5} \frac{E_t\left[RI_{t+\tau}\right]}{(1+r)^{\tau}} + \frac{\omega E_t\left[RI_{t+5}\right]}{(1+r-\omega)(1+r)^5}$$

where $V_{RIF,t}$ is the pseudo-target price at time t, $BVPS$ is the equity book value per share, r is the equity cost of capital (see RIM with Perpetuity Assumption), $E[RI]$ is the expected residual income, ω is the industry rate of reversion, and τ is a time index (Bradshaw 2004).

The industry rate of reversion of residual income ω is estimated by the following regression for each of the 48 industries (Fama and French 1997) using all observations with book value, earnings before extraordinary items and market value on COMPUSTAT between 1998 and 2014 (Dechow et al. 1999; Bradshaw 2004): $RI_t = \eta + \omega RI_{t-1} + \varepsilon_t$, where RI is the residual income realized in period t and ω is the industry rate of reversion (fade rate). Residual income is the income before extraordinary items (item #18) cleansed of special items (item #17), taxed at a notional rate of 35% and less a capital charge based on the industry cost of capital (see above) times beginning equity book value (item #60) and finally scaled by the beginning market equity (item #25 multiplied by item #199). We winsorize *RI* at the top and bottom 0.5% levels (Dechow et al. 1999) and employ an outlier robust regression.

Dividend Discount Model V_{DDM}:

$$V_{DDM,t} = \sum_{\tau=1}^{5} \frac{DPS_0(1 + LTG)^{\tau}}{(1 + r)^{\tau}} + \frac{NEPS_1(1 + LTG)^5}{r(1 + r)^5}$$

where $V_{DDM,t}$ is the pseudo-target price at time t, DPS_0 is the most current dividend per share, LTG is analyst's long-term EPS growth forecast, r is the equity cost of capital (see RIM with Perpetuity Assumption) and $NEPS_1$ $(=EPS_3/(1+LTG)^2)$ is the expected normalized one-year-ahead earnings per share (Gordon and Gordon 1997). Missing three-year ahead analysts' EPS forecasts EPS_3 are extrapolated by analyst's long-term EPS growth forecasts (see RIM with Perpetuity Assumption). Dividend per share DPS_0 is computed by COMPUSTAT item #21 divided by item #25 assuming that data is available three-month after the fiscal-year end.

Models classified as heuristic valuation methods (V_{PE}, V_{PEG} and V_{PB})

Price-Earnings Model V_{PE}:

$$V_{PE,t} = E_t\left[EPS_{t+2}\right] * PE$$

where $V_{PE,t}$ is the pseudo-target price at time t, EPS_{t+2} is analyst's two-year-ahead EPS forecast and PE is the industry forward price-earnings ratio (Bradshaw 2002). First, we compute a monthly forward price-earnings ratio for every U.S. firm with non-missing data based on the mean consensus analysts' EPS forecast with a two-year horizon. Second, we identify the monthly median price-earnings ratio PE for every 48 industries (Fama and French 1997) based on the positive firm price-earnings ratios. We use SIC-Codes provided by CRSP to match the firm price-earnings ratios and the 48 industries. The pseudo-target price is based on the industry price-earnings-ratio in effect for the month prior to the target price release date.

Price-earnings-growth model V_{PEG}:

$$V_{PEG,t} = E_t\left[EPS_{t+2}\right] * LTG * 100$$

where $V_{PEG,t}$ is the pseudo-target price at time t, EPS_{t+2} is analyst's two-year-ahead EPS forecast and LTG is analyst's long-term EPS growth forecast (Bradshaw 2004).

Price-book model V_{PB}:

$$V_{PB,t} = E_t\left[BVPS_{t+2}\right] * PB$$

where $V_{PB,t}$ is the pseudo-target price at time t, $BVPS_{t+2}$ is the extrapolated two-year-ahead book-value per share (see RIM with Perpetuity Assumption), and PB is the industry price-book ratio. Firstly, we compute a monthly price-book ratio for every U.S. firm with non-missing data in COMPUSTAT. To compute price-book ratios we use annual COMPUSTAT data (item #199/(item #60/item #25)) and hold the ratios constant over twelve months. We assume that data is available three months after a fiscal-year end. Second, we compute the monthly median price-book ratio PB for every 48 industries (Fama and French 1997) based on positive firm price-book ratios. We use SIC-Codes provided by COMPUSTAT to match the firm price-book ratios and the 48 industries. The pseudo-target price is based on the industry price-book ratio PB in effect for the month prior to the target price release date.

Model to approximate the *ex post* intrinsic value of a stock

Residual Income Valuation with Perpetuity Assumption V_{int} based on actual future data:

$$V_{int,t} = BVPS_t + \sum_{\tau=1}^{3} \frac{E_t\left[RI_{t+\tau}\right]}{(1+r)^{\tau}} + \frac{(1+g)E_t\left[RI_{t+3}\right]}{(r-g)(1+r)^3}$$

where $V_{int,t}$ is the ex-post intrinsic value of a stock at time t, $BVPS$ is the equity book value per share, $E[RI]$ is residual income ($AEPS_{t+\tau}$-r*$BVPS_{t+\tau-1}$), $AEPS$ is actual earnings per share (COMPUSTAT item #237 divided by item #25), r is the equity cost of capital, g is a growth rate, and τ is a time index. We use moderate growth rates g based on inflation. We replace missing intrinsic values or intrinsic values lower than the current *BVPS*s with the current *BVPS*s.

Appendix 2

Variable descriptions

Variable	Description
	Main variables
$SOPH_{jit}$	Sophisticated valuation' variable is a categorical variable set equal to 1 if analyst *j*'s target price for firm *i* at time *t* is inferred to be based on a sophisticated valuation model, and 0 otherwise (see Sect. 3)
$SENT_t$	Investor sentiment is approximated by the monthly Baker and Wurgler (2006, 2007) investor sentiment index at the target price release month *t*
$SENTl1_t$	One-month lagged investor sentiment is approximated by the monthly Baker and Wurgler (2006, 2007) investor sentiment index with a time lag of one month at the target price release month *t*
$SENT_t$ *(Instr.)*	Predicted investor sentiment by regressing $SENT_t$ on the instrumental variables $MICH_t$ and EMV_t (2SLS approach)

Variable	Description
$BLFIT_{jit}$	'BL fit' variable is a categorical variable set equal to 1 if the pseudo-target price based on the sophisticated valuation V_{SOPH} results in a pseudo-target-to-share price (for analyst *j*'s target price for firm *i* at time *t*) closer to the firm's long-term BL ratio than the pseudo-target price based on the heuristic valuation V_{HEUR}, and 0 otherwise (see Sect. 3)
TP_{jit}	Analyst *j*'s target price for firm *i* at time *t* scaled by the firm's total assets per share
TPP_{jit}	Ratio of analyst *j*'s target price for firm *i* at time *t* to the closing price of firm *i* on the trading day before the target price release date *t*
$TPEXC_{jit}$	Target price excess, calculated as the difference between analyst *j*'s target price for firm *i* at time *t* minus the ex-post intrinsic value $V_{int,it}$ scaled by the closing price of firm *i* on the trading day before the target price release date *t* (see Sect. 3)
$TPERR_{jit}$	Target price error, calculated as the difference between the analyst *j*'s target price for firm *i* at time *t* minus the one-year-ahead share price (or the last available share price) scaled by the closing price of firm *i* on the trading day before the target price release date *t*
$TPREV_{jit}$	Analyst *j*'s target price revisions for firm *i* on time *t,* calculated as analyst's target price divided by analyst's previous target price minus 1 (Asquith et al. 2005)
$FRET_{jit}$	Firm *i*'s one-year future return, calculated as the cumulative 250-days ex-dividend stock return (or maximum available returns in the case of delisted firms) following the target price release date *t* of target price *j* (Clarkson et al. 2020)
$ARET_{jit}$	Firm *i*'s short-term abnormal return, calculated as the difference between the firm's buy-and-hold return and the buy-and-hold return on the NYSE/AMEX/Nasdaq value-weighted market index starting at the target price release date *t* of target price *j* and ending two days subsequent to the target price release date (Brav and Lehavy 2003)
	Instrumental variables (IVs) to estimate $SENT_t$ *(Instr.)*
$MICH_t$	Index of Consumer Sentiment (University of Michigan Surveys of Consumers) with a time lag of 12 months at the target price release month *t*
EMV_t	Newspaper-based U.S. Equity Market Volatility tracker (Baker et al. 2019) with a time lag of 6 months at the target price release month *t*
	Control variables
$PostREG_t$	'Post-regulation' variable is set equal to 1 if the target price is announced after April 30, 2003, and 0 before (e.g., Barniv et al. 2009; Chen and Chen. 2009)
$FEPS_{jit}$	Analyst *j*'s one-year-ahead EPS forecast for firm *i* at time *t* scaled by the closing price of firm *i* on the trading day before the EPS forecast release date *t*
$FEPSA_{jit}$	Analyst *j*'s one-year-ahead EPS forecast for firm *i* at time *t* scaled by the total assets per share of firm *i*
$EPSREV_{jit}$	Analyst *j*'s earnings forecast revision for firm *i* at time *t* is calculated as analyst *j*'s one-year-ahead EPS forecast for firm *i* at time *t* divided by analyst *j*'s previous one-year-ahead EPS forecast for firm *i* minus 1 (Asquith et al. 2005)
$FDIFF_{jit}$	'EPS forecasts difference' is the difference between analyst *j*'s two- and one-year-ahead EPS forecast for firm *i* at time *t* scaled by the closing price of firm *i* on the trading day before the EPS forecast date *t* (Clarkson et al. 2020)
$FDIFFA_{jit}$	'EPS forecasts difference' is the difference between analyst *j*'s two- and one-year-ahead EPS forecast for firm *i* at time *t* scaled by firm's total assets per share
$IncFLTG_{jit}$	Long-term EPS growth forecast indicator variable is set equal to 1 if the target price *j* for firm *i* at time *t* is accompanied by an individual long-term EPS growth forecast, and 0 otherwise
$FLTG_{jit}$	Analyst *j*'s long-term EPS growth rate for firm *i* at time *t*. If there is no individual long-term EPS growth forecast ($IncFLTG=0$), *FLTG* is replaced by the median consensus long-term EPS growth forecast
$IncREC_{jit}$	Stock recommendation indicator variable is set equal to 1 if the target price *j* for firm *i* at time *t* is accompanied by a stock recommendation, and 0 otherwise

Variable	Description
REC_{jit}	Analyst *j*'s stock recommendations REC_{jit} for firm *i* at time *t* (1 for a 'sell' recommendation, 2 for a 'underperform', 3 for a 'hold', 4 for a 'buy' and 5 for a 'strong buy'), if there is no recommendation on the target price release date *t*, REC_{jit} is replaced by the median consensus stock recommendation
$RECREV_{jit}$	Analyst *j*'s stock recommendation revision for firm *i* at time *t* is calculated as analyst *j*'s stock recommendation (1 for a 'sell' recommendation, 2 for a 'underperform', 3 for a 'hold', 4 for a 'buy' and 5 for a 'strong buy') for firm *i* at time *t* minus analyst *j*'s previous stock recommendation for firm *i* multiplied by 1/4 (see Feldman et al. 2012; Ho et al. 2018). If there is no recommendation on the target price release date, $RECREV_{jit}$ is set to 0
CSD_{it}	Firm *i*'s daily return volatility at time *t* calculated over the last 250-trading-day period ending one day before the target price release date *t*
$CBETA_{it}$	Firm *i*'s CAPM beta (Sharpe 1964; Lintner 1965; Mossin 1966) at time *t*, estimated from a regression of firm *i*'s monthly returns minus the risk-free rate on monthly value-weighted market returns minus the risk-free rate over a period of 60 months (minimum 24 months) preceding the target price month
CBM_{it}	Firm *i*'s book-to-market ratio at time *t* (e.g., Fama and French 1992; Lui et al. 2007) which is calculated as the book value of equity per share (item #60 divided by item #25) divided by the share price at the end of the most recent fiscal year
$CSIZE_{it}$	firm *i*'s size at time *t* (e.g., Banz 1981; Fama and French 1992, 1993), calculated as the log of the market capitalization on the trading day before the target price release date *t*
$CEXF_{it}$	Firm *i*'s external finance at time *t*, calculated as the change in firm i's assets (item #6) minus the change in retained earnings (item #36) divided by total assets of the prior fiscal year. When the change in retained earnings is not available, we use net income (item #172) less common dividends (item #21) instead (Baker and Wurgler 2006)
$CPRET_{it}$	Firm *i*'s past stock return at time *t* calculated as the cumulative return over the 250-trading day period ending on the day before the target price release date *t*
CWH_{it}	Firm *i*'s 52-week high price is the highest stock price of firm *i* over the 52-week period preceding the target price release date *t* scaled by the closing price on the trading day before the target price release date (Clarkson et al. 2020)
$AFEXP_{jit}$	Analyst *j*'s firm-specific experience $AFEXP_{j,t}$ is calculated as the number of years (divided by 100) in which the analyst has issued target prices for the firm *i* up to the target price release date *t* (Clement 1999)
$ANFIR_{jt}$	Number of firms followed by the analyst is calculated as the number of firms (divided by 100) for which the analyst *j* supplied at least one EPS forecast in a given year (see Clement 1999)
$ANIND_{jt}$	Number of industries followed by the analyst is measured as the number of the 48 Fama and French (1997) industries (divided by 100) for which the analyst *j* supplied at least one EPS forecast in a given year (Clement 1999)
$ABSIZ_{jt}$	Brokerage size measured as the number of analysts (divided by 100) associated with a particular broker in a given year
$AROUND_{jit}$	'Rounding' is a categorical variable set equal to 1 if the analyst *j*'s target price for firm *i* at time *t* is rounded to the nearest dollar, and 0 otherwise
IND	Is a vector of dummy variables indicating in which of the 12 Fama and French industries the firm was operating on the target price release date. The variable of the industry "Business Equipment" is omitted and hence the corresponding fixed effect is reflected by the constant of the equation

Acknowledgements We gratefully acknowledge helpful comments by Rashad Abdel-Khalik, Peter Clarkson, Jeff Coulton, Christi Gleason, Frank Heflin, Ole-Kristian hope, Alan Hodgson, Jesper Haga, Andrew Jackson, Andreea Moraru Arfire, Peter Pope, Marco Wilkens, Anne Wyatt, and participants at the American Accounting Association annual meeting in San Francisco 2019, European Accounting Association conference in Cyprus 2019, the EIASM workshop on accounting and regulation in Siena, workshops at University of Augsburg, UNSW Sydney, University of Queensland, Brisbane. The paper was previously circulated under the title “Target price optimism, investor sentiment, and the informativeness of target prices”.

References

Aiken LG, West SG (1991) Multiple regression: Testing and interpreting interactions. Sage Publications, London

Allee KD, Erickson D, Esplin AM and Larocque SA (2021) Independent and investment-bank analysts' target prices. Journal of Financial Reporting (published online)

Arand D and Kerl AG (2012) Analyst research and investor reactions: evidence from the 2008 financial crisis. Working paper, University of Giessen. Available at: https://ssrn.com/abstract=2126605

Asquith P, Mikhail MB, Au AS (2005) Information content of equity analyst reports. J Finance Econ 75(2):245–282

Bagnoli M, Clement M, Crawley M and Watts S (2014) The relative profitability of analysts' stock recommendations: What role does investor sentiment play? Working paper, Purdue University, University of Texas at Austin and Indiana University. Available at: https://www.fox.temple.edu/wp-content/uploads/2014/03/BCCW-Temple.pdf

Baker M, Wurgler J (2006) Investor sentiment and the cross-section of stock returns. J Finance 61(4):1645–1680

Baker M, Wurgler J (2007) Investor sentiment in the stock market. J Econ Perspect 21(2):129–151

Baker SR, Bloom N, Davis SJ (2016) Measuring economic policy uncertainty. Q J Econ 131(4):1593–1636

Baker SR, Bloom N, Davis SJ and Kost KJ (2019). Policy news and stock market volatility. Working paper No. 25720, National Bureau of Economic Research. Available at: https://www.nber.org/papers/w25720

Bandyopadhyay SP, Brown LD, Richardson GD (1995) Analysts' use of earnings forecasts in predicting stock returns: Forecast horizon effects. Int J Forecast 11(3):429–445

Banz RW (1981) The relationship between return and market value of common stocks. J Financ Econ 9(1):3–18

Barber BM, Lehavy R, McNichols M, Trueman B (2003) Reassessing the returns to analysts' stock recommendations. Financ Anal J 59(2):88–96

Barber BM, Lehavy R, McNichols M, Trueman B (2006) Buys, holds, and sells: the distribution of investment banks' stock ratings and the implications for the profitability of analysts' recommendations. J Account Econ 41(1):87–117

Barniv R, Hope O-K, Myring MJ, Thomas WB (2009) Do analysts practice what they preach and should investors listen? Effects of recent regulations. Account Rev 84(4):1015–1039

Bascle G (2008) Controlling for endogeneity with instrumental variables in strategic management research. Strateg Organ 6(3):285–327

Bergman NK, Roychowdhury S (2008) Investor sentiment and corporate disclosure. J Account Res 46(5):1057–1083

Bilinski P, Lyssimachou D, Walker M (2013) Target price accuracy: International evidence. Account Rev 88(3):825–851

Bilinski P, Cumming D, Hass L, Stathopoulos K, Walker M (2019) Strategic distortions in analyst forecasts in the presence of short-term institutional investors. Acc Bus Res 49(3):305–341

Black F (1986) Noise. J Finance 41(3):528–543

Block SB (1999) A study of financial analysts: practice and theory. Financ Anal J 55(4):86–95

Bonini S, Zanetti L, Bianchini R, Salvi A (2010) Target price accuracy in equity research. J Bus Finance Acc 37(9–10):1177–1217

Bonini S and Kerl AG (2014) Subjective valuation and target price accuracy. Working paper, Bocconi University and University of Giessen. Available at: https://ssrn.com/abstract=2168856

Bradshaw MT (2002) The use of target prices to justify sell-side analysts' stock recommendations. Acc Horiz 16(1):27–41

Bradshaw MT (2004) How do analysts use their earnings forecasts in generating stock recommendations? Acc Rev 79(1):25–50

Bradshaw MT (2009) Analyst information processing, financial regulation, and academic research. Acc Rev 84(4):1073–1083

Bradshaw MT, Richardson SA, Sloan RG (2006) The relation between corporate financing activities, analysts' forecasts and stock returns. J Acc Econ 42(1):53–85

Bradshaw MT, Brown LD, Huang K (2013) Do sell-side analysts exhibit differential target price forecasting ability? Rev Acc Stud 18(4):930–955

Bradshaw MT, Lee LF, Peterson K (2016) The interactive role of difficulty and incentives in explaining the annual earnings forecast walkdown. Acc Rev 91(4):995–1021
Bradshaw MT, Huang AG, Tan H (2019) The effects of analyst-country institutions on biased research: evidence from target prices. J Acc Res 57(1):85–120
Bradshaw MT, Ertimur Y and O'Brien P (2017) Financial analysts and their contribution to well-functioning capital markets, Foundations and Trends® in Accounting 8 (3): 119–191.
Bradshaw MT (2011) Analysts' forecasts: What do we know after decades of work? Working paper, Boston College. Available at: https://ssrn.com/abstract=1880339
Brav A, Lehavy R (2003) An empirical analysis of analysts' target prices: short-term informativeness and long-term dynamics. J Finance 58(5):1933–1968
Brown GW, Cliff MT (2005) Investor sentiment and asset valuation. J Bus 78(2):405–440
Brown LD, Call AC, Clement MB, Sharp NY (2015) Inside the "Black box" of sell-side financial analysts. J Acc Res 53(1):1–47
Buxbaum M, Schultze W and Tiras SL (2022) The predictive value of analysts' private information in target prices for future prices and short-run abnormal returns. Working paper, University of Augsburg and Kelley School of Business / Indiana University - Indianapolis
Cameron AC, Gelbach JB, Miller DL (2011) Robust inference with multiway clustering. J Bus Econ Stat 29(2):238–249
Campbell JY and Shiller RJ (2001) Valuation ratios and the long-run stock market outlook: An update, Working paper 8221, National Bureau of Economic Research. Available at: https://www.nber.org/system/files/working_papers/w8221/w8221.pdf
Campbell JY, Shiller RJ (1988) Stock prices, earnings, and expected dividends. J Finance 43(3):661–676
Campbell JY, Shiller RJ (1998) Valuation ratios and the long-run stock market outlook. J Portf Manag 24(2):11–26
Chen C, Chen PF (2009) NASD rule 2711 and changes in analysts' independence in making stock recommendations. Account Rev 84(4):1041–1071
Chen WEI, Hribar P, Melessa S (2018) Incorrect inferences when using residuals as dependent variables. J Acc Res 56(3):751–796
Clarkson P, Nekrasov A, Simon A, Tutticci I (2020) Target price forecasts: the roles of the 52-week high price and recent investor sentiment. J Bus Finance Acc 47(9–10):1365–1399
Clement MB (1999) Analyst forecast accuracy: do ability, resources, and portfolio complexity matter? J Acc Econ 27(3):285–303
Cornell B, Landsman WR, Stubben S (2017) Accounting information, investor sentiment, and market pricing. J Law Finance Acc 2(2):325–345
Da Z, Schaumburg E (2011) Relative valuation and analyst target price forecasts. J Financ Mark 14(1):161–192
Da Z, Hong KP, Lee S (2016) What drives target price forecasts and their investment value? J Bus Finance Acc 43(3–4):487–510
Dechow PM, You H (2020) Understanding the determinants of analyst target price implied returns. Acc Rev 95(6):125–149
Dechow PM, Hutton AP, Sloan RG (1999) An empirical assessment of the residual income valuation model. J Acc Econ 26(1–3):1–34
Demirakos EG, Strong NC, Walker M (2004) What valuation models do analysts use? Account Horiz 18(4):221–240
Demirakos EG, Strong NC, Walker M (2010) Does valuation model choice affect target price accuracy? Eur Acc Rev 19(1):35–72
Dong Y, Hu N (2016) The impact of NASD rule 2711 and NYSE rule 472 on analyst behavior: the strategic timing of recommendations issued on weekends. J Bus Finance Acc 43(7–8):950–975
Engelberg J, McLean RD, Pontiff J (2020) Analysts and anomalies. J Acc Econ 69(1):101249
Fama EF, French KR (1992) The cross-section of expected stock returns. J Finance 47(2):427–465
Fama EF, French KR (1993) Common risk factors in the returns on stocks and bonds. J Financ Econ 33(1):3–56
Fama EF, French KR (1997) Industry costs of equity. J Financ Econ 43(2):153–193
Feldman R, Zivnat J, Zhang Y (2012) Analysts' earnings forecast, recommendation, and target price revisions. J Portf Manag 38(3):120–132
Frankel R, Lee CM (1998) Accounting valuation, market expectation, and cross-sectional stock returns. J Acc Econ 25(3):283–319
Glaum M, Friedrich N (2006) After the bubble: Valuation of telecommunications companies by financial analysts. J Int Financ Manag Acc 17(2):160–174

Gleason CA, Johnson W, Li H (2013) Valuation model use and the price target performance of sell-side equity analysts. Contemp Acc Res 30(1):80–115
Gordon JR, Gordon MJ (1997) The finite horizon expected return model. Financ Anal J 53(3):52–61
Gow ID, Ormazabal G, Taylor DJ (2010) Correcting for cross-sectional and time-series dependence in accounting research. Acc Rev 85(2):483–512
Harjoto MA, and Jo H (2015) Legal vs. normative CSR: Differential impact on analyst dispersion, stock return volatility, cost of capital, and firm value. Journal of Business Ethics 128 (1): 1–20
Hayes AF (2013) Introduction to mediation, moderation, and conditional process analysis. The Guilford Press, New York
Ho TQ, Strong N, Walker M (2018) Modelling analysts' target price revisions following good and bad news? Account Bus Res 48(1):37–61
Hribar P, McInnis J (2012) Investor sentiment and analysts' earnings forecast errors. Manag Sci 58(2):293–307
Huang J, Mian GM, Sankaraguruswamy S (2009) The value of combining the information content of analyst recommendations and target prices. J Financ Mark 12(4):754–777
Huang S, Tan H, Wang X and Yu C (2022) Valuation uncertainty and analysts' use of DCF models. Review of accounting studies (published online)
Imam S, Barker R, Clubb C (2008) The use of valuation models by UK investment analysts. Eur Acc Rev 17(3):503–535
Imam S, Chan J, Shah SZA (2013) Equity valuation models and target price accuracy in Europe: Evidence from equity reports. Int Rev Financ Anal 28:9–19
Jacob J, Lys TZ, Neale MA (1999) Expertise in forecasting performance of security analysts. J Acc Econ 28(1):51–82
Jegadeesh N, Titman S (1993) Returns to buying winners and selling losers: Implications for stock market efficiency. J Finance 48(1):65–91
Kaplanski G, Levy H (2017) Analysts and sentiment: a causality study. Q Rev Econ Finance 63:315–327
Larcker DF, Rusticus TO (2010) On the use of instrumental variables in accounting research. J Acc Econ 49(3):186–205
Lee C, Myers J, Swaminathan B (1999) What is the intrinsic value of the dow? J Finance 54(5):1693–1741
Lee WY, Jiang CX, Indro DC (2002) Stock market volatility, excess returns, and the role of investor sentiment. J Bank Finance 26(12):2277–2299
Lintner J (1965) The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. Rev Econ Stat 47(1):13–37
Loh RK, Stulz RM (2018) Is sell-side research more valuable in bad times? J Finance 73(3):959–1013
Lui D, Markov S, Tamayo A (2007) What makes a stock risky? Evidence from sell-side analysts' risk ratings. J Acc Res 45(3):629–665
Lundholm R, O'Keefe T (2001) Reconciling value estimates from the discounted cash flow model and the residual income model. Contemp Acc Res 18(2):311–335
Mikhail MB, Walther BR, Willis RH (1997) Do security analysts improve their performance with experience? J Acc Res 35:131–157
Miwa K, Ueda K (2016) Analysts' preference for growth investing and vulnerability to market-wide sentiment. Q Rev Econ Finance 61:40–52
Mossin J (1966) Equilibrium in a capital asset market. Econometrica: J Econ Soc 34 (4): 768–783
Petersen MA (2009) Estimating standard errors in finance panel data sets: comparing approaches. Rev Financ Stud 22(1):435–480
Qian H (2009) Time variation in analyst optimism: an investor sentiment explanation. J Behav Finance 10(3):182–193
Qiu L and Welch I (2004). Investor sentiment measures. Working paper No. 10794, National Bureau of Economic Research. Available at: https://www.nber.org/papers/w10794
Roger T, Roger P, Schatt A (2018) Behavioral bias in number processing: evidence from analysts' expectations. J Econ Behav Organ 149:315–331
Sharpe WF (1964) Capital asset prices: a theory of market equilibrium under conditions of risk. J Financ 19(3):425–442
Shiller RJ (1981) Do stock prices move too much to be justified by subsequent changes in dividends? Am Econ Rev 71(3):421–436
Smales LA (2017) The importance of fear: investor sentiment and stock market returns. Appl Econ 49(34):3395–3421
Stock JH and Watson MW (2012) Introduction to econometrics (3rd ed.) Pearson
Stock JH and Yogo M (2002) Testing for weak instruments in linear IV regression, Technical working paper 284, National Bureau of Economic Research. Available at: http://www.nber.org/papers/T0284

Subramanyam KR, Venkatachalam M (2007) Earnings, cash flows, and ex post intrinsic value of equity. Acc Rev 82(2):457–481
Walther BR, Willis RH (2013) Do investor expectations affect sell-side analysts' forecast bias and forecast accuracy? Rev Acc Stud 18(1):207–227
Whaley RE (2000) The investor fear gauge. J Portf Manag 26(3):12–17
Womack KL (1996) Do brokerage analysts' recommendations have investment value? J Finance 51(1):137–167