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The asymmetric mispricing information in analysts' target prices

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Abstract
We study the mispricing information present in the target prices of US and international analysts. We hypothesize that asymmetry in the value-relevance of the information that managers supply to analysts, combined with asymmetry in the incentives facing analysts to curry favor with managers, leads to analyst-claimed undervaluation being more predictive of future stock returns than analyst-claimed overvaluation. Our empirical tests isolate analyst-claimed mispricing by first removing analysts' estimates of the cost of equity from the returns implied by target prices and then separating analyst-claimed undervaluation from overvaluation. We find that target prices only predict future returns (at 16 cents to 18 cents on the dollar) when analysts claim undervaluation, not when they claim overvaluation. We also observe that analyst-claimed undervaluation predicts future returns more strongly after firms experience low returns and when macro-driven valuation uncertainty is low.

Keywords Analysts · Target prices · Mispricing · Cost of equity

JEL classification G12 · G17 · M41

1 Introduction

A target price is an analyst's explicit forecast of where a firm's stock price will be in 12 months' time and is a key part of their report. While it is well documented that analysts' target prices contain information about future stock returns

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(Brav and Lehavy 2003; Asquith et al. 2005; Da and Schumberg 2011; Gleason et al. 2013; Dechow and You 2020), less attention has been put on investigating the mispricing versus risk-related components of this predictive power. This paper aims to isolate and study the mispricing component using the target prices and costs of equity disclosed by US and international analysts, controlling for the risk-related component.

While analysts face strong incentives to provide information that investors can use to earn abnormal returns in general (Irvine 2004; Mikhail et al. 2007), we hypothesize that target prices indicating analyst-claimed undervaluation are more predictive of future stock returns than those indicating analyst-claimed overvaluation. We propose that this asymmetry arises because of the asymmetry in the incentives that managers face to supply value-relevant information to analysts, combined with asymmetry in how analysts convert this information into target prices.

The first asymmetry we highlight is that managers face compensation-based incentives that asymmetrically orient them toward revealing good news rather than bad news (Kothari et al. 2009; Feng and McVay 2010). That is, firms are more likely to supply analysts with information that is relevant to when their equity is undervalued than when it is overvalued. This asymmetry is important for analysts' target prices because managers are an important information source for analysts (Green et al. 2014; Soltes 2014). While managers also supply value-relevant information to investors at large via public disclosures (Francis et al. 1997), managers may guide analysts to better understand the firm's performance in their private interactions (Brown et al. 2015; Francis et al. 1997; Soltes 2014), leading to analysts' outputs that predict market price adjustments (Gleason and Lee 2003). The combination of manager incentives toward revealing good news and analysts being the channel for such revelation leads us to hypothesize that managers will be more likely to supply analysts with information that is relevant to their firm being undervalued rather than to being overvalued, and thus that analysts' target prices will be more likely to embed value-relevant information provided by managers when analysts' target prices signal that the stock is undervalued than overvalued.

Reinforcing the first asymmetry above is a second asymmetry—namely, that managers may be more willing to provide private information to analysts with optimistic views of the company (Lin and McNichols 1998; Chen and Matsumoto 2006). This asymmetry is important because analysts who claim undervaluation are more likely to have access to private information from managers. However, the higher information content of analysts' claimed undervaluation may be offset by optimistic target prices or an excess weighting of managers' guidance (Francis and Philbrick 1993; Feng and McVay 2010). Combined, these two asymmetries lead us to our main hypothesis that analyst-claimed undervaluation will be more predictive of future stock returns than will analyst-claimed overvaluation.

We also expand beyond our main hypothesis by exploring four supplemental hypotheses. First, because target prices are inherently noisy predictors of returns (Dechow and You 2020), analysts often issue 'bold' or 'strategically magnified' price targets to better highlight to investors that they have value-relevant information (Clement and Tse 2005). In addition, because analysts' signals of overvaluation may be optimistically biased to gain access to managers, signals that a stock may be undervalued may be optimistic. We therefore predict that analyst-claimed undervaluation will map into future returns in a less than dollar-for-dollar manner.

Second, if the information in analysts' target prices is obtained from private interactions with managers about publicly available information (Brown et al. 2015; Francis et al. 1997; Soltes 2014), we expect the information content of analysts' target prices to be short lived. This reasoning comes from the evidence that mispricing is corrected over time (Bernard and Thomas 1989; Lee et al. 1999). We therefore predict that analyst-claimed undervaluation will be less predictive of future stock returns the further the returns are beyond the analyst's report date.

Third, stronger recent declines in a firm's stock price put more pressure on managers to communicate with investors and correct undervaluation (Bushee and Miller 2012; Sletten 2012). Price declines also create stronger incentives for analysts to build into their target prices manager-supplied information that is relevant to undervaluation (Cunningham 2021; Graham and Zweig 2006; Keshk and Wang 2018). Accordingly, we predict that the mapping of analyst-claimed undervaluation into future returns will be negatively associated with prior-period returns.

Lastly, prior research suggests that analysts' ability to identify mispricing is weaker and managers supply less value-relevant information when macro uncertainty is high (Amiram et al. 2018; Hope and Kang 2005; Kim et al. 2016). In combination with macroeconomic uncertainty, analysts acquire less private information when earnings volatility is high (Altschuler et al. 2015). The link between uncertainty and analysts' access to private information leads to our prediction that the mapping of analyst-claimed undervaluation into future returns will be negatively related to macro-driven valuation uncertainty.

We center the empirical tests of our hypotheses on analyst-claimed mispricing, *MIS*, defined as the ex-dividend predicted return implied by the analyst's target price, *IRET*, less the analyst's estimate of the firm's cost of equity, *COE*. We then isolate analyst-claimed undervaluation from overvaluation by defining *UNDERVAL* as $MIS > 0$ and *OVERVAL* as $MIS \leq 0$. We use analysts' target prices and costs of equity from US and international company analyst reports in Thomson ONE's Investext database that contain the text string "cost of equity." From each report, we extract *COE* as well as the one-year-ahead target price, the firm's ticker, and other items. After matching to realized stock return and annual financial statement data, we arrive at a panel dataset of 9,781 US and 64,285 international analyst-firm-report observations over the years 2001–2017.

To test our main hypothesis that analyst-claimed undervaluation will better predict stock returns than will analyst-claimed overvaluation, we regress realized one-year-ahead ex-dividend stock returns, *FRET*, on *COE*, *UNDERVAL*, and *OVERVAL*. We increase the power of our regressions by controlling for firm characteristics commonly seen as capturing priced risk exposures (Fama and French 2015) and by including company, issuer, and year fixed effects. We find that the target prices of US and international analysts reliably predict stock returns when analysts claim undervaluation, but not when they claim overvaluation.

Next, consistent with our first supplemental hypothesis, we document that analyst-claimed undervaluation maps into future returns in a way that is reliably less than dollar-for-dollar—just 18 cents per dollar for US analysts and 16 cents per dollar for international analysts. Consistent with our second supplemental hypothesis, we show that analyst-claimed undervaluation is reliably positively related to future returns one- and two-quarters ahead, but not beyond the second quarter. Lastly, consistent with our third and fourth supplemental hypotheses, we observe that the mapping of analyst-claimed undervaluation into future returns is reliably negatively related to prior-period firm-returns and to macro-driven valuation uncertainty as proxied by the standard deviation of the returns implied by analysts' target prices, measured at the country level over the year prior to analysts' report dates.

We see our study as contributing to the literature on analyst target prices in several ways. By means of analysts' COE estimates, we introduce an economically grounded way of isolating the mispricing-claimed component of analysts' target prices and then separating that mispricing into analyst-claimed undervaluation versus overvaluation. We document a strong new asymmetry, that analysts' target prices contain information about undervaluation but not overvaluation, and at a rate that is substantially less than dollar-for-dollar. We also corroborate the work of Dechow and You (2020), who propose that analyst target prices contain predictable errors from analysts' misinterpreting the return implications of common risk factors, in that we show that controlling for common risk factors increases the power of the predictive properties of analyst-claimed mispricing. Further, we reconcile Dechow and You's (2020) finding that analysts' target prices include noisy expected return information with Balakrishnan et al. (2021) result that analysts' cost of equity estimates are unbiased predictors of future returns. While *COE* may be unbiased, other firm characteristics are incremental to analyst's cost of equity for explaining returns such that *COE* is not a sufficient measure of the firm's expected 12-month ahead return. Finally, we add to recent research that has found that analysts incorrectly weight the information in public anomaly signals (Engelberg et al. 2020). Our results indicate that, despite Engelberg et al.'s (2020) results, which indicate that the returns implied by analysts' target prices move in the opposite direction to public anomaly signals, analysts' target prices do contain information about mispricing—only asymmetrically so.

The remainder of the paper proceeds as follows. Section 2 describes our data, key variables, and descriptive statistics. Section 3 presents our empirical tests, results of the tests of our main and supplemental hypotheses, and associated robustness analyses. Section 4 discusses caveats, and Section 5 concludes.

2 Data and descriptive statistics

2.1 Data sources and description

Given the global nature of capital markets and analysts, we gathered analysts' target prices and cost of equity estimates for US and international observations by searching the text of all analysts' reports in Thomson ONE's Investext database.[1]

[1] Almost all brokers contribute their reports into the Investext database. The only major broker we are aware of that does not is Goldman Sachs.

Per Table 1 Panel A, we searched analyst reports issued between Jan. 1, 2001, and Dec. 31, 2017, for the case-insensitive text string "cost of equity" anywhere in the report. We retained only those reports contributed by brokers and for which the report type was company (not industries, geographic or investing/economic). This yielded 432,393 analyst reports: 80,081 US analyst reports (geography = United States) and 350,118 international analyst reports (geography = not United States). Our other data requirements are shown in Table 1 Panel B. To the analyst reports, we matched stock prices, returns, and dividends from CRSP and Datastream using versions of company names. We required stock prices for the year prior to and after the analysts' report. We collected accounting information pertaining to risk factors from Compustat and Factset (Fama and French 2015), winsorizing accounting variables at the first and 99th percentiles of our panel dataset. From the Investext reports, we extracted several variables with textual algorithms. We provide the details of our extraction and matching techniques in the Appendix. We first extracted analysts' cost of equity and then analysts' target prices. We also extracted analysts' recommendations, which we categorize as buy, sell, or hold/missing. These data requirements yielded a sample of 9,781 US and 64,285 analyst reports.

In Table 2, we describe key aspects of these analysts' reports. Panel A shows that, of the 96 non-US countries, the top 15 by the number of analysts-firm-report observations include Australia, China, United Kingdom, Taiwan, Germany, and Singapore. Also, while the number of US firm reports that satisfy our data requirements increased from 110 in 2001 to 817 in 2017, the number of international reports increased from 0 to 8,700 during the same period.[2] In panel B, we list the top 10 US and international issuers. Reflecting the dominance of global and US-focused investment banks, five investment banks appear in both lists (Morgan Stanley, UBS, Deutsche Bank, JP Morgan, and Credit Suisse), while five issuers appear in one list only (Barclays, Singular Research, Piper Jaffray, Citi, and Jefferies in the US; HSBC Global Research, Macquarie, Raiffeisen Centro Bank, ESN, and Unicredit Research outside the US).

2.2 Key variables

The key variables in our panel datasets are the forecasted one-year-ahead returns implied by analysts' target prices, *IRET*; realized one-year-ahead returns, *FRET*; analysts' cost of equity estimates, *COE*; and analyst-claimed mispricing, *MIS*. We define *IRET* on an ex-dividend basis as:

$$IRET = \frac{E_t^A(P_{t+1})}{p_t} - 1, \tag{1}$$

where p_t is the closing price on the day before the analysts' report and $E_t^A\left(P_{t+1}\right)$ is the analyst's 12-month ahead target price, namely their expectation of the firm's

[2] Reflecting the larger and more diverse nature of international-firm analyst reports, recent analyst research has begun to focus on and exploit these data (Bilinski et al. 2013; Bradshaw et al. 2019).

Table 1 Sample selection

Panel A: Investext search criteria

Asset class:	All
Dates:	Custom, 01/01/01 to 12/31/17
Keywords:	"Cost of equity" in Text
Report type:	Company
Geography:	United States (or Not United States)
Contributor:	Non-broker Research removed/excluded

Panel B: Identification of usable analyst reports containing the text "cost of equity," target prices, sufficient stock return data, and basic annual accounting data

	Geography	
	US	International
Analyst reports in Investext that contain "cost of equity"	80,081	350,118
- Reports without sufficient stock return data	−13,772	−116,443
- Reports without basic annual accounting data	−7,938	−12,257
- Reports where cost of equity is not able to be identified[a]	−13,114	−93,864
- Reports where target price is not able to be identified[b]	−35,476	−63,269
= Number of usable analyst-firm-report observations	9,781	64,285

Criteria used to identify analyst reports in Thomson ONE's Investext database that contain analysts' cost of equity, analysts' target prices, and firm tickers

[a] Of which 4,341 (US) and 4,062 (international) were issued by Morningstar

[b] Of which 19,429 (US) and 19,104 (international) were issued by Morningstar

stock price in 12-months' time. Along the same ex-dividend lines, we define *FRET* as:

$$FRET = \frac{p_{t+1}}{p_t} - 1, \tag{2}$$

where p_{t+1} is the firm's realized closing stock price 12 months after the date of the analyst's report.,[3][4] We then define our measure of analyst-claimed mispricing *MIS* as:

$$MIS \equiv IRET - COE, \tag{3}$$

where *COE* is the analyst's cost of equity estimate disclosed in the same report as the target price. We subtract *COE* to isolate the part of *IRET* that analysts claim is mispricing because research has found that *COE* is an unbiased estimate of the

[3] For US stocks, we adjust returns for delisting following Shumway and Warther (1999) using the delisting returns from CRSP. Our results are largely unchanged when delisting returns are not included.

[4] In untabulated analyses, we find that our results are robust to redefining *FRET* to be on a cum-dividend basis.

Table 2 Sample distribution by country, year, and issuer

Panel A: Number of analyst-firm-report observations by country (top 15 of 96) and by year

Country	# obs		US	International
		Year	# obs	# obs
US	9,781	2001	110	0
Australia	6,878	2002	152	356
China	5,647	2003	225	944
United Kingdom	4,624	2004	514	1,170
Taiwan	4,406	2005	525	1,719
Germany	3,540	2006	227	1,991
Singapore	2,695	2007	488	2,827
Thailand	2,580	2008	420	3,750
Cayman Islands	2,511	2009	590	4,907
India	2,467	2010	707	5,205
Hong Kong	2,283	2011	741	4,705
Canada	1,977	2012	719	4,232
Switzerland	1,931	2013	848	4,337
Mexico	1,758	2014	838	5,020
Malaysia	1,732	2015	843	5,865
		2016	1,017	8,557
		2017	817	8,700

Panel B: Number of observations by issuer (by geography, top 10 out of 812 issuers)

US		International	
Issuer	# obs	Issuer	# obs
Morgan Stanley	1,583	Morgan Stanley	12,834
Credit Suisse	946	Deutsche Bank	6,801
JP Morgan	763	HSBC Global Research	6,523
Barclays	672	JP Morgan	6,389
Singular Research	640	UBS	5,462
Piper Jaffray	507	Credit Suisse	4,005
Citi	467	Macquarie	1,979
Jefferies	426	Raiffeisen Centro Bank	1,210
Deutsche Bank	382	ESN	1,005
UBS	276	Unicredit Research	969

The distribution for the global dataset of 9,781 US and 64,285 international analyst-firm-report observations 2001–2017 by country and year in Panel A and by issuer in Panel B

firm's annual expected return (Balakrishnan et al. 2021). However, to increase the power of our mispricing-focused tests, we also control for firm characteristics that may capture firms' risk exposures beyond *COE* (Dechow and You 2020). To test the asymmetry proposition, we divide *MIS* into two parts: $UNDERVAL = MIS$ if $MIS > 0$ and zero otherwise, and $OVERVAL = MIS$ if $MIS \leq 0$ and zero otherwise.

2.3 Descriptive statistics

In Table 3, we present descriptive statistics on *FRET*, *IRET*, *COE*, *MIS*, *UNDERVAL*, and *OVERVAL*. Per panels A and B, for US (international) analyst-report observations the mean *FRET* is 13% (9%), and the mean *COE* is 11% (11%). At one level, the closeness of the means of *FRET* and *COE* to each other suggests that analysts' cost of equity capture realized returns well. However, as also reported in panels A and B, the spreads in *FRET* and *COE* are more than an order of magnitude different, with the standard deviation *FRET* being 46% (44%) as compared to just 3% (3%) for *COE*. Similarly, at 51% (32%) the standard deviation of *IRET* far exceeds the standard deviation of *COE*, and at 51% (32%), the standard deviation of *MIS* far exceeds the 3% (3%) standard deviation of *COE*. We posit that such large differences make it unlikely that *COE* measures expected future returns in a way that is fully responsive to time varying or across-company differences in firms' expected returns. We therefore propose that, while *COE* will play a measurable role in the formation of analysts' target prices, it will not explain as much variation in *FRET* as will *MIS*.

Panel C provides further insight into analysts' *COE* by graphing the frequency distribution of *COE* in bins of one-half percent. The great majority of analyst *COEs* lie between 6 and 15%, but the distribution is clearly not smooth. Markedly greater frequencies are observed at whole and half percentages, implying that analysts commonly round their *COE* to the nearest 1%, and a measurable fraction of analyst *COE* are greater than 20%. Panel D then plots key percentiles of the pooled US + international distribution of *MIS* (in black) and *COE* (in red) by the calendar year of the report. We note that while the median *MIS* is close to zero, the first, fifth, 95$^{\text{th}}$, and 99$^{\text{th}}$ percentiles of *MIS* have substantial spread, albeit narrowing over time. We also note that consistent with our asymmetry-based proposition that analyst-claimed undervaluation is more likely than analyst-claimed overvaluation, positive *MIS* tend to be further from the median at the same percentile than negative *MIS*. Per panels A and B, for US (International) observations *MIS* is positive 66% (52%) of the time.

In panel E, we compare our sample of Investext-based analyst reports and firms with those in IBES. After finding that 72% (56%) of our analyst reports for US (International) companies can be matched to IBES, we compare *IRET* and the natural log of the fiscal year-end US dollar (USD) market value of equity *LnMV* in our pooled US + international dataset versus in IBES. We observe that our pooled dataset *IRET* mean of 15% is much lower than the *IBES* mean *IRET* of 55%, one reason for which is that, to avoid picking up errors in analyst reports or our textual extraction methods, we only include Investext analyst reports where *IRET* lies between –90% and 300%. Supporting this concern about error-based outliers, at 12% and 18% the median values of *IRET* are much closer together than are the means. At the same time, we note that the firms in our sample are on average larger than the firms in IBES. Our results may therefore not generalize to the more numerous firms covered by IBES.

Table 3 Descriptive statistics and Pearson correlations

Panel A: US

	N	Mean	SD	Min.	P5	P25	P50	P75	P95	Max.	% > 0
FRET	9,781	13%	46%	-179%	-50%	-12%	9%	31%	84%	810%	62%
IRET	9,781	27%	51%	-90%	-34%	5%	19%	37%	128%	300%	81%
COE	9,781	11%	3%	5%	7%	9%	10%	12%	16%	29%	100%
MIS	9,781	16%	51%	-112%	-46%	-6%	8%	26%	118%	291%	66%
UNDERVAL	6,455	24%	43%	0	0	0	8%	26%	118%	291%	100%
OVERVAL	3,326	-8%	19%	-112%	-46%	-6%	0	0	0	0	0%
IBESDUM	9,781	72%									

	FRET	*IRET*	*MIS*	*COE*
FRET	1			
IRET	0.099	1		
MIS	0.096	0.999	1	
COE	0.057	0.009	-0.044	1

Panel B: International

	N	Mean	SD	Min.	P5	P25	P50	P75	P95	Max.	% > 0
FRET	64,285	9%	44%	-99%	-49%	-15%	4%	26%	78%	948%	56%
IRET	64,285	13%	32%	-90%	-27%	-1%	11%	24%	58%	300%	73%
COE	64,285	11%	3%	5%	7%	9%	10%	12%	16%	30%	100%
MIS	64,285	2%	32%	-116%	-39%	-12%	1%	14%	47%	293%	52%
UNDERVAL	33,428	11%	24%	0	0	0	1%	14%	47%	293%	100%
OVERVAL	30,857	-9%	16%	-116%	-39%	-12%	0	0	0	0	0%
IBESDUM	64,285	56%									

	FRET	*IRET*	*MIS*	*COE*
FRET	1			
IRET	0.03	1		
MIS	0.03	0.99	1	
COE	0.08	0.05	-0.04	1

Lastly, panel F graphs the distributions of *MIS* by country for the 15 countries with the most reports in our dataset. Panel F shows that there is variation across countries in the median *MIS* and the spread in *MIS* across countries. US observations have a median *MIS* that is most above zero as well as one of the largest within-country spreads in *MIS*. India has the lowest median *MIS*. The interquartile range in *MIS* for Singapore, Malaysia, and Australia are comparatively small. In light of these cross-country differences, in our regressions we include country fixed effects.

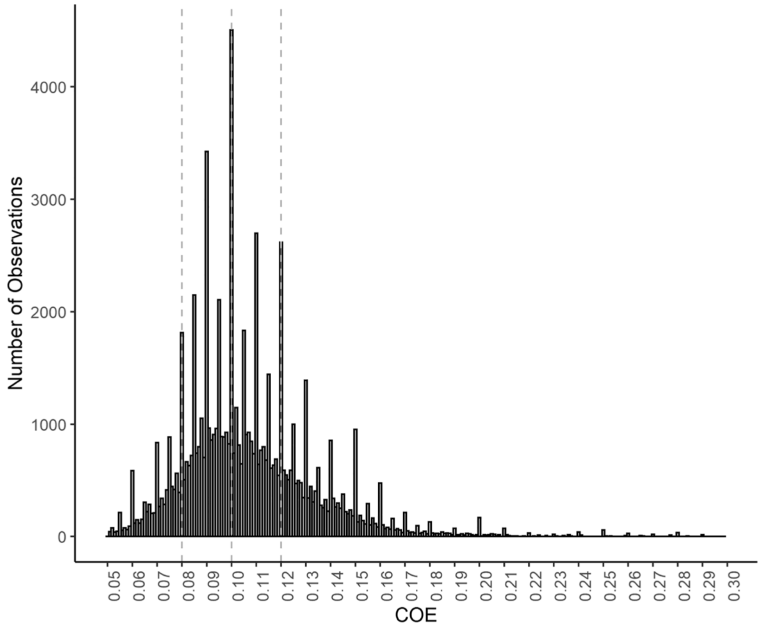
3 Empirical analyses

3.1 Tests of our main hypothesis

Table 4 reports the results of regressions that test our main hypothesis that analyst-claimed undervaluation will be more predictive of future stock returns than analyst-claimed overvaluation, and our first supplemental hypothesis. The regressions fit within the following general structure.

Table 3 (continued)

Panel C: Cost of Equity Distribution



Panel D: MIS and COE Distributions by Year

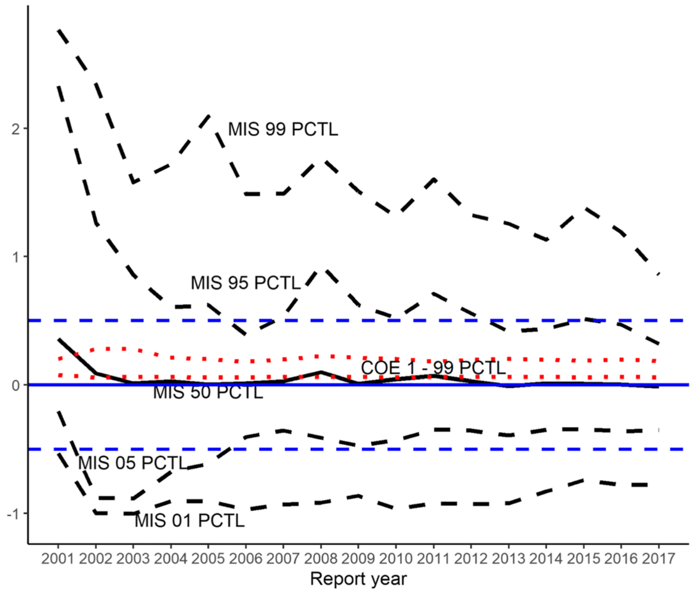
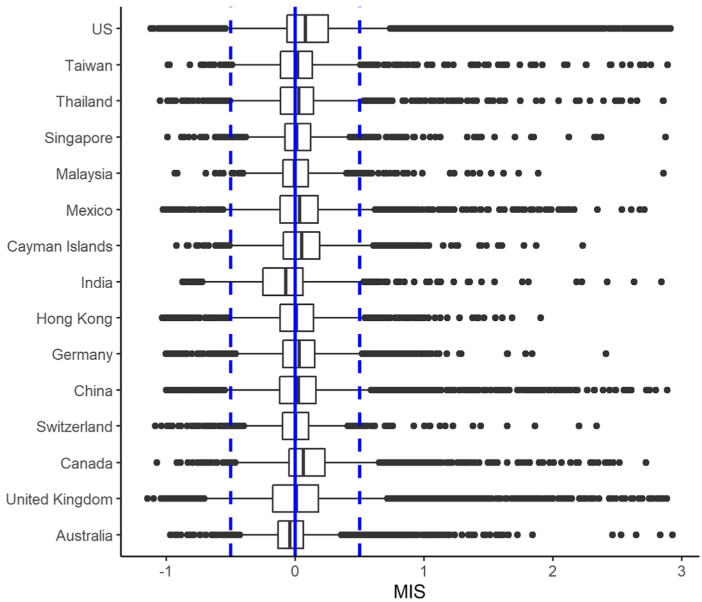


Table 3 (continued)

Panel E: Comparisons of our sample with IBES data

Dataset	Variable	Mean	StdDev	Min	P10	P25	Median	P75	P90	Max
Our Sample	*IRET*	0.15	0.35	-0.9	-0.15	0	0.12	0.26	0.44	3
IBES	*IRET*	0.55	3.9	-675	-0.15	0.04	0.18	0.4	1.25	907
Our Sample	*Ln MV*	14.3	2.8	2.6	10.0	13.5	14.8	16.0	17.1	20.5
IBES	*Ln MV*	8.0	1.8	-3.5	5.7	6.8	8.0	9.2	10.3	13.4

Panel F: MIS Distributions by Country



Panels A and B show descriptive statistics and Pearson correlations for the US and international analyst-firm-report observations in 2001–2017. Variable definitions are as follows. *FRET* is the realized one-year-ahead stock return. *IRET* is the forecasted one-year-ahead stock return implied by the analyst's target price. *COE* is the analyst's cost of equity. *MIS*=*IRET* – *COE*. *OVERVAL*=*MIS*>0. *UNDERVAL*=*MIS*≤0. *IBESDUM* is an indicator variable equal to one if the analyst's target price could be matched to IBES. Panel C compares *IRET* and *Ln MV* the natural log of USD market capitalization from our sample with the same variables for all IBES detailed 12-month target price forecasts that could be matched to end-of-fiscal-year market value in Compustat. Panel D graphs a histogram of *COE* with bin widths of one-half percent. Panel E plots the distribution of *MIS* by year of analysts' reports plotting the median and the first, firth, 95th and 99th percentiles in solid and dashed lines. The dotted lines show the first and 99th percentiles of *COE* with reference lines plotted at –0.5, 0 and 0.5. Panel F graphs box and whisker plots for *MIS* by country for the 15 countries with the most reports in our sample with reference lines at −0.5, 0 and 0.5. The graphed boxes show the median, interquartile range, and outliers outside of the interquartile range

$$FRET_{it} = \mathrm{a} + \alpha\ MIS_{ijct} + \beta_U\ UNDERVAL_{ijct} + \beta_O\ OVERVAL_{ijct} + \gamma\ COE_{ijct} + \lambda\ CONTROLS + \theta_c + \pi_j + \omega_{y[t]} + \vartheta_i + e_{it}, \quad (4)$$

where $FRET_{it}$ is the realized ex-dividend 365-calendar-day buy-and-hold stock return for firm i starting on the day of the analyst report t, COE_{ijct} is the *COE* in the analyst report for firm i issued by broker j in country c on day t, and $MIS_{ijct} = IRET_{ijct} - COE_{ijct}$, where $IRET_{ijct}$ is the forecasted one-year-ahead ex-dividend stock return implied by the analyst's target price for firm i in the report issued by broker j in country c on day t. *CONTROLS* is a set of firm characteristics that seek to capture risk exposures and λ is a vector of associated risk parameters.[5] To increase statistical power and address inferential threats arising from time-invariant firm and issuer characteristics and systematic market-wide forces, we follow Balakrishnan et al. (2021) and include the potential for countryθ_c, issuerπ_j, year $\omega_{y[t]}$ and firm ϑ_i fixed effects, denoted by subscripts c, j, $y[t]$, and i, respectively. We cluster standard errors by firm and year. For US observations, country fixed effects are excluded. For *UNDERVAL*, *OVERVAL*, and *COE*, we report t-statistics on the null that their associated coefficient is zero and one in () and [], respectively.

The key results in Table 4 are those for US model (3) and international model (6) that separate *MIS* into its mutually exclusive *UNDERVAL* and *OVERVAL* components. The results for models (3) and (6) show that analyst-claimed undervaluation reliably predicts stock returns but analyst-claimed overvaluation does not. The estimated coefficients on *UNDERVAL* are 0.18 (t-statistic = 4.0) for US analysts and 0.16 (t-statistic = 5.3) for international analysts, whereas the estimated coefficients on *OVERVAL* are 0.10 (t-statistic = 1.3) for US analysts and 0.03 (t-statistic = 1.0) for international analysts.

We note three sub-results in Table 4. First, all six US and international models confirm Balakrishnan et al. (2021) finding that the estimated coefficient on *COE* is insignificantly different from one. Second, both US model (1) and international model (4) find a small but reliably positive coefficient on *MIS*. Thus, before separating *MIS* into its *UNDERVAL* and *OVERVAL* components, analyst-claimed mispricing on average reliably predicts one-year-ahead returns. Third, when in US model (2) and international model (5) we control for firm characteristics that seek to capture risk exposures, the coefficient on *MIS* doubles for US analysts (rising from 0.09 to 0.17) and triples for international analysts (rising from 0.04 to 0.12). This supports Dechow and You's (2020) perspective that analyst target prices contain predictable errors arising from analysts' misinterpreting the return implications of common risk factors, in that we find that controlling for common risk factors increases the predictive ability of analyst-claimed mispricing. Our results also reconcile Dechow and You's (2020) finding that analysts' target prices include noisy expected return information with Balakrishnan et al. (2021)

[5] The firm characteristics we include are *LnMVE*, the natural log of the market value of equity in USD at the most recent fiscal year-end prior to the analyst's report date; *BOOK-to-MARKET*, the book value of the firm's common shareholder equity in USD at the most recent fiscal year-end prior to the report date divided by the market value of equity in USD; *INVESTMENT*, the percentage change in total assets over the two fiscal years prior to the report date; *PROFITABILITY*, net income for the fiscal year prior to the report date divided by total assets at the end of the fiscal year before that; and *MOMENTUM*, 12-month stock return momentum. We also include analysts' recommendations *REC*, captured by *SELL* = –1, *HOLD_or_MISSING* = 0, and *BUY* = 1.

Table 4 Regressions that project one-year-ahead realized stock returns onto analyst-claimed mispricing

Independent variables	Predicted coef	Dependent variable *FRET* is 1-year-ahead realized stock return					
		US analyst models			International analyst models		
		(1)	(2)	(3)	(4)	(5)	(6)
MIS	$0<\alpha$	0.09	0.17		0.04	0.12	
		(3.7)	(4.1)		(2.3)	(5.9)	
UNDERVAL (*MIS* > 0)	$0<\beta_U<1$			0.18			0.16
				(4.0)			(5.3)
				[−17.9]			[−28.1]
OVERVAL (*MIS* ≤ 0)	$0<\beta_O<\beta_U$			0.10			0.03
				(1.3)			(1.0)
COE	$\gamma=1$	1.06	1.29	1.28	1.21	0.94	0.92
		(1.6)	(2.2)	(2.2)	(3.2)	(3.8)	(3.8)
		[0.1]	[0.5]	[0.5]	[0.6]	[−0.2]	[−0.2]
LnMVE	<0		−0.25	−0.25		−0.24	−0.24
			(−5.5)	(−5.5)		(−9.2)	(−9.3)
BOOK-to-MARKET	>0		0.11	0.11		−0.003	−0.004
			(1.7)	(1.8)		(−0.1)	(−0.1)
INVESTMENT	>0		−0.01	−0.01		0.07	0.07
			(−0.3)	(−0.4)		(4.3)	(4.3)
PROFITABILITY	>0		0.03	0.03		−0.002	−0.001
			(1.4)	(1.3)		(−0.1)	(−0.0)
MOM	<0		−0.20	−0.20		−0.19	−0.18
			(−5.4)	(−5.3)		(−2.9)	(−3.0)
REC			−0.05	−0.04		−0.01	−0.01
			(−2.6)	(−2.2)		(−1.4)	(−1.0)
Constant		0.00	−0.05	−0.04	−0.04	−0.01	−0.01
		(0.0)	(−2.6)	(−2.2)	(−1.4)	(−1.4)	(−1.0)
# observations		9,781	9,781	9,781	64,235	64,235	64,235
Fixed effects		None	All	All	None	All	All
Adj. R^2 when no FEs included		1.3%	1.0%	3.6%	0.7%	0.1%	2.1%
Adj. R^2 with all FEs included			43.9%	43.9%		34.9%	35.0%

Panel regressions of realized one-year-ahead stock returns, *FRET,* on analyst-claimed mispricing, *MIS*; analyst-claimed undervaluation, *UNDERVAL* = *MIS* if *MIS* > 0, else zero; analyst-claimed overvaluation, *OVERVAL* = *MIS* if *MIS* ≤ 0, else zero; and *COE*, where *MIS* = *IRET* – *COE*. *IRET* is the forecasted one-year-ahead stock returns implied by the analyst's target price, and *COE* is the analyst's cost of equity for the firm. Firm characteristics are as follows. *LnMVE* is the natural log of the market value of equity in USD at the fiscal year-end prior to the report date. *BOOK-to-MARKET* is annual common shareholder equity divided by market value of equity in USD. *INVESTMENT* is the annual percentage change in total assets between the fiscal year prior to the report date and the year before that one. *PROFITABILITY* is net income for the fiscal year prior to the report date divided by total assets at the end of the year before that. *MOMENTUM (MOM)* is the 12-month return (with dividends) for the 12 months ending the day before the analyst's report. *REC* is the analyst's stock recommendation, classified as *SELL* = –1, *BUY* = 1, *HOLD_or_MISSING* = 0. *t*-statistics versus nulls of zero and one are in (.) and [.], respectively. Standard errors are clustered by firm and year. Data are panels of US and international analyst-firm-report observations over 2001–2017 result that analysts' *COE* estimates are unbiased predictors of future returns, because, while analyst *COEs* are unbiased, the reliably positive estimated coefficients on *MIS* indicate that analysts' *COE* estimates are not sufficient measures of a firm's expected 12-month-ahead return.

3.2 Tests of our supplemental hypotheses

Our first supplemental hypothesis is that, because analysts may issue bold or strategically magnified price targets to emphasize to investors that they have value-relevant information, *UNDERVAL* will map into future returns in a less than dollar-for-dollar manner. The results in Table 4 for US model (3) and international model (6) strongly support this since the t-statistics (in []) testing the null hypothesis that the coefficients on *UNDERVAL* = 1 are −17.9 and −28.1, respectively. Thus the estimated coefficients on *UNDERVAL* of 0.18 for US analysts and 0.16 for international analysts indicate that analyst-claimed undervaluation maps into future returns at 18 cents per dollar for US analysts and 16 cents per dollar for international analysts.

Our second supplemental hypothesis is that mispricing identified through analyst-claimed undervaluation will be corrected over time. Table 5 presents evidence consistent with this being the case. In all four of models (1) and (2) for US analysts and models (5) and (6) for international analysts, the estimated coefficients on *UNDERVAL* are reliably positive, indicating that analyst-claimed undervaluation predicts returns in the first and the second quarters beyond the analyst report date. At the same time, in all of models (3) and (4) for US analysts and models (7) and (8) for international analysts, the estimated coefficients on *UNDERVAL* are insignificant, indicating that analyst-claimed undervaluation does not predict returns in the third and the fourth quarters beyond the analyst report date.[6] The weakening strength of analysts' target price information is also apparent in the coefficient on *COE*, as the predictive information in analysts' cost of equity also declines moving further away from the analysts' report date. These findings together suggest that the information in target prices is short-lived, whether that information is about mispricing or about risk.

[6] Decomposing the one-year-ahead return into four separate quarters ahead reveals that for the international sample, *OVERVAL* is reliably positively associated with future returns at the first-quarter-ahead horizon. In the US and international samples, the coefficients on *COE* decline monotonically as the future return horizon increases, and *COE* forecasts returns for only the first quarter ahead for the US sample and for the first, second, and third quarters ahead for the international sample. These results suggest that analysts' *COEs* may capture firms' true costs of equity with noise or that firms' true costs of equity may vary noisily over time. Given the similarities in the patterns of declining coefficients for *UNDERVAL* and *COE* as the future return horizon extends out from the analyst report date, and the interrelations between *UNDERVAL* and *COE* (*UNDERVAL* being defined as *IRET* – *COE*, when *IRET* – *COE* > 0, 0 otherwise), it may be that the coefficient on *UNDERVAL* is picking up mismeasured *COE*, and vice versa, thereby decreasing our ability to separate mispricing from mismeasured risk.

Table 5 Regressions that project first- through fourth-quarter-ahead realized stock returns onto analyst-claimed mispricing

Dependent variable is the firm's future return *FRET* over the specified one-quarter-long horizon

	US analyst models				International analyst models			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent variables	1st Q ahead	2nd Q ahead	3rd Q ahead	4th Q ahead	1st Q ahead	2nd Q ahead	3rd Q ahead	4th Q ahead
	(2)	(3)	(4)	(5)	(7)	(8)	(9)	(10)
UNDERVAL MIS > 0)	0.06	0.05	0.02	0.01	0.07	0.05	0.02	0.02
	(3.7)	(2.4)	(1.0)	(0.9)	(9.1)	(3.7)	(1.5)	(1.5)
OVERVAL (*MIS* ≤ 0)	0.01	0.04	−0.04	0.01	0.03	−0.01	0.00	0.00
	(0.3)	(1.4)	(−1.5)	(1.1)	(2.8)	(−0.5)	(0.2)	(0.3)
COE	0.55	0.18	0.16	0.11	0.30	0.28	0.22	0.03
	(1.8)	(1.3)	(1.4)	(0.9)	(4.5)	(2.5)	(3.2)	(0.7)
Firm characteristics?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# observations	9,781	9,781	9,781	9,781	64,285	64,285	64,285	64,285
Fixed effects	All	All	All	All	All	All	All	All
Adj. R^2 no FEs included	2.0%	1.1%	0.6%	0.2%	1.4%	0.6%	0.4%	0.6%
Adj. R^2 all FEs included	21.6%	17.3%	14.4%	15.4%	20.7%	14.1%	11.7%	17.4%

Panel regressions of future one-quarter-ahead stock returns, *FRET*, on analyst-claimed mispricing, *MIS*; analyst-claimed undervaluation, *UNDERVAL* = *MIS* if *MIS* > 0, else zero; analyst-claimed overvaluation, *OVERVAL* = *MIS* if *MIS* ≤ 0, else zero; and *COE*, where *MIS* = *IRET* – *COE*, *IRET* is the forecasted one-year-ahead stock returns implied by the analyst's target price, and *COE* is the analyst's cost of equity for the firm. Firm characteristics are as follows. *LnMVE* is the natural log of the market value of equity in USD at the fiscal year-end prior to the report date. *BOOK-to-MARKET* is annual common shareholder equity in USD divided by market value of equity in USD. *INVESTMENT* is the annual percentage change in total assets between the fiscal year prior to the report date and the year before that one. *PROFITABILITY* is net income for the fiscal year prior to the report date divided by total assets at the end of the year before that. *MOMENTUM* (*MOM*) is the 12-month return (with dividends) for the 12 months ending the day before the analyst's report. Fixed effects are All = country, issuer, year, and firm. *T*-statistics versus a null of zero are in (.). Standard errors are clustered by firm and year. Data are panels of US and international analyst-firm-report observations over 2001–2017

Table 6 presents the results of regressions that test our third supplemental hypothesis that the mapping of *UNDERVAL* into future returns will be negatively related to prior-period returns, and our fourth supplemental hypothesis that the mapping will be negatively related to macro-driven valuation uncertainty. We measure prior-period returns using *MOMENTUM (MOM)*, our 12-month-momentum control variable, and macro-driven valuation uncertainty using the standard deviation of the returns implied by analysts' target prices at the country level over the year prior to analysts' report dates *sdlRET*.[7] The results in Table 6 are consistent with our predictions. The coefficients on *UNDERVAL * MOM* are −0.14 (t-statistic = −3.0) for the US sample per model (1) and −0.16 (t-statistic = −2.45) for the international sample per model (2), while the coefficient on *UNDERVAL * sdRET* is −0.58 (t-statistic = −4.5) per model (3). It is also the case that there is some evidence for the information content of *OVERVAL* after controlling for the interactions with *MOM* and *sdRET.* After controlling for *OVERVAL * sdlRET*, the coefficient on *OVERVAL* is significantly positive, and the coefficient on *OVERVAL*MOM* for the international sample indicates that the coefficient on *OVERVAL* becomes stronger when recent returns have been higher.

3.3 Robustness tests

3.3.1 The information in IRET

Model (5) in Table 5 and models (1) and (2) in Table 6 suggest that, under certain *MOM* conditions, analysts' target prices contain information about overvaluation. Here we explore alternative ways in which analysts' claims about undervaluation may forecast returns. Analysts' *IRET*s can be high because analysts' have updated their target prices to include positive news that the market has not yet priced. Alternatively, analysts' *IRET*s can be high because market prices have declined and analysts' have not updated their target prices or have not lowered their target prices to the same extent as the market price. In the first case, analysts are providing independent positive information that the market later learns and prices. In the second case, analysts take a contrarian view by not changing target prices when transitory fluctuations in market prices occur. In other words, in the second case, analysts' weight their own private signal more than the market signal (Aharoni et al. 2017; Chen and Jiang 2006).

To distinguish between the two possibilities, we test whether analysts' *IRET*s are contrarian when analysts provide high *IRETs.* If analysts' claims of undervaluation are primarily driven by contrarian positions where they do not adjust target prices in response to transitory fluctuations in market prices, we expect a negative correlation between prior stock returns, *MOM*, and *IRET* when *IRETs* are high.

[7] We use the cross-sectional standard deviation of *IRET* as our measure of uncertainty because it captures the systematic tendency for issuing bold forecasts such that bold forecasts cannot signal information as cleanly (Clement and Tse 2005). We also use this measure because some measures of uncertainty, such as VIX (Chicago Board Options Exchange's Volatility Index), are not available for all countries and years in our sample.

Table 6 Return momentum and uncertainty as attenuation explanations

		Dependent variable *FRET* is 1-year-ahead stock return		
Independent variables	Expected coef	US	International	International
		(1)	(2)	(3)
UNDERVAL (*MIS* > 0)	$0<\beta_U<1$	0.20	0.16	0.36
		(4.6)	(6.4)	(6.2)
OVERVAL (*MIS* ≤ 0)	$0<\beta_O<\beta_U$	0.07	0.01	0.12
		(0.8)	(0.3)	(2.0)
*UNDERVAL * MOM*	< 0	−0.14	−0.16	
		(−3.0)	(−2.4)	
*OVERVAL * MOM*		0.17	0.15	
		(1.5)	(2.4)	
*UNDERVAL * sdIRET*	< 0			−0.58
				(−4.5)
*OVERVAL * sdIRET*				−0.31
				(−1.8)
COE	$\gamma=1$	1.26	0.90	1.04
		(2.2)	(3.9)	(4.0)
Firm characteristics included?		Yes	Yes	Yes
# observations		9,781	64,285	64,285
Fixed effects		All	All	All
Adj. R^2 when no FEs included		3.8%	2.3%	2.8%
Adj. R^2		44.2%	35.2%	36.8%

Panel regressions to evaluate 12-month-return momentum as an attenuation on the relations between realized one-year-ahead stock returns, *FRET*; analyst-claimed undervaluation, *UNDERVAL* = *MIS* > 0, else zero; analyst-claimed overvaluation, *OVERVAL* = *MIS* ≤ 0, else zero; and *COE*, where *MIS* = *IRET* – *COE*, *IRET* is the forecasted one-year-ahead stock return implied by the analyst's target price, and *COE* is the analyst's cost of equity for the firm. Firm characteristics are as follows. *LnMVE* is the natural log of the market value of equity in USD at the fiscal year-end prior to the report date. *BOOK-to-MARKET* is annual common shareholder equity in USD divided by market value of equity in USD. *INVESTMENT* is the annual percentage change in total assets between the fiscal year prior to the report date and the year before that one. *PROFITABILITY* is net income for the fiscal year prior to the report date divided by total assets at the end of the year before that. *MOMENTUM (MOM)* is the 12-month return (with dividends) for the 12 months ending the day before the analyst's report. *sdIRET* is the country-level standard deviation of target price implied returns in the year prior to the analyst's report. *t*-statistics versus a null of zero are in (.). Standard errors are clustered by firm and year. Data are panels of US and international analyst-firm-report observations over 2001–2017

As our focus is on the relations between *IRET* and *MOM* at different points in the conditional distribution of *IRET*, we test our hypothesis using quantile rather than standard linear regressions (Koenker and Bassett 1978).[8]

[8] Examples of accounting research that has employed quantile regressions include Armstrong et al. (2015).

Table 7 Quantile regressions on the determinants of the implied returns in analysts' target priced when prior-period stock returns have been positive versus negative

IRET Quantile	(1) Intercept	(2) *REC*	(3) *COE*	(4) *MOM+*	(5) *MOM-*	(6) *MVE*
10	−0.02	0.17	−0.89	−0.08	0.04	−0.00
	(3.6)	(98.2)	(−15.0)	(−17.2)	(3.0)	(−3.3)
25	−0.04	0.17	0.01	−0.04	−0.09	−0.00
	(−12.3)	(174.8)	(0.4)	(−15.3)	(−15.6)	(−4.3)
50	−0.00	0.18	0.36	−0.02	−0.20	−0.00
	(−0.3)	(216.5)	(14.7)	(−12.2)	(−34.1)	(−4.5)
75	0.02	0.19	0.87	−0.01	−0.45	−0.00
	(5.5)	(169.5)	(24.3)	(−3.7)	(−35.3)	(−3.4)
90	0.02	0.22	1.78	0.03	−0.92	−0.00
	(2.3)	(89.5)	(20.7)	(3.4)	(−35.0)	(−1.8)

Panel quantile regressions based on forecasted one-year-ahead stock return implied by the analyst's target price, *IRET*. Quantile regressions are estimated on the full data set at the 10th, 25th, 50th, 75th, and 90th quantiles of the *IRET* distribution. *REC* is the analyst's stock recommendation, classified as *SELL* = –1, *BUY* = 1, *HOLD_or_MISSING* = 0. *COE* is the analyst's cost of equity for the firm. *MOM+* is the 12-month return (with dividends) for the 12 months ending the day before the analyst's report for returns greater than or equal to zero and zero otherwise, and *MOM–* is similarly for returns less than zero and zero otherwise. *MVE* is the market value of equity in USD at the fiscal year-end prior to the analyst's report date. *t*-statistics are in (.). Data are panels of US and international analyst-firm-report observations, 2001–2017

Table 7 presents the results of estimating the quantile regressions, where the coefficients of interest are on positive momentum *MOM+* and negative momentum *MOM-*. *MOM+* is the firm's 12-month-return *MOM* ending the day before the analyst's report date when $MOM > 0$ and zero otherwise and *MOM–* is the 12-month return when $MOM < 0$ and zero otherwise.

Consistent with our earlier evidence that analyst undervaluation maps into future returns, Table 7 shows that analysts issue target prices that are boldest in terms of embedding the most positive *IRET* when prior 12-month-return *MOM* has been negative. The coefficient of −0.92 on *MOM-* in the 90th quantile *IRET* regression indicates that a 1% more negative *MOM-* is associated with an 0.92% higher *IRET*, almost an inverse one-to-one relation. In comparison, the coefficient of 0.03 on *MOM+* is just 1/30th as large. At the same time, however, it is also the case that the negative coefficient of −0.08 on *MOM+* in the 10th quantile *IRET* regression is reliably negative and implies that a 1% more positive *MOM+* associates with an 0.08% lower *IRET*. While the coefficient on *MOM+* in the 10th quantile *IRET* regression is an order of magnitude smaller than is the coefficient on *MOM-* in the 90th quantile *IRET* regression and only twice as large as the coefficient on *MOM-* in the 10th quantile regression, it is negative and reliably so.

This table suggests that an important determinant of analysts' claimed undervaluation is transitory declines in market prices. In other words, *UNDERVAL* may forecast returns, in part, because analysts correctly identify when market declines are transitory.

Table 8 Regressions that project one-year-ahead realized stock returns onto analyst-claimed mispricing but using *IRET* instead of *MIS* to define *UNDERVAL#* and *OVERVAL#*

Independent variables	Expected coef	Dependent variable *FRET* is 1-year-ahead stock return			
		US		International	
		(1)	(2)	(3)	(4)
IRET	$0<\alpha$	0.17		0.12	
		(4.1)		(5.9)	
UNDERVAL# (*IRET* > 0)	$0<\beta_U<1$		0.18		0.15
			(4.1)		(5.5)
			[−18.7]		[−31.2]
OVERVAL# (*IRET* ≤ 0)	$0<\beta_O<\beta_U$		0.08		0.003
			(0.9)		(0.08)
COE	$\gamma=1$	1.13	1.12	0.83	0.82
		(2.0)	(2.0)	(3.4)	(3.5)
# observations		9,781	9,781	64,235	64,235
Control variables		Yes	Yes	Yes	Yes
Fixed effects		All	All	All	All
Adj. R^2 when no FEs included		3.6%	3.6%	2.0%	2.1%
Adj. R^2 with all FEs included		44.0%	44.0%	34.9%	35.0%

Panel regressions of firms realized one-year-ahead stock returns *FRET* on analyst-claimed mispricing along the lines of the regressions reported in Table 4 but using the forecasted one-year-ahead stock returns implied by the analyst's target price, *IRET*, instead of *MIS* to define analyst-claimed undervaluation as *UNDERVAL#* = *IRET* > 0, else zero, and analyst-claimed overvaluation *OVERVAL#* = *IRET* ≤ 0, else zero

3.3.2 IRET and measurement error in MIS

Prior research finds that analysts' target prices include noise pertaining to risk information (Dechow and You 2020). Thus, despite being correlated with future returns, analysts' *COE* are noisy reflections of risk with the implication that *MIS* may fail to properly separate mispricing information from risk-based information in analysts' target prices. To assess this concern, we repeat our Table 4 main tests in Table 8 by replacing *MIS* with *IRET* and by decomposing *IRET* into *UNDERVAL#* and *OVERVAL#* based on *IRET* > 0 and *IRET* ≤ 0, respectively. For presentation purposes, we include but do not report parameter estimates on the control variables since they are nearly identical to those in Table 4. The key result in Table 8 is that the coefficient estimates on *UNDERVAL#* and *OVERVAL#* are very similar in magnitude and statistical significance to those seen for *UNDERVAL* and *OVERVAL* in Table 4.

3.3.3 Other robustness tests

We present the results of two more robustness tests in Table 9. First, Green et al. (2016) find that many analysts do not scale up the DCF-based valuations that often underlie

Table 9 Other tests using scaled forward IRET and different clustering

Independent variables	Scaled-up *IRET* (1)	(2)	Different standard error clustering (3)	(4)	(5)	(6)
IRET	0.11					
	(5.9)					
UNDERVAL# (*IRET* > 0)		0.14	0.16	0.16	0.16	0.16
		(5.8)	(8.3)	(6.0)	(8.7)	(9.7)
OVERVAL# (*IRET* ≤ 0)		−0.00	0.03	0.03	0.03	0.03
		(−0.0)	(1.3)	(1.2)	(1.5)	(1.7)
COE	0.73	0.82	0.95	0.95	0.95	0.95
	(3.1)	(3.4)	(6.1)	(4.0)	(5.9)	(6.7)
# observations	74,066	74,066	74,066	74,066	74,066	74,066
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	All	All	All	All	All	All
Adj. R^2 when no FEs included	2.1%	2.2%	2.2%	2.2%	2.2%	2.2%
Adj. R^2 with all FEs included	35.9%	36.0%	36.0%	36.0%	36.0%	36.0%

Panel regressions of firms' realized one-year-ahead stock returns, *FRET,* on the analyst-claimed mispricing, *MIS*, and *COE*, where *MIS* = *IRET* – *COE*, *IRET* is the forecasted one-year-ahead stock returns implied by the analyst's target price, and *COE* is the analyst's cost of equity for the firm. In columns (1) and (2), *IRET* used is *Scaled Forward IRET*. In columns (3)–(6), different clustering methods are used. Firm characteristics included as controls are as follows. *LnMVE* is the natural log of the market value of equity in USD at the fiscal year-end prior to the report date. *BOOK-to-MARKET* is annual common shareholder equity in USD divided by market value of equity in USD. *INVESTMENT* is the annual percentage change in total assets between the fiscal year prior to the report date and the year before that one. *PROFITABILITY* is net income for the fiscal year prior to the report date divided by total assets at the end of the year before that. *MOMENTUM (MOM)* is the 12-month return (with dividends) for the 12 months ending the day before the analyst's report. *REC* is the analyst's stock recommendation, classified as *SELL* = −1, *BUY* = 1, *HOLD_or_MISSING* = 0. *t*-statistics versus nulls of zero and one are in (.) and [.], respectively. Standard errors are clustered by firm and year. Data are panels of US and international analyst-firm-report observations over 2001–2017

their target prices to account for the time between the date of valuation in their DCF model and the date the target price date. Using pooled US and international observations, we therefore repeat our primary regressions using *IRET* scaled up to account for target prices that are for the end of year t target prices rather than the end of year t + 1 target prices. The results reported in columns (1) and (2) are highly similar to those in Tables 4 and 8. Second, we examine different methods of clustering in computing the standard errors of coefficient estimates. The results in columns (3)–(6) indicate no effects on the inferences that obtain in Tables 4 and 8 across clustering methods.

4 Caveats

While we show that US and international sell-side equity analysts identify undervaluation but not overvaluation in the stock prices of the firms they cover, our study comes with some caveats. First, we focus only on the first moment of the returns implied by analysts' target prices. Joos et al. (2016) and Joos and Piotroski (2017) show that there is valuable information in the high/base/low multi-target price scenarios that some analysts provide, meaning there could be relations between such scenarios and the *COE*-based measures of analyst-claimed mispricing that we develop in our study. Second, because we require that an analyst's report contain both a target price and a cost of equity figure, we cannot generalize our findings to analyst target prices that are not accompanied by a disclosed cost of equity—which is likely to be the great majority of target prices. Lastly, despite the large number of observations in our global dataset and the careful approach we take in identifying analysts' *COE*s from their reports, there may be inadvertent biases in our data arising from the textual extraction methods we use.

5 Conclusion

Our goal is to study the predictive properties of analyst-claimed mispricing using the target prices and costs of equity disclosed by US and international analysts. We hypothesize that asymmetry in the incentives that managers face to supply value-relevant information to analysts combines with asymmetry in the incentives that analysts have to curry favor with and not contradict managers lead to analyst-claimed undervaluation being more predictive of future stock returns than analyst-claimed overvaluation.

We center the empirical tests of our hypotheses on analyst-claimed mispricing, *MIS*, defined as the ex-dividend predicted return implied by the analyst's target price, *IRET*, less the analyst's estimate of the firm's cost of equity, *COE*. We isolate analyst-claimed undervaluation from overvaluation by defining *UNDERVAL* as $MIS > 0$ and *OVERVAL* as $MIS \leq 0$ and use analysts' target prices and costs of equity from US and international company analyst reports in Thomson ONE's Investext database containing the text string "cost of equity." When we regress within a fixed-effects structure realized one-year-ahead ex-dividend stock returns *FRET* on *COE*, *UNDERVAL*, and *OVERVAL* and controls for firms' priced risk exposures, we find that the target prices of US and international analysts reliably predict stock returns when analysts claim undervaluation but not when they claim overvaluation.

We also expand beyond our main hypothesis by exploring four supplemental hypotheses and find support for each. Specifically, we find that analyst-claimed undervaluation maps into future returns in a manner that is less than dollar-for-dollar; analyst-claimed undervaluation is less predictive of future stock returns the further the returns are beyond the analyst's report date; and the mapping of analyst-claimed undervaluation into future returns is negatively related to prior-period returns and to macro-driven valuation uncertainty.

Our study contributes to the literature on target prices in how it introduces an economically grounded way of isolating the mispricing-claimed component of analysts' target prices and thus separating analyst-claimed undervaluation from analyst-claimed overvaluation. We also build on the work of Dechow and You (2020), who propose that, while consensus analyst target prices contain value-relevant information, they also contain predictable errors from analysts' misinterpreting the return implications of common risk factors. We show that controlling for these common risk factors increases the power of measuring the predictive properties of analyst-claimed mispricing. Further, we reconcile the finding of Dechow and You (2020) that analysts' target prices include noisy expected return information with the result of Balakrishnan et al. (2021) that analysts' cost of equity estimates are unbiased predictors of annual returns. We show that, while an analyst's cost of equity is unbiased, it is not a sufficient measure of expected returns because not only does it substantially understate the variation in realized returns but other risk factors, such as firm size and 12-month momentum, are incrementally predictive of returns.

Overall our study contributes new knowledge to the academic literature on analyst target prices, the cost of equity, and market efficiency. We also believe that our study's findings can be readily brought into the classroom in the teaching and practice of financial statement analysis and valuation (Sommers and Easton 2019), and we encourage our readers to do so.

Appendix

In this Appendix, we describe the procedures we followed in downloading analyst reports from the Thomson Reuters Thomson ONE Investext database (cf. Table 1) and extracting analysts' cost of equity and target prices, firm ticker, the report date, the broker name, and the lead analyst name from the reports. We built our dataset of analysts' cost of equity estimates for US and international observations by searching the text of the universe of analysts' PDF reports that are stored in Thomson ONE's Investext database. We identified all analyst reports issued between Jan. 1, 2001, and Dec. 31, 2017, that contained at least one occurrence of the text string "cost of equity" anywhere in the report. We then retained only those reports that were provided by brokers and where the report type was company (rather than industries, geographic, or investing/economic). This yielded 80,663 US analyst reports (where geography = United States) and 351,730 international analyst reports (where geography = not United States).

The broker name, lead analyst name, and report date are provided in the summary information of the reports by Thomson ONE. This summary information is also presented in a standardized format such that automated extraction is straightforward and mostly free from error.

We then extract the cost of equity numbers from the reports. As noted by Balakrishnan et al. (2021), systematically extracting these numbers, or indeed anything, from reports is challenging because analysts use various techniques to state the cost of equity. Manual extraction of costs of equity, target prices, and other data items from such a large number of reports is infeasible.

To reduce the computational burden, we use only the first 50,000 characters of each report. Most often, analysts' reports contain two columns on each page, and sentences typically wrap onto a separate line within the column. The PDFs, however, may incorrectly identify text and number combinations that cross columns in the raw text as comprising a single sentence, even though readers can see that these combinations fall into different columns. We therefore first separate the text portions of the reports into its columns and remove line breaks to allow us to capture full sentences. To identify columns, we require at least six contiguous words with only single separating spaces and identify the first column as all of the words before the line encounters multiple spaces. After the multiple spaces, we apply the same criteria to identify the second column. For tabular material, we require that the phrase of interest (e.g., "cost of equity") that is followed by multiple spaces and then a number not be followed by single-spaced words. After this initial structuring of the raw text of the reports, we use regular expression-matching approaches to extract the necessary items from the reports.

We collect the cost of equity figures and the price targets from the reports. We also use the text of the reports and the summary information provided by Thomson ONE in the combined report PDFs to match the reports to price and accounting information. We first describe here the methods we used for extracting cost of equity numbers and target prices from analysts' reports, and we then describe how we match the information extracted from the analyst reports with other price and accounting data.

To extract the cost of equity numbers, we create a regular expression that finds a number that has "%" or "percent" following it and then scan before and after this number, looking for "cost" and "equity" without encountering either another number or a comma, period, or semicolon. The number must be between 5 and 30 and may have up to three decimal places. These search criteria capture "5.7%" from a sentence such as "ROA is 9.8%, the risk-free rate is 3.0%, while the cost of equity is 5.7%." We randomly sample one report from each brokerage to check the efficacy of this algorithm. With only minor exceptions, this algorithm avoids errors in the cost of equity number. In a few instances the algorithm incorrectly identifies a cost of equity, for example, in text such as "we lower our cost of equity estimate from 7.0% to 6.8%."

We then read the text of a random sample of 500 reports in which we did not identify a cost of equity and add more specific ways of reporting to capture more cost of equity estimates. For example, cost of equity is often abbreviated as "COE" or "Koe," and there are some other more specific ways to state the cost of equity, such as "Cost of Equity, $Ke = Rf + \beta$ x (RM-Rf), 7.8%." We continue to add these more specific reporting approaches while iteratively sampling 500 reports with missing measures of cost of equity and adding to the algorithm.

As a final step, we examine all reports from which we cannot extract a cost of equity number. There are some common reasons that we do not get a cost of equity number from these reports. Some of the reports are industry reports, some are debt analyst reports, and some discuss the cost of equity without giving a number. Finally, some do have cost of equity numbers, but adding to the algorithm to capture these numbers is difficult and generates many errors in the cost of equity numbers extracted for other reports. An example of such a statement is the following: "We estimate cost of equity following a multi-step process, including estimating beta over a five year window, using the risk free rate and equity premium from Bloomberg, and then using the CAPM. The resulting number is 7.8%."

While many analysts provide annual target prices in their reports, not all do so. When analysts provide a target price, it is often stated in a prominent place in the report. However, the format that analysts use differs, and the wording may also differ. We read many analyst reports and discovered that analysts' most common approach, when providing a 12-month target price, is to discuss the target price using the word "target" and "price" or directly provide it in a table. To extract the target price, we create a regular expression that finds a number that has no more than two decimal places and is not followed by "%" or "percent" and then scan before and after this number, looking for "target" and "price" without encountering another number or a comma, period, or semicolon. The most common errors in the matching process are for time expressions such as "12 months" or "1–2 years." To address this, we remove matches that result in numbers that are exactly equal to 12 or are less than or equal to 2. After examining a random sample of 200 reports, we notice that extreme implied returns from the target prices can occur when we incorrectly extract a target price, for example, when we incorrectly match a table header that can include an index number such as 1 or 2 or a year such as 2008 rather than the target price. We look at all target prices that yield implied returns, relative to the end of day price on the day before the report date that are greater than 300% or implied returns less than −90%. All of these observations are errors from our extraction process. An supplemental random sample of 200 reports shows that these errors are uncommon with less extreme implied returns. To remove these errors, we require target price to yield implied returns that are between −90% and 300%. However, our results are not sensitive to minor changes in these cutoffs (such as −50% and 100%).

To extract recommendations, we extract keywords that are not surrounded by other numbers or text. The words are not case sensitive. For buy recommendations, we use the following words: buy, outperform, and overweight; for hold recommendations, hold, neutral, and equal-weight; and for sell recommendations, sell, underperform, and underweight.

To match to price and accounting data from other databases, we identify the company that is the subject of a report. We use two features of the report to try to get the best matches possible for the company of the report. First, ticker symbols are available in most reports, and, second, in the summary information of a report, Thomson ONE provides a title for the report that is most frequently the name of the company that is the subject of the report. While most reports include a company ticker on the first page of the report, not all do so, and the format in which the ticker is provided varies substantially across reports. Supplementally, the format of the ticker across countries varies, and in some countries, tickers are given by numbers or number-letter combinations. These features complicate the company matching process. Because of the differences in tickers, we perform slightly different matching procedures for US and non-US company reports.

For the US sample, we begin by searching for a ticker. We first use presentation formats that simplify the extraction of the ticker. These formats typically take a form such as "NYSE|AA." We allow for many similar formats, with the common feature being that some identifier occurs near an all-capitalized set of letters. The identifiers include "ticker," "symbol," "nasdaq," "exchange," "nyse," "amex," "otc," "bloomberg," "reuters," "ric," and "stock code." Absent such an identifier, tickers are used in sentences or sometimes presented separately in the report. This presents a particular challenge, for example, when the actual ticker is "A" or "EPS" or "FCF." To circumvent this challenge, we collect all all-capitalized words in the first page of a report in which we have not identified a ticker. We match each of these potential tickers to the list of all tickers from the CRSP names file for when the report was written. These potential matches include true matches as well as false ticker matches.

For all potential matches, we compare the names from the Thomson ONE summary information with the names in the CRSP names file. After removing abbreviations and common abbreviations such as "CO" and "INC" in both files, we identify a match if the name in one file can fit into the name in another file. For example, if the Thomson ONE summary information gives the name as "Walmart" and the CRSP names file gives the name as "Walmart Stores," because "Walmart" is completely included in "Walmart Stores" the associated tickers are labeled a match. If this match fails, we also search for abbreviations. Thus "Bnk" does not fit into "Bank," but removing vowels makes a match. If the nonvowel version of the names match, then we also label the tickers as a match. If this process results in multiple ticker matches, the possible ticker that shows up most frequently in the report is used. If the frequencies of multiple possible tickers are tied, then the longest possible ticker is used. Using these tickers and the CRSP names file, we get the CRSP Permno identifier to merge CRSP data with the analyst reports. Following this procedure, we can extract tickers for 65,286 reports. Requiring the cost of equity number and the ticker yields a sample of 51,032 reports.

Moving to the non-US reports presents supplemental challenges. Most challenging is that not all non-US stocks have full capitals as their standard ticker. Another challenge is that the set of identifiers has to be greatly expanded. Therefore, we take an alternative approach to matching reports to company data.

The company data come from Datastream and FactSet. We first select all companies with available prices from FactSet. We then use the company name provided by Thomson ONE and match the first word of this name to the first word of the company name provided by FactSet. This matching process does not produce a match when the name provided by Thomson ONE is not the name of the company in the report. This appears to occur occasionally when the report is an industry summary with only one name listed in the report or when the brokerage is listed rather than an individual company. We then calculate a measure of the spelling distance between the names from the two sources using the first 20 characters of the names. We require a maximum spelling distance of 50% of the length of the FactSet name, meaning that, if the number of additions, deletions, and transformations required to change the Thomson ONE name into the FactSet name is more than half the length of the FactSet name, we remove the match. If the spelling distance is less than or equal to 15%, we keep the match. For spelling distances between 15 and 50%, we search for the ticker from FactSet in the report. If the ticker is found in the report, we also search for the country as either the exchange country or the exchange ID or the country ID from FactSet. If we find the ticker and the country in the report, we keep the match.

Even though Thomson ONE provides the issuer name in the summary information of the reports, the issuer name is not always presented in exactly the same format. Sometimes issuers from the same broker but in different segments are stated differently. We manually go through all issuer names in the table of contents of each PDF file and simplify the names to identify unique issuers.

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Data availability Data are available from the sources cited in the text.

Declarations

None.

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