Valuation Models*

Francesca Bastianello Paul H. Décaire Marius Guenzel†

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Abstract

Valuation models lie at the core of both financial theory and practice, yet we lack systematic evidence on how professionals value assets, which models perform best, and why. To make progress on these questions, we analyze valuation models in 1.1 million equity analyst reports. While, on average, simpler multiples-based models generate more accurate forecasts than more complex discounted cash flow (DCF) models, this masks important heterogeneity: skilled analysts produce superior forecasts with DCF models, especially for hard-to-value firms, underscoring the importance of expertise when employing complex models. To establish that model-specific expertise matters, we exploit a quasi-exogenous shock that forced some analysts to switch valuation models, and show that their forecast accuracy subsequently declines relative to analysts with established experience using the new approach. This highlights a fundamental trade-off between simplicity and sophistication in valuation, where optimal method choice depends on analyst characteristics, such as skill. Finally, given their unconditional superior performance, we study how analysts determine multiples. Analysts use historical, current, and peer-based reference points to contextualize their choice of multiples, but they do not use these benchmarks mechanically when determining their prices. Moreover, we show that sensitivity analyses have become increasingly common, bull and bear scenarios are asymmetric and account for greater downside risk, and their inclusion is associated with more conservative forecasts.

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†Bastianello is at the University of Chicago, Booth School of Business. Décaire is at the W. P. Carey School of Business at Arizona State University. Guenzel is at the Wharton School of the University of Pennsylvania. We thank Daniil Garbuzov, Leah Li and Luke Li for outstanding research assistance.
francesca.bastianello@chicagobooth.edu, paul.decaire@asu.edu, and mguenzel@wharton.upenn.edu.

1 Introduction

Valuation models lie at the heart of financial decision-making, guiding how investors, analysts, and managers determine asset values and allocate capital. While there is a wide range of models that vary in their complexity, a lack of comprehensive large-scale evidence limits our understanding of how these models are used in practice, how they perform, and what factors drive their performance.

To make progress, we analyze valuation models from 1.1 million equity reports. On average, we document that simple multiples-based methods produce more accurate forecasts compared to more complex discounted cash flow (DCF) methods. However, this hides substantial heterogeneity. Skilled analysts produce more accurate forecasts when using DCFs, particularly for hard-to-value firms. This suggests that the sophistication of DCF methods can translate into better forecasts, but only when applied by analysts with sufficient expertise and judgment. Consistent with the notion of method-specific expertise, we show that analysts who are plausibly exogenously forced to adopt an unfamiliar method produce significantly less accurate forecasts. Then, prompted by the superior performance of multiples, we examine how analysts determine prices using these models. We find that analysts confront historical, current, and peers' reference points to contextualize their choice of multiples, but rarely use those values directly when determining prices. Moreover, multiples are strongly correlated with established proxies for risk and long-term growth expectations, indicating that, regardless of how analysts determine these values, multiples reflect the theoretical fundamentals underlying prices. Finally, bull and bear scenario analyses have become increasingly common, they display a pronounced downside asymmetry, and influence baseline valuations by shaping how analysts internally represent firm prospects.

To establish our findings, we augment the data introduced in Bastianello, Decaire, and Guenzel (2025) with newly collected granular information on how valuation methods are implemented in practice. Our first dataset documents the valuation methods underlying price target forecasts, which are the main quantitative output in analysts' equity reports, as well as the price targets themselves. This dataset covers the near-universe of sell-side analysts' reports on Refinitiv since 2000.[1] Our second dataset provides detailed insights into how analysts implement multiples-based valuation methods. Specifically, we collect: (i) the type of reference point employed (peer-based, historical prices, or current prices); (ii) the numerical values of both the analyst's *chosen* reference point and the multiple (for instance, peers trade at 3x EPS while the analyst applies a 2x multiple); and (iii) the approach to sensitivity analysis, including the construction of bull and bear scenarios, among other features.

We begin our analysis by documenting a number of summarizing facts about analysts' choice of valuation models. At 62%, the majority of reports use multiples-based methods to derive their price target forecasts, with the most common multiple, price-to-earnings, being used in 32% of cases. DCF methods are used in 43% of cases. At the same time, there are nontrivial differences across industries, time, and analysts. For instance, DCF methods are relatively more common in growth industries such as information, during periods when popular multiples-based methods are infeasible,[2] among more experienced analysts, as well as in certain geographic regions (e.g., in Europe relative to the U.S.), even after accounting for analyst-firm sorting.

Next, we evaluate the performance of different methods, with respect to forecast levels, forecast errors, and forecast accuracy (i.e. absolute forecast errors). Three striking results emerge. First, multiples-based methods, which are generally simpler than DCF approaches, outperform DCF methods. While price targets are overly optimistic on average, multiples-based methods produce lower forecasts in levels, leading to higher forecast accuracy. Using a

[1] This sample closely aligns, in terms of firm coverage and characteristics, with that of commercial databases such as the Institutional Brokers' Estimate System (IBES), which also focuses on sell-side analysts.

[2] Most pronounced in the data, DCF methods were substantially more popular during the Great Recession, when negative EPS forecasts rendered price-to-earnings (P-E) multiples infeasible.

series of granular fixed effects, the outperformance of multiples-based methods persists within firms, years, and firm-years, i.e., holding constant all firm characteristics in a given year, as well as within analyst-years, i.e., holding fixed analyst expertise and location.

Second, across all considered subsamples split by firm characteristics, there is no case in which DCF methods outperform multiples-based approaches. DCF underperformance persists across both low and high categories of firm size, age, leverage, profitability, growth potential, and R&D intensity, as well as for both easy-to-value and hard-to-value firms, as measured by lagged average forecast errors for each firm. Interpreted more broadly, these results suggest calibration challenges inherent to models with more degrees of freedom.

Third, we find robust evidence that analyst characteristics, and particularly analyst skill and method expertise, can systematically overturn the average DCF underperformance. More skilled analysts, identified as those who on average issued more accurate forecasts in the past, in fact outperform when using DCF methods compared to multiples-based approaches. This result is robust to various definitions of past forecast accuracy, including residualized measures that account for previous method usage and firms' industry. We further show that the DCF outperformance by skilled analysts is particularly strong for hard-to-value firms, suggesting that analyst skill is most valuable when valuation tasks are complex and when the flexibility of DCF models can be effectively leveraged.

To establish the importance of method-specific expertise, on top of analyst skill, we exploit a quasi-exogenous shock that forced analysts to adopt unfamiliar valuation methods. Specifically, as a consequence of the Great Financial Recession (GFR), popular multiples-based methods, such as P-E multiples, became infeasible due to negative EPS forecasts, forcing analysts to predominantly employ DCF models (cf. footnote 2). Analysts forced to switch valuation methods saw their forecast accuracy subsequently decline relative to forecasters covering the same firms, but who were already proficient with DCF methods. The switching-to-DCF underperformance is unique to the GFR period associated with forced model switching, and is absent during other periods where valuation method switches are voluntary–cases where analysts deliberately decide to change their approach in response to changes in the firm's situation or due to personal preference. This highlights a novel trade-off to understand forecast performance: the interaction of analyst expertise with model sophistication. Some models can, in theory, better capture the complexity of stock valuation, but their benefits are realized empirically only by more sophisticated analysts.

Finally, given the prevalence and unconditionally superior performance of multiples, we examine in detail how analysts form price expectations using multiple-based models. While multiples can be viewed as heuristics that implicitly incorporate growth expectations and discount rates into a single numerical value, analysts need not *explicitly* form estimates of these parameters. Instead, they can rely on reference points–either time-series benchmarks (historical valuations) or cross-sectional comparisons (peer multiples)–to anchor their assessments. This approach reduces the valuation problem to simple questions on whether the firm will grow faster than peers or its own historical rate, and whether its risk exposure exceeds that of comparable firms or its past profile. If analysts perceive the firm as riskier than the reference point, they assign a lower multiple; if they expect higher growth potential, they assign a higher multiple. These reference points establish bounds for reasonable valuation, allowing analysts to contextualize their expectation within a simple and tractable empirical framework.

This general interpretation applies to most valuation multiples used in practice. Specifically, we organize our discussion of multiples valuation around the price-to-earnings ratio and the enterprise-value to EBITDA ratio, multiples in the *earnings family*, as they account for 90% of all valuation multiples used in practice (Bastianello, Decaire, and Guenzel, 2025). We provide a brief analysis of other types of valuation multiples, including cash-flow, sales, and book value multiples, later in the paper.

We first document analysts' use of reference points. Historical metrics appear in 17%

percent of reports, current valuation benchmarks in 14% percent, and peer comparisons in 17% percent. The remaining reports do not disclose any reference points. Empirically, the choice of using a particular reference point is primarily driven by individual style or preference, rather than characteristics attributable to firms, or time-varying trends: some analysts favor comparing firms to historical performance while others benchmark them against their peers. This suggests that internal representation, rather than externally prescribed norms, drives how financial professionals determine their benchmarks.

Then, we show that reference points are not mechanically used in valuation models when producing price targets. Specifically, analysts directly use their reference points to generate price targets in only 13-15% of cases, suggesting selective rather than automatic use. Instead, the relationship between reference points and multiple selection reflects analysts' own assessments of firm potential: the distance between reference point and valuation multiple is substantial on average and varies over time. As such, historical and peer information serve as reference points to contextualize analysts' reasoning by benchmarking against the existing market view (Bastianello and Imas, 2025).

Importantly, we further find that analysts do not systematically ex-post select reference points to justify predetermined multiple choices, such as cherry-picking high reference points to justify optimism. Empirically, the primary adjustment mechanism through which analysts express their assessment of firm potential is the multiple selection itself, not the reference point. This pattern supports the characterization of reference points as semi-objective benchmarks.

Next, we examine whether analysts' multiple adjustments track changes in the underlying theoretical drivers (i.e., firm risk and growth), even though multiples do not require analysts to form explicit beliefs about these parameters. Using CAPM betas as proxies for risk and *real* GDP growth as a measure of long-term growth expectations (Decaire and Guenzel, 2025; Decaire and Graham, 2024), we document a strong negative relationship between valuation multiples and beta and a positive relation with real GDP growth, consistent with standard valuation theory. This pattern admits two non-mutually exclusive interpretations. First, analysts can precisely, or broadly, form beliefs about these parameters when determining their multiples, consistent with the notion that multiples are *actively* derived from these primitives. Second, if multiples are derived from market prices that already embed forward-looking beliefs about risk and growth, they naturally inherit these properties. Although disentangling these mechanisms lies beyond the scope of our analysis, the results indicate that multiples are connected to their theoretical underpinnings.

In a final analysis, we examine how analysts incorporate scenario analyses into their valuations. We document a sharp rise in the use of bull and bear cases over time, now appearing in more than 40% of reports, reflecting a structural shift in practice rather than a cyclical response to macroeconomic uncertainty. Scenario forecasts are asymmetric, with baseline valuations placed much closer to the bull than the bear case. When constructing these scenarios, analysts typically adjust both the valuation multiple and the underlying driver rather than fundamentals alone, corroborating the notion that multiples are treated as forward-looking inputs rather than mechanical benchmarks. Scenario adoption is also associated with more conservative baseline forecasts, suggesting that the act of constructing bull–bear scenarios shapes how analysts internally represent firm prospects and leads them to internalize more downside risk in their baseline valuations.

Overall, we study how economic agents actually use models, as structured reductions of a complex reality, not just which models they choose. Our setting makes visible the shadow modeling that normally remains hidden: the anchors, adjustments, and scenario constructions that surround formal frameworks. In doing so, the paper documents how professionals adapt models to uncertainty in the field.

Literature. Our paper contributes to the literature on expectation formation in financial economics. While extensive work examines how financial agents develop beliefs about firms and assets both in corporate finance and in asset pricing, the focus has been mostly on studying the parameters within given valuation frameworks, discount rates, or growth expectations, rather than model selection itself.[3] Existing work offers limited evidence on how and why professionals choose among competing valuation approaches in practice, and we advance the literature in that regard.

Additionally, we provide a comprehensive analysis of how equity analysts conceptualize and implement valuation multiples in practice. Existing research provides in-depth analysis of other types of models (Decaire and Graham, 2024; Bastianello, Decaire, and Guenzel, 2025), and among the early notable attempts at studying multiples specifically, Ben-David and Chinco (2024) analyze 500 equity reports to characterize analyst valuation methods with a particular focus on one type of multiples, the price-to-earnings ratio. Our systematic examination of 1.1 million analyst reports enables us to document previously undetected patterns, establish robust stylized facts, and reconcile conflicting findings about professional valuation practices.

Finally, we contribute to a literature in behavioral economics that has studied the models that people adopt when solving problems.[4] We measure people's chosen models and underlying reasoning in a high-stakes field setting, and provide evidence that the optimal choice of model can depend on individual characteristics, such as experience and skill.

[3] Investors' belief formation has previously been studied both in corporate finance (Graham and Harvey, 2001; Brav, Lehavy, and Michaely, 2005; Krüger, Landier, and Thesmar, 2015; Levi and Welch, 2017; Welch, 2019; Decaire and Bessembinder, 2021; Dessaint, Otto, and Thesmar, 2021; Graham, 2022; Gormsen and Huber, 2022, 2023; Decaire, 2023; Eaton et al., 2023; Hommel, Landier, and Thesmar, 2023; Jensen, 2024; Dessaint, Gondhi, and Peress, 2025) and in asset pricing (e.g., Malmendier and Nagel, 2011; Barberis, 2018; Bordalo et al., 2019, 2020, 2024b; Guenzel and Malmendier, 2020; Delao and Myers, 2023; Nagel and Xu, 2023; Decaire and Graham, 2024; Decaire, Sosyura, and Wittry, 2024; Decaire and Guenzel, 2025; Ben-David and Chinco, 2024; Andolfatto and Bastianello, 2025; Bastianello and Fontanier, 2025a,b; Bastianello, 2025a,b).

[4] See Kleinberg et al., 2018; Martínez-Marquina, Niederle, and Vespa, 2019; Schwartzstein and Sunderam, 2021; Kendall and Charles, 2022; Aina, 2023; Bordalo et al., 2024a; Fréchette, Vespa, and Yuksel, 2024; Haaland et al., 2024; Oprea, 2024; Augenblick et al., 2025; Bastianello and Imas, 2025, among others.

2 Data

At the heart of our analysis is the construction of an augmented dataset introduced in Bastianello, Decaire, and Guenzel (2025), which contains additional granular information on financial professionals' valuation approaches, specifically their use of multiples (as we will show in the next section, the most frequently employed valuation tool in the data).

We defer to Bastianello, Decaire, and Guenzel (2025) for a detailed description of the initial dataset and provide only a high-level overview here. Specifically, we collect the full universe of equity analyst reports from Refinitiv Eikon between 2000 and 2025, apply light filters, and obtain 2.1 million reports. Using *Gemini Flash 2.0*, we extract key metadata and valuation-method information, retaining only single-firm reports with consistent pricing data and sufficient text length. After converting reports to text format, the final sample contains 1.38 million reports used to analyze financial professionals' valuation methods.

We then expand on this dataset by collecting, again via a large language model,[5] additional information about how analysts operationalize multiples-based models for a random subset of 51,905 reports (after light data filters). The augmented dataset provides granular visibility into how analysts implement multiple-based valuation in practice. For each report, we identify the type of benchmark used to anchor the valuation, i.e., whether the analyst relies on peer firms, historical trading patterns, or contemporaneous market prices. We also extract the quantitative inputs underlying these choices, including both the value of the benchmark itself and the multiple ultimately applied by the analyst (for example, a peer group trading at 3× EPS alongside a chosen 2× valuation multiple). In addition, the dataset captures whether analysts include sensitivity analyses, and if so, how they structure these analyses, encompassing the construction of bull and bear cases and any additional scenario work

[5] For this more involved task relative to the extraction of the method itself, we use *Claude Sonnet 4*. Appendix A contains the full prompt to extract the data on multiples usage. Also, we convert each PDF to text before sending it to the Claude API, which improves processing speed and accuracy relative to readily submitting PDFs as image-based documents.

reflected in the report. This allows us to move from the more common analysis of point estimates to account for the ranges and uncertainty surrounding analysts' valuations.

Together, these elements allow us to characterize not only which methods analysts use, but how they implement them in a detailed, numerical manner.

3 Summary Facts

3.1 Summary Facts About Valuation Method Usage

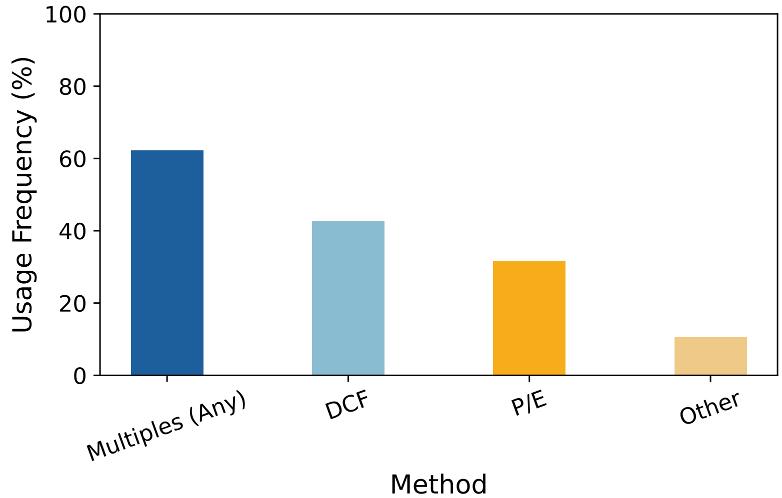
This section presents baseline descriptive facts on the usage of different valuation methods in the full sample, comprising a near-universe of equity reports, along with several heterogeneity patterns. When analyzing forecast accuracy subsequently, these patterns will provide a baseline for understanding the sources of performance differences. We will selectively account for them to assess which aspects of heterogeneity drive (or do not drive) the observed performance results.

Valuation method frequency. Figure I presents aggregate frequencies of valuation methods as well as their heterogeneity across various dimensions. With the exception of Panel E, the figure reproduces the evidence from Bastianello, Decaire, and Guenzel (2025).

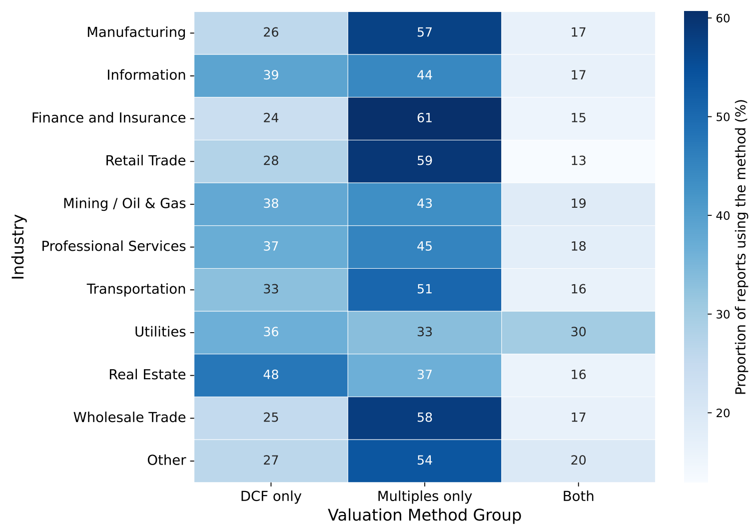
Panel A shows that, on average, multiples are used for price target forecasts in the majority of cases (about 62%), while DCF methods account for just under 40%. Within multiples-based approaches, price-to-earnings (P-E) multiples are the most common.

Panel B documents intuitive cross-industry variation. For instance, DCF methods are relatively more prevalent in growth-oriented industries such as information, whereas multiples-based approaches are more common in manufacturing, wholesale trade, and finance and insurance. Only a small fraction of reports combine DCF and multiples methods, and this pattern holds across industries.

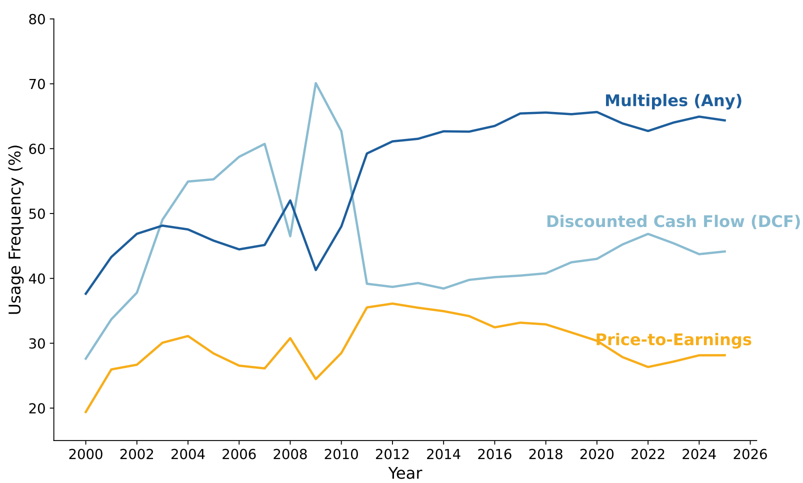
Panel A: Valuation Method Frequency



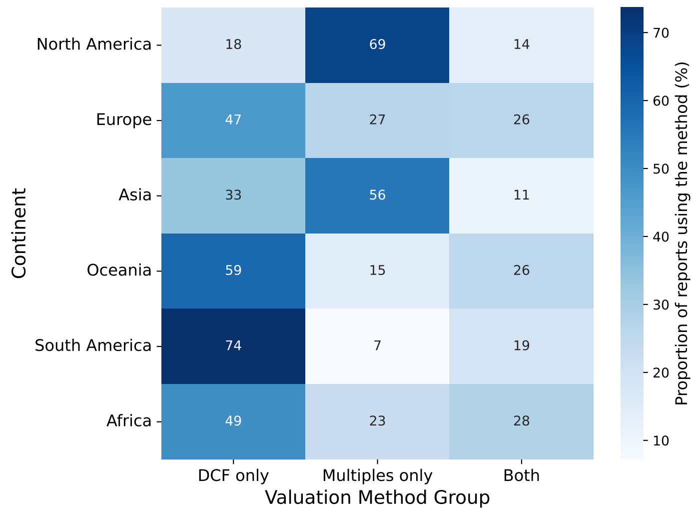
Panel B: Valuation Method Usage by Industry (Top-10 by Report Volume)



Panel C: Valuation Method Usage by Year



Panel D: Valuation Method Usage by Continent



Panel E: Valuation Method Usage by Analyst Country (Top 10 within NA/EU/Asia)

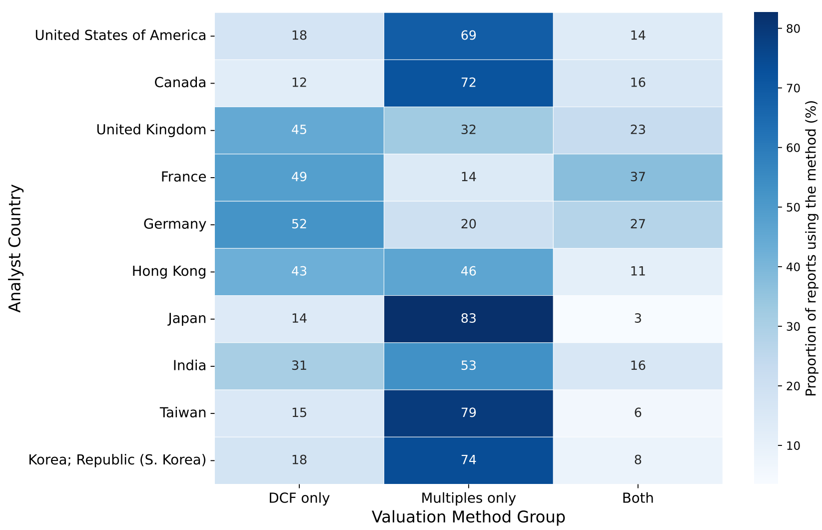


Figure I:
Valuation Methods Heterogeneity

This figure shows the propensity to use different valuation methods, alongside heterogeneities. Panel A shows overall frequencies for multiples, price-to-earnings (P-E) methods specifically, discounted cash flow (DCF) methods, and other methods. Panel B shows method frequency by the 10 largest industries by report volume. Panel C plots time trends of multiples, P-E, and DCF method usage. Panel D displays usage by continent, and Panel E depicts usage by country of analysts, focusing on North America, Europe, and Asia.

Panel C then plots the frequency of valuation method use over time, showing notable variation in the reliance on multiples-based methods during the Great Recession—specifically in 2009—when negative EPS forecasts made such methods infeasible. We will use this temporal pattern later in Section 4.3 as the basis for a quasi-experiment, exploiting instances where analysts were effectively forced to switch valuation methods.

Finally, Panels D and E document cross-geographic variation in valuation method usage. Panel D shows that DCF methods are substantially more common in Europe, whereas multiples-based approaches dominate in North America. Similar, more granular patterns emerge at the country level in Panel E: for instance, analysts in the U.S. and Canada tend to favor multiples, while DCF methods are relatively more prevalent across all major European countries in our sample.

Geographic differences – sorting versus "style." A natural question arising from the patterns in Panels D and E of Figure I is whether these geographic differences reflect analyst sorting into different types of firms or differential analyst "style." In other words, do cross-region differences in analysts' firm coverage explain the geographic variation, or do analysts in different regions exhibit distinct valuation styles? Figure II explores this question by sequentially introducing fixed effects to the patterns shown in Panels D and E of Figure I. Specifically, we first add firm fixed effects and then firm-by-year fixed effects to hold constant all firm characteristics within a given year, thereby isolating the residual tendency of analysts from different geographies to favor one valuation method over another.

As shown in Panel A of Figure II, European analysts continue to rely more heavily on DCF methods relative to North American analysts, and this pattern similarly holds across countries in Panel B. The estimated coefficients are similar with and without fixed effects, indicating that the geographic differences documented in Figure I primarily reflect variation in analyst style rather than sorting across firms.

Analyst experience. Finally, Table I examines the association between analysts' experience and their propensity to use different valuation methods. Each year, we sort analysts into quartiles based on their cumulative experience up to that point. We find that analysts increasingly rely on multiples as they gain experience. This result holds with and without fixed effects, including firm-by-year fixed effects, although the magnitude of the coefficient

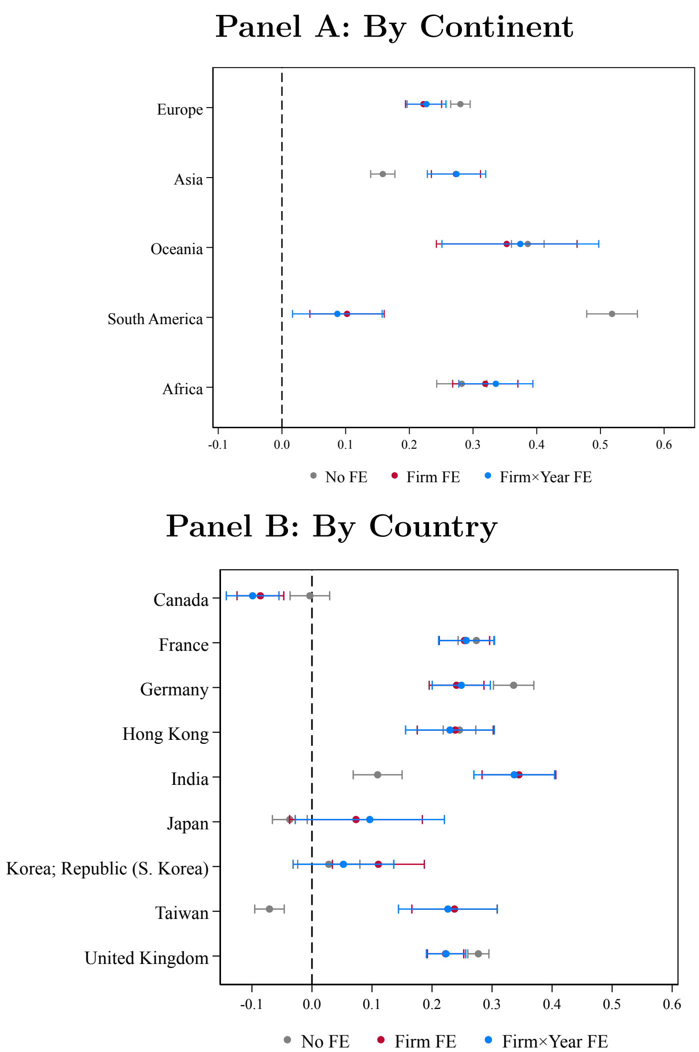


Figure II:
Geographic Variation in Valuation Methods

This figure shows how analysts' reliance on discounted cash flow (DCF) valuation as their sole method varies across geographic regions. Panel A plots coefficient estimates of the likelihood of DCF usage by analysts from different continents relative to North America as the baseline category. Panel B repeats the analysis at the country level, restricting to the top ten countries (by report count) within North America, Europe, and Asia. The gray, red, and blue dots and bars represent coefficient estimates and their 95%-confidence intervals from regressions with no fixed effects, firm fixed effects, and firm-by-year fixed effects, respectively.

declines with the sequential inclusion of fixed effects. That is, the shift toward multiples with experience reflects both the gradual development of analysts' professional approach and differences in the types of firms they cover over time.

3.2 Summary Facts About Valuation Method Performance

Having established the baseline facts on valuation method usage in the previous section, we next examine the forecast performance associated with different valuation methods. Specifically, we analyze forecast levels, forecast errors, and and forecast accuracy, the latter measuring absolute forecast errors. As alluded to earlier, our analysis of forecast outcomes builds on the baseline patterns, selectively accounting for these sources of variation to assess which aspects of heterogeneity drive—or do not drive—the observed performance results.

Table II presents the results on the association between valuation method usage and forecast outcomes, with forecast levels reported in Panel A, forecast errors in Panel B, and absolute forecast errors (i.e., forecast accuracy) in Panel C. Throughout the paper, we define forecast levels as expected log returns, the natural logarithm of the analyst's price target divided by the current price. We define forecast errors as realized log returns (i.e., the natural logarithm of the 12-month realized price divided by the current price) minus expected log returns.

Each panel reports nine different specifications that progressively incorporate fixed effects. The key independent variable of interest is an indicator equal to one if an analyst relied exclusively on a DCF method for their forecast, and zero otherwise; that is, if they used either a multiples-based approach or a combination of DCF and multiples methods.

Unconditionally, in column (1) of each panel, we find that DCF-only forecasts are associated with higher forecast levels (Panel A), more negative forecast errors (Panel B), and—given that analysts are on average optimistic—less accurate forecasts (Panel C).

Strikingly, the remaining eight columns in each panel show that the underperformance of DCF-based forecasts persists, both statistically and economically, across all specifications, even after the inclusion of an increasingly granular set of fixed effects. Specifically, the DCF underperformance persists with the inclusion of year, industry, and firm fixed effects in columns 2 to 4; with analyst fixed effects in column 5; and with both firm and analyst fixed effects in column 6. Moreover, it remains even with firm-by-year fixed effects in column 7, that is, when holding constant all value-relevant information for a given firm in a given year.

The pattern even persists with analyst-by-year fixed effects in column 8 (and with both firm-by-year and analyst-by-year fixed effects in column 9), that is, when holding constant factors such as analyst location and experience, indicating that the DCF underperformance documented in Table II is not driven by these underlying differences.

Instead, Table II reveals a systematic and widespread pattern of DCF underperformance, as an empirical regularity that cannot be explained by sample composition and likely reflects structural features and calibration challenges inherent to DCF approaches, while leaving open the possibility of heterogeneity across firms and analysts which we turn to next in Section 4.

4 Drivers of Valuation Method Performance

Having established the systematic underperformance of DCF methods in the previous section in Table II, we now ask whether this underperformance is universal or whether there exist contexts and subsamples in which DCF methods in fact perform better. We begin by examining heterogeneity across firms, focusing on whether they are relatively easy or hard to value, and then turn to heterogeneity in analyst skill. The final subsection of this section presents a natural experiment that analyzes forecast accuracy when analysts are "forced" to switch valuation methods for quasi-random reasons.

4.1 Do DCF Methods Outperform for Hard-to-Value Firms?

Table III breaks down the underperformance of DCF-based methods across subsamples defined by firm characteristics. Panel A examines ex-ante firm characteristics (i.e., firm attributes measured in the year prior to the forecast), while Panel B considers heterogeneity by valuation difficulty, distinguishing between hard-to-value and easy-to-value firms based on lagged forecast errors, as defined in more detail below.

Panel A includes a range of cross-sectional firm characteristics, such as leverage, firm size, R&D intensity, firm age, profitability, and growth as measured by the market-to-book ratio. Across all characteristics, there is no systematic difference in DCF underperformance between high- and low-characteristic groups. In other words, based on ex-ante evidence, DCF underperformance does not vary systematically by firm type; in particular, there is no evidence that DCF methods do better (either in absolute terms or relative to multiples-based methods) for firms that, based on their characteristics, are likely more complex or inherently harder to forecast, where one might have expected the more sophisticated DCF approach to add value over simpler multiples-based methods.

This conclusion is corroborated in Panel B, which examines heterogeneity across easy- versus hard-to-value firms, defined based on lagged forecast errors. For each firm-year, we compute the average absolute forecast error of all analysts who issued forecasts for that firm in the prior year and classify firms as easy-to-value if this average error falls in the lower half of the distribution, and hard-to-value if it falls in the upper half. We conduct this sorting both using raw lagged forecast errors and using residualized forecast errors: after controlling for valuation method, or for both method and firm industry. Panel B shows that, DCF methods perform equally poorly or even worse for hard-to-value firms relative to easy-to-value firms, and in no subsample do DCF-based forecasts outperform multiples-based forecasts.

Taken together, the evidence in Table III indicates that the underperformance of DCF-based forecasts is broad-based rather than concentrated in specific firm types or valuation contexts, suggesting that it reflects more inherent features of the method rather than differences in firm complexity or forecast difficulty.

4.2 Do DCF Methods Outperform When Used by Skilled Analysts?

While Table III finds no evidence that the more complex DCF-based methods yield superior forecast accuracy for any of the firm characteristics or valuation difficulty metrics considered, a related question is whether analyst skill interacts with method performance. To this end, Table IV and Figure III examine how analyst skill moderates the relationship between valuation method choice and forecast accuracy.

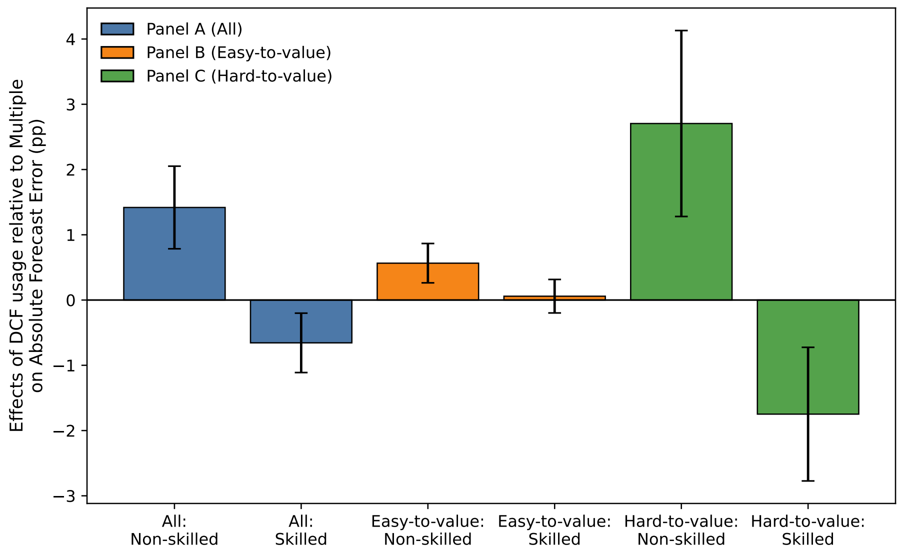


Figure III:
Analyst Skill and Forecast Accuracy

This figure plots coefficient estimates corresponding to column 4 in each panel of Table IV, examining the association between analyst skill and forecast accuracy. The first bar in each colored subset represents the effect of exclusive DCF usage on absolute forecast errors, relative to multiples-based usage, for 'non-skilled' analysts, defined as those with above-median previous-year absolute forecast errors residualized on firm fixed effects. The second bar in each subset represents the effect of exclusive DCF usage for 'skilled' analysts. Blue bars are estimated on the full sample. Orange bars are estimated on the subsample of easy-to-value firms, whereas green bars are estimated on the subsample of hard-to-value firms, as defined in Section 4.1 and Table IV.

Using lagged forecast error as a proxy for skill is consistent with evidence that performance persistence reflects underlying ability. In mutual funds, Hendricks, Patel, and Zeckhauser (1993) and Brown and Goetzmann (1995) document short-term persistence in returns, while Carhart (1997) attributes part of it to systematic factors. Similarly, in the analyst setting, Hong and Kubik (2003) show that prior forecast accuracy predicts career success, Hilary and Hsu (2013) link consistency in accuracy to credibility and market impact, and So (2013) interpret predictable forecast errors as evidence of persistent skill.

Panel A of Table IV reveals substantial heterogeneity in forecast accuracy by analyst skill. Skilled analysts, as proxied by lower lagged absolute forecast errors, perform significantly better with DCF methods relative to multiples-based methods. This pattern holds across all skill metrics based on lagged forecast errors, including both continuous and indicator measures, as well as raw and residualized specifications. (We note that the seemingly large differences in the level coefficient on DCF only between the indicator and continuous skill specifications simply reflect that the continuous skill measure is never zero in our sample; thus, the interaction effect is always relevant and needs to be accounted for in interpreting those specifications.) The first two bars of Figure III illustrate the outperformance of DCF methods among skilled analysts, based on column 4 of Panel A.

These results are consistent with the notion that the effectiveness of DCF methods depends critically on analyst ability: while DCF approaches offer greater flexibility and potential precision, they also demand higher skill to apply effectively.

Honing in on the notion that method effectiveness depends on analyst skill, Panels B and C of Table IV further examine how the skill–accuracy relationship varies with firm valuation difficulty. We find that the superior performance of DCF methods among skilled analysts is driven by forecasts for hard-to-value firms, defined as in Table III based on the average lagged forecast error across analysts for each firm. Specifically, Panel B shows that skilled analysts perform equally well with DCF methods as with multiples-based methods; that is, there is no DCF underperformance among skilled analysts for easy-to-value firms. In contrast, Panel C shows that skilled analysts significantly outperform with DCF methods relative to multiples-based methods. Quantitatively, the magnitude of this DCF outperformance among skilled analysts is roughly comparable to the DCF underperformance observed among less skilled analysts. The remaining four bars of Figure III illustrate the 'break-even' performance of

DCF methods among skilled analysts for easy-to-value firms, as well as their outperformance for hard-to-value firms, based on column 4 of Panels B and C.

Together, the results in Table 4 and Figure III show that the effectiveness of DCF methods depends critically on analyst skill and firm complexity. While DCF approaches generally underperform on average, skilled analysts eliminate this gap for easy-to-value firms and achieve superior accuracy for hard-to-value firms. These findings suggest that the sophistication of DCF methods can translate into better forecasts, but only when applied by analysts with sufficient expertise and judgment.

4.3 Natural Experiment: Forced Adoption of Valuation Methods

We conclude this section by examining the role of method-specific expertise, complementing the evidence on forecasting skill documented above. To this end, we exploit a quasi-experiment during the Great Financial Recession, when the most widely used multiple-based approach, the P-E multiple method, became non-operational for analysts who forecasted negative EPS. This shock effectively forced these analysts to abandon this method and switch to alternative approaches, most notably DCF models, which are more flexible in such settings.

Table V evaluates the forecasting performance of these forced DCF switchers, holding fixed the firm being analyzed; that is, comparing them to forecasters who already possessed DCF expertise and predominantly employed the DCF method prior to the shock. Specifically, the table analyzes forced switches in 2009 during the height of the recession, when the use of P-E multiples plummeted (see Panel C of Figure I), and reports these results in column 2. Column 1 presents the corresponding full-sample comparison, shedding light on analysts' forecasting performance when they switch to DCF methods *voluntarily* rather than as a result of the shock.

Column 2 shows that analysts who were forced to switch to DCF, and who used the method infrequently beforehand, exhibit predictable and systematic forecast errors of more than 6 percent in magnitude, based on the point estimate. By contrast, there is no statistical evidence of predictable forecast errors for analysts evaluating the same firm in the same year with a DCF approach but who were already frequent users of the method. The difference between forced switchers and analysts with established DCF expertise is economically large and statistically significant. Turning to column 1, we see a markedly different pattern: when analysts switch to DCF voluntarily despite having limited prior experience with the model, there is no detectable predictability in their forecast errors.

Taken together, these findings highlight the importance of method-specific expertise for forecasting performance and suggest that whether a theoretically more sophisticated and flexible model like DCF is adopted voluntarily or under constraint plays a meaningful role in determining its effectiveness.

5 A Closer Examination of Multiples-Based Methods

Given that multiples-based methods are empirically the most commonly employed model (as well as the fact that they yield higher forecast accuracy, at least on average), this section examines how analysts think about prices through the multiple approach. We start with the general pricing formula:

$$\mathrm{E}[\mathrm{P}_0] = \sum_{i=1}^{\infty} \frac{Earnings_{i-1}(1+g_i)}{(1+r_i)^i} \tag{1}$$

where g_i is the expected earnings or cash flow growth in year i, and r_i is the discount rate for year i. Thus, prices equal the discounted sum of all expected cash flows from time 1 to infinity.

To make the valuation problem tractable, multiples impose two assumptions: (1) growth remains constant from time 2 onward, and (2) the term structure of discount rates is flat, yielding a single discount rate across all horizons. These assumptions collapse the infinite sum to:

$$\mathrm{E}[\mathrm{P}_0] = \frac{Earnings_0(1+g_1)}{r-g_T} \tag{2}$$

$$\mathrm{E}[\mathrm{P}_0] = \underbrace{Earnings_1}_{\text{Forward Earnings}} * \underbrace{\frac{1}{r-g_T}}_{\text{Valuation multiple}} \tag{3}$$

where g_1 is the expectation of earnings/cash flow growth over the next year, r is the constant discount rate, and g_T is a long-term growth expectation meant to approximate the analyst's growth expectation for the firm over year two to infinity. This effectively boils down any valuation exercise to answering three simpler questions: determining forward earnings, and assessing the two components of the valuation multiple, the appropriate discount rate and the long-run growth rate.[6]

Theoretical drivers and reference points. In the next two subsections, we organize the analysis around the two channels through which multiples can embed information about prices. On the theoretical side, the valuation framework above implies that multiples should vary systematically with a firm's risk profile and long-run growth rates. On the practical side, analysts often rely on reference points, such as historical valuation levels or peer multiples, that provide intuitive anchors without requiring explicit estimation of discount rates or growth rates. These channels are not mutually exclusive: analysts may either form beliefs about the underlying fundamentals or draw on benchmarks that already embed market participants' forward-looking views. Accordingly, the next subsection examines whether observed multiples comove with empirical proxies for risk and long-term growth as implied by theory, and the following subsection turns to the role of reference points, documenting their prevalence, whether and how analysts adjust from them, and the extent to which they contextualize and provide bounds on reasonable valuations in practice.

[6] While the derivation above is expressed in terms of earnings–and applies almost identically to cash-flow–based multiples, which together account for more than 90% of multiples used in practice (Bastianello, Decaire, and Guenzel, 2025)–the same intuition extends to other multiple types as well.

5.1 Chosen Multiples Embed Risk and Growth Fundamentals

To study whether analysts' choice of multiples relate to valuation fundamentals, consistent with theoretical predictions (cf. equation (3)), we examine the relationship between chosen multiples and proxies for risk and long-term growth rates, respectively. Following Decaire and Guenzel (2025) and Decaire and Graham (2024), we use CAPM betas to proxy for risk and real GDP growth to proxy for long-term growth expectations. Consistent with the theoretical foundation of multiple, Table VI documents a strong negative relation between valuation multiples and CAPM betas, and a positive relation with real GDP growth.

These patterns shed light on analyst reasoning through two non-mutually exclusive interpretations. First, analysts may form explicit beliefs about firm risk exposure and growth expectations when valuing firms with multiples, effectively implementing equation (3) directly. Alternatively, if analysts draw their multiples from market prices (whether historical, current, or peer-based) and those prices embed forward-looking assessments of risk and growth, then the multiples will inherit these features mechanically. Although our tests cannot distinguish between these channels, the evidence indicates that analysts rely on multiples that incorporate forward-looking information, whether deliberately or indirectly.

5.2 Reference Points Anchor, But Do Not Dictate, Valuation Multiples

The evidence in Table VI shows that chosen multiples embed forward-looking information about risk and growth. Yet, as alluded to above, analysts need not form explicit estimates of and beliefs about these primitives when applying multiples. In practice, they often rely on reference points, including historical valuation levels or peer multiples, that provide intuitive anchors and reduce the valuation task to relative comparisons. Instead of estimating discount rates and long-run growth directly, analysts compare the firm's expected growth and risk profile to these benchmarks and adjust upward or downward accordingly. Firms perceived as riskier than the benchmark receive lower multiples; those expected to grow more quickly receive higher ones. In this way, reference points offer a set of semi-objective bounds on reasonable valuations and a practical framework for contextualizing expectations.

To understand how these reference points contribute to the valuation process, we next examine their prevalence, how analysts select among them, and the extent to which analysts adjust away from these anchors when forming their price targets.

Prevalence and drivers of reference points. Analysts disclose their choice of reference points in 38% of reports in our dataset. For the remaining reports, three possibilities exist: analysts form explicit and separate forecasts about discount rates and growth expectations, reference points are not disclosed, or our extraction strategy via Claude missed some cases. Nevertheless, given the significant share of reports that explicitly provide the reference point information, our analysis allows us to draw robust conclusions for a significant share of reports and analysts.

Digging deeper into the different categories of reference points, historical metrics appear in 17% percent of reports, current valuation benchmarks in 14% percent, and peer comparisons in 17% percent. We note that these three magnitudes add to more than 38%, indicating that in some cases, analysts use more than one type of reference point in their valuation.

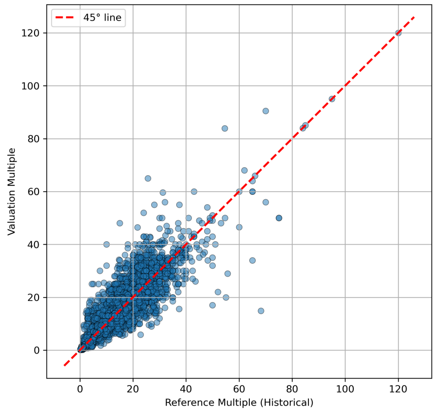
Next, we ask which factors drive the choice of reference points, estimating the contribution of analyst, firm, and time determinants. Table IX provides evidence that the choice of reference points appears to be driven primarily by individual analyst style, rather than firm characteristics, or time-varying trends. Some analysts favor comparing firms to their historical performance, while others benchmark against industry peers. This conclusion is derived by comparing columns 1, 2, and 3 with column 4 across all three panels of Table IX: omitting analyst fixed effects produces the largest reduction in adjusted R^2 relative to omitting either firm or year fixed effects. These results suggest that individual cognitive frameworks as well as valuation style and preferences, rather than objective firm attributes or normative practices, primarily determine how financial professionals select their benchmarks in practice.

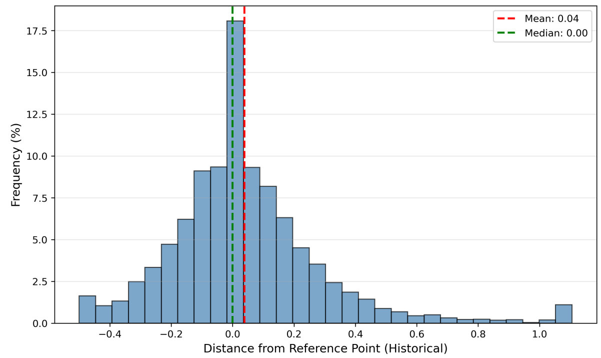
Reference points as anchors for adjustment. Having shown that multiples reflect theoretical valuation drivers, and that analysts frequently employ reference points in multiple-based models, we next show that reference points are *not* mechanically used in valuation models when generating price targets. Instead, reference points serve as anchors, from which analysts adjust to reflect their subjective forward-looking assessments of a firm's risk and growth prospects.

To establish these conclusions, Panels A, C, and E of Figure IV show that, while analysts' choice of multiples is correlated with the discussed reference point, it is rarely equal to the reference point (i.e., most points do not fall on the 45 degree line). This holds across historical, current, and peer-based reference points. Consistent with this, Panels B, D, and F show that analysts use the reference point precisely as the numerical value of their multiple to derive their price target in 13-15% of cases, and the average the distance between the multiple and reference point used is non-trivial, amounting to 14-22% of the reference point values in absolute terms.

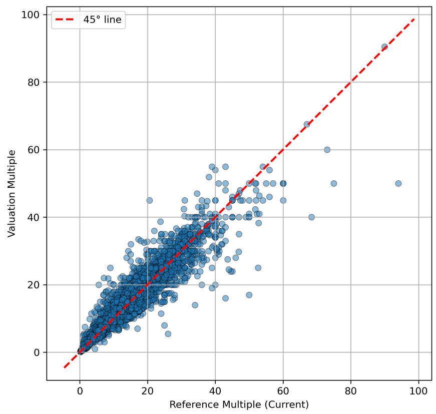
The conclusion that the relationship between reference points and valuation multiples is far from mechanical as applied by analysts is corroborated in Figure V. Panels A, C, and E show that the distance between analysts' chosen multiple and their reference point varies meaningfully over time. Additionally, when analysts employ a reference point *range* (e.g., over the past 3 years, the P-E multiple of the firm has ranged between 10x and 18x), the distance between the multiple used in the valuation and the lower bound of the multiple range fluctuates over time as well (Panel B, D, and F of Figure V). These fluctuations indicate that when analysts' expected price targets are more optimistic (i.e., reflecting higher growth expectations or lower perceived risk relative to the benchmark) they systematically select multiples above their reference points, and vice versa.

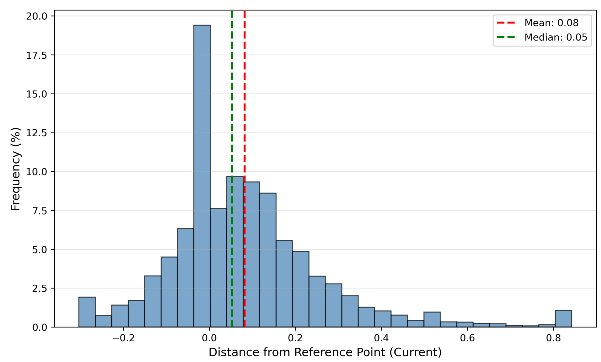
Taken together, the evidence points to a classic anchor-and-adjust process: historical,



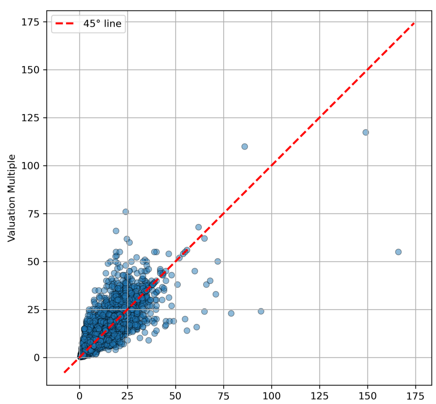


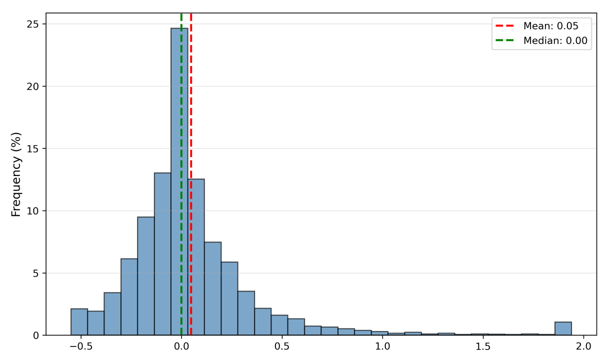
Cross-Section: Historical **Distribution: Historical**





Cross-Section: Current **Distribution: Current**

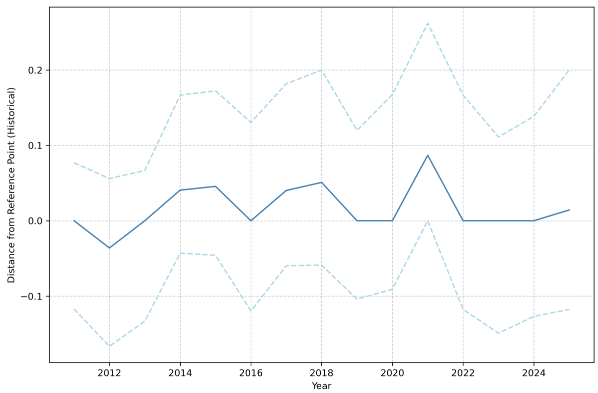




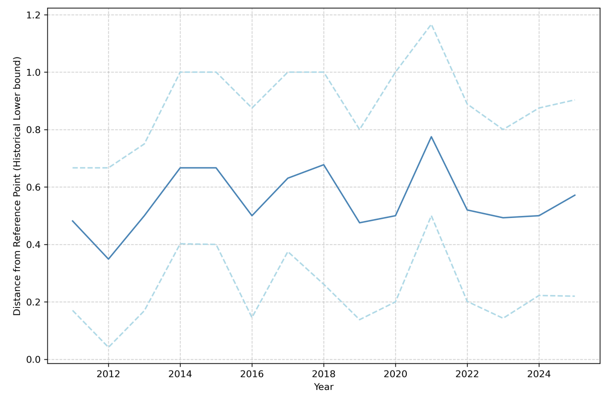
Cross-Section: Peers **Distribution: Peers**

Figure IV:
Reference Points and Valuation Multiples

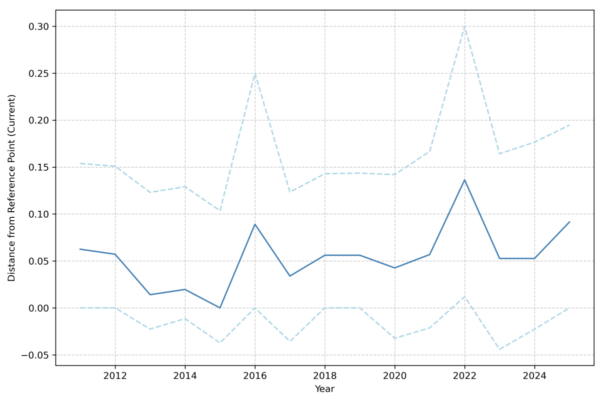
This figure shows the relationship between analysts' reference points and chosen multiples across three different benchmarking approaches: historical (Panels A to B), current (Panels C to D), and peer comparisons (Panels E to F). The left panels plot analysts' chosen valuation multiples against their stated reference point, with the 45-degree line indicating where multiples precisely equal the reference point. The right panels show the distribution of percentage deviations between chosen multiples and reference points. The analysis pools all multiple types (earnings, sales, book value, and cash flow), Results are similar for each type separately.



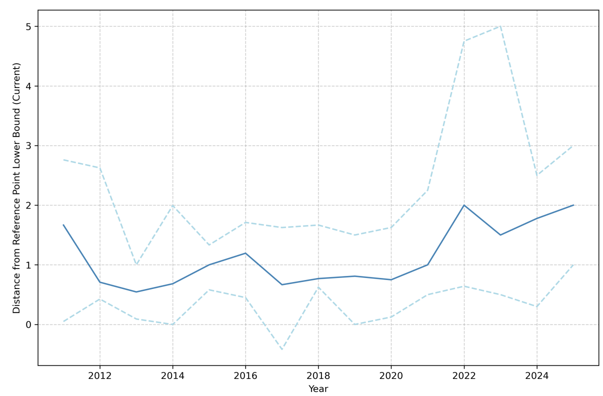
Distance to Average: Historical



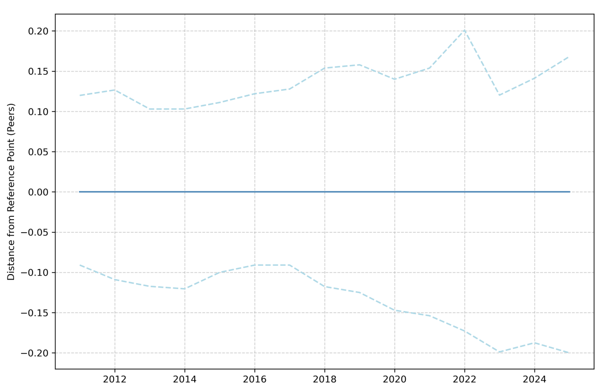
Distance to Lower Bound: Historical



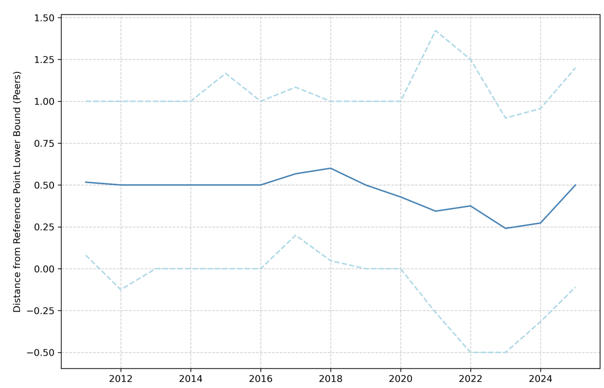
Distance to Average: Current



Distance to Lower Bound: Current



Distance to Average: Peers



Distance to Lower Bound: Peers

Figure V:
Distance to Reference Point Values over Time

This figure shows the distance between analysts' references points and chosen multiples across three benchmarking approaches: historical (Panels A to B), current (Panels C to D), and peer comparisons (Panels E to F). The left panels plot the percentage deviation of chosen multiples from reference point midpoints when analysts provide either point estimates or ranges. The right panels show, for range estimates only, where chosen multiples fall within the reference point interval, normalized from 0 (lower bound) to 1 (upper bound). Values greater than 0 or 1 are possible if the choice of multiple falls outside the provided range. The analysis pools all multiple types (earnings, sales, book value, and cash flow). Results are similar for each type separately.

current, and peer benchmarks provide the initial anchor, but analysts systematically adjust away from them to incorporate their own assessments of a firm's prospects and arrive at the final valuation.

To validate this intuition further, we directly link analysts' subjective assessment of the firm's potential, measured via the sentiment in the report text, to how their final valuation multiple compares to the reference point. The sentiment data comes from Bastianello, Decaire, and Guenzel (2025). Columns 1 to 6 in Table VII show that, when analysts are more optimistic about the firm's potential and express higher textual sentiment, they tend to select a valuation multiple that is greater than their reference points. A positive relationship between sentiment and distance between multiple and reference point persists even with firm-interacted-with-year fixed effects, effectively comparing the residual multiple-reference-point relation of analysts forecasting the same firm in the same year. Table VIII further shows that the distance to the reference point is, as one would expect, positively and significantly related to forecast levels (though it is insignificantly related to absolute forecast errors).

Overall, the results confirm that analysts' final multiples reflect systematic adjustments from benchmark anchors based on their subjective evaluations.

Analysts do not ex-post select reference points. In a final analysis on the relationship between reference anchors and chosen multiples, we ask whether reference points may be selected ex-post to justify "predetermined" multiple choices, such as cherry-picking high reference points to justify optimism. The empirical evidence is at odds with this. Specifically, columns 7 to 9 of Table VII show that reference point values are *uncorrelated* with analysts' sentiment. As such, the primary margin of adjustment through which analysts express their assessment of firm potential is the multiple selection itself, not the reference point. This pattern supports the view that reference points serve as semi-objective anchors rather than instruments for rationalizing predetermined valuations.

5.3 Sensitivity Analysis (Bull and Bear Scenarios)

In a final set of analyses, we move beyond analysts' point estimates and examine whether, and how, they incorporate scenarios and valuation ranges into their assessments. To this end, our prompt collects detailed information on the usage and operationalization of bull and bear case scenarios in reports that complement the baseline ("main") price target forecasts.

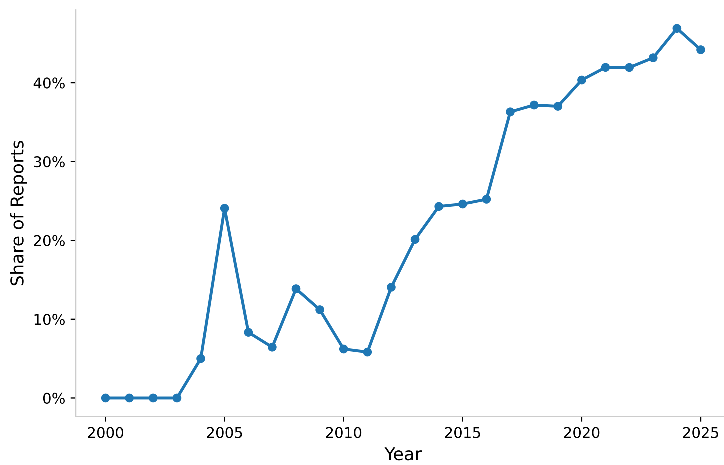


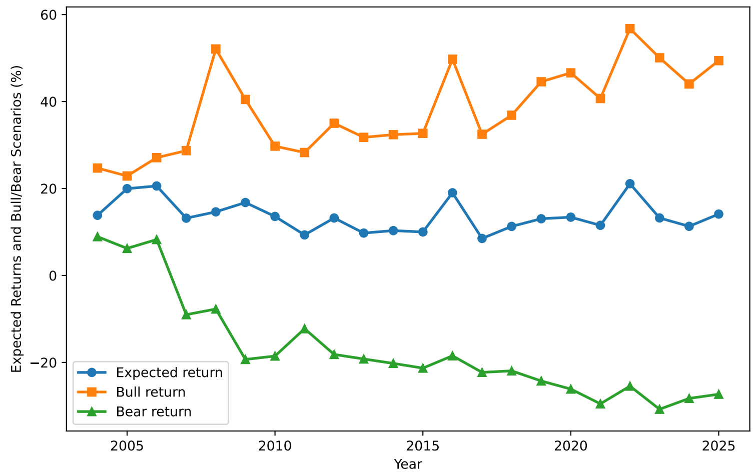
Figure VI:
Bull/Bear Scenario Analysis Propensity Over Time

This figure shows the fraction of reports that include sensitivity analyses, expressed through bull and/or bear scenarios, over time.

As a starting point, Figure VI shows that the propensity to include sensitivity analysis has increased sharply over time, rising from roughly 5 to 10 percent in the early to mid-2000s to more than 40 percent in recent years. Perhaps surprisingly, this increase in bull/bear analysis is relatively monotonic and not strongly correlated with macroeconomic conditions such as recessions. In particular, there is no discernible temporary uptick in bull/bear scenarios during the Great Financial Recession or around the COVID period, that is, times of heightened macroeconomic uncertainty when one might have expected greater use of scenario analysis. Instead, the rise in scenario analysis appears to reflect a broader shift in valuation practice rather than a cyclical response to macroeconomic uncertainty.

Next, Figure VII examines the structure and implementation of scenario analysis by

Panel A: Bull/Bear Forecasts



Panel B: Adjustment Levers

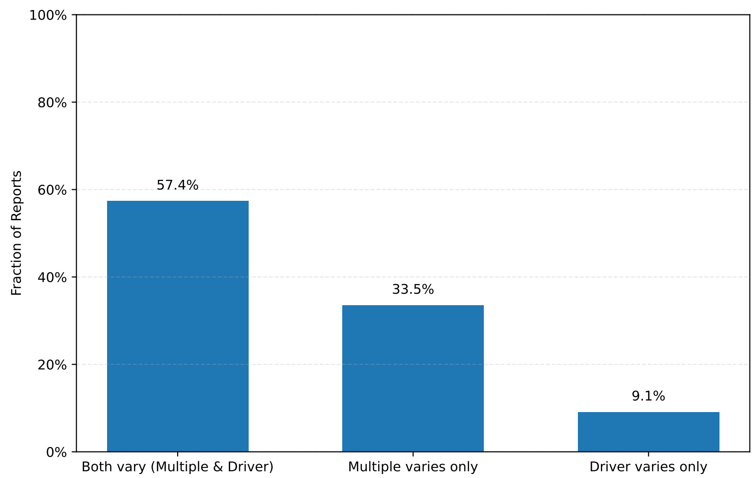


Figure VII:
Bull/Bear Forecasts and Adjustment Levers

This figure shows bull/bear forecasts and adjustment levers. Panel A plots average bull and bear expected returns over time, alongside the baseline expected returns. Panel B reports the propensity to use different adjustment levers (cases where both the multiple and the fundamental driver vary, where only the multiple varies, and where only the driver varies), based on the subsample of reports for which this information is available.

analysts. Panel A plots bull and bear case estimates over time alongside the baseline expected returns from analysts' main forecasts. The figure shows that analysts account for substantially more downside risk in their sensitivity analyses: baseline expected returns are, on average, significantly closer to the bull case than to the bear case. This pattern holds across time, underscoring the persistent asymmetry analysts build into their scenario evaluations.

Panel B then provides evidence on how analysts operationalize their scenario analyses.

Following equation (3), they can adjust from their baseline estimate by changing the multiple upward or downward, altering the driver (such as expected EPS), or modifying both. Among the reports that specify how scenarios are constructed, analysts most frequently adjust both components and only rarely adjust the driver alone. This corroborates the conclusions above that analysts do not treat multiples as mechanically fixed quantities but as forward-looking inputs that move with their assessments of fundamentals: meaningful scenario variation frequently involves adjusting the multiple alongside the driver, while changes in fundamentals alone are infrequently viewed as sufficient.

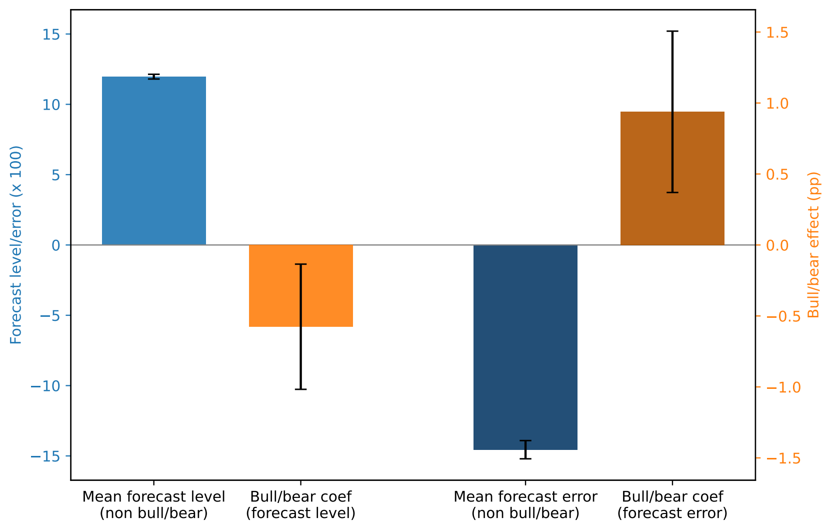


Figure VIII:
Bull/Bear Scenario Adoption and Forecast Outcomes

This figure shows the association between bull/bear scenario adoption and the levels (left two bars) and errors (right two bars) of the baseline forecast. The blue bars report the average forecast level and forecast error for reports that do not include any bull or bear scenario analysis. The orange bars show the effect of the presence of bull/bear scenarios on the baseline forecast levels and errors.

Finally, Figure VIII examines whether the adoption of scenario analyses is associated with differences in baseline estimates. In principle, the answer could go either way: scenario analysis might accompany more cautious baseline forecasts if analysts internalize downside risks when constructing alternatives, or it might leave baseline forecasts unchanged if scenarios are treated as a purely supplemental disclosure. We find evidence for the former for both forecast levels and forecast errors. Scenario adoption is associated with significantly less optimistic baseline forecasts on average (comparing the first two bars), which in turn leads to less negative forecast errors (comparing the last two bars).

Taken together, while we caveat that these results are not causal, the patterns are suggestive that engaging in scenario analysis (re)shapes how analysts internally represent firm prospects, prompting them to internalize more downside risk in their baseline valuations and, in turn, produce more conservative (and ultimately less overly optimistic) forecasts.

6 Conclusion

Economic and financial models, as structured reductions of a complex reality, are indispensable for organizing information, forming expectations, and guiding decisions. Because of this, they are pervasive in professional forecasting and valuation. Yet surprisingly little is known about how economic agents actually work with valuation models, and choose between different available models, in practice.

We provide new, large-scale evidence on how professionals select and apply valuation models in real forecasting environments. Drawing on 1.1 million equity reports, we document substantial heterogeneity in model choice. On average, multiples outperform DCF. However, this masks important heterogeneity. W show that skilled analysts excel with DCFs for harder firms, and we use a quasi-exogenous model switch to show that when analysts are forced to switch models, they underperform substantially, therefore highlighting how method-specific expertise is crucial for forecast accuracy.

Turning to the key components of multiples-based valuation, we show that reference points serve as anchors rather than mechanical inputs in the formation of price targets. Moreover, sensitivity analyses, expressed through bull and bear scenarios, have become increasingly prevalent and reveal systematic asymmetries, with analysts placing greater weight on downside risk than upside potential.

A central feature of all economic models is the unavoidable presence of model and parameter uncertainty: agents must decide what to include, what to abstract from, and which assumptions are most fragile. Yet this process is rarely observable in data. Our setting allows us to see this directly: analysts reveal the margins they view as uncertain through the adjustments they make from reference points to their baseline models, and from those baseline models to the bull and bear scenarios that frame their sensitivity analyses. Taken together, our paper provides a window into how economic agents adopt models and confront model uncertainty in the field.

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Tables

Table I:
Analyst Experience and Valuation Method Propensity

This table examines the association between analyst experience and the propensity to use different valuation methods. Analysts are sorted each year into quartiles of experience, based on the number of years they appear in the data prior to the year of interest, from Q1 (lowest experience) to Q4 (highest experience). Panel A reports the likelihood that analysts rely exclusively on DCF methods in forming their price targets, while Panel B reports the likelihood that analysts rely exclusively on multiples-based methods. The regressions are estimated using ordinary least squares. Standard errors (in parentheses) are estimated using heteroskedastic-consistent estimators and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: DCF Usage

Dependent variable:	Likelihood of only DCF usage ×100		
	(1)	(2)	(3)
Q2 vs Q1	-6.85***	-0.05	-0.37
	(0.39)	(0.32)	(0.37)
Q3 vs Q1	-11.28***	-0.52	-0.33
	(0.44)	(0.36)	(0.41)
Q4 (highest) vs Q1	-11.62***	0.33	0.24
	(0.50)	(0.40)	(0.43)
Firm FE	No	Yes	No
Firm × Year FE	No	No	Yes
Observations	1,173,337	1,170,989	1,144,573
F statistic	260.73	2.26	1.05
R^2	0.010	0.366	0.486

Panel B: Multiple Usage

Dependent variable:	Likelihood of only Multiple usage ×100		
	(1)	(2)	(3)
Q2 vs Q1	9.32***	1.57***	2.29***
	(0.42)	(0.33)	(0.38)
Q3 vs Q1	15.34***	3.11***	3.29***
	(0.50)	(0.39)	(0.45)
Q4 (highest) vs Q1	16.35***	1.73***	2.00***
	(0.56)	(0.42)	(0.46)
Firm FE	No	Yes	No
Firm × Year FE	No	No	Yes
Observations	1,173,337	1,170,989	1,144,573
F statistic	395.59	21.42	19.25
R^2	0.016	0.423	0.524

Table II:
Valuation Methods and Forecast Outcomes

This table examines the association between valuation method usage and forecast outcomes. Panel A reports results for forecast levels, Panel B for forecast errors, and Panel C for absolute forecast errors. Forecast levels are defined as expected log returns, computed as the natural logarithm of the analyst's price target divided by the current price. Forecast errors are defined as realized log returns, i.e., the natural logarithm of the 12-month realized price divided by the current price, minus expected log returns. *DCF only* is an indicator for whether a report relies exclusively on DCF methods in forming the price target. The regressions are estimated using ordinary least squares. Standard errors (in parentheses) are estimated using heteroskedastic-consistent estimators and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Forecast (×100)

Dependent variable:	Forecast$_{i,j,t}$ × 100								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DCF only$_{i,j,t}$	1.69***	1.49***	1.37***	0.76***	1.07***	0.73***	0.43***	0.99***	0.59***
	(0.15)	(0.15)	(0.15)	(0.10)	(0.13)	(0.11)	(0.11)	(0.15)	(0.12)
Year FE	No	Yes	No	No	No	No	No	No	No
Industry FE	No	No	Yes	No	No	No	No	No	No
Firm FE	No	No	No	Yes	No	Yes	No	No	No
Analyst FE	No	No	No	No	Yes	Yes	No	No	No
Firm × Year FE	No	No	No	No	No	No	Yes	No	Yes
Analyst × Year FE	No	No	No	No	No	No	No	Yes	Yes
Observations	1,173,337	1,173,337	1,155,184	1,170,989	1,173,010	1,170,653	1,144,573	1,167,276	1,138,304
F statistic	125.67	100.62	83.83	55.37	66.45	47.47	16.96	46.19	25.69
R^2	0.002	0.033	0.017	0.271	0.163	0.329	0.487	0.274	0.577

Panel B: Forecast Error (×100)

Dependent variable:	Forecast Error$_{i,j,t}$ × 100								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DCF only$_{i,j,t}$	-4.43***	-4.14***	-4.01***	-1.21***	-1.68***	-0.96***	-0.63***	-1.94***	-1.18***
	(0.67)	(0.66)	(0.66)	(0.29)	(0.62)	(0.31)	(0.23)	(0.69)	(0.22)
Year FE	No	Yes	No	No	No	No	No	No	No
Industry FE	No	No	Yes	No	No	No	No	No	No
Firm FE	No	No	No	Yes	No	Yes	No	No	No
Analyst FE	No	No	No	No	Yes	Yes	No	No	No
Firm × Year FE	No	No	No	No	No	No	Yes	No	Yes
Analyst × Year FE	No	No	No	No	No	No	No	Yes	Yes
Observations	1,032,792	1,032,792	1,032,736	1,030,829	1,032,442	1,030,468	1,008,949	1,026,373	1,002,521
F statistic	43.74	39.11	36.52	16.84	7.32	9.28	7.33	7.86	29.78
R^2	0.001	0.039	0.007	0.464	0.144	0.502	0.802	0.289	0.836

Panel C: Absolute Forecast Error (×100)

Dependent variable:	Absolute Forecast Error$_{i,j,t}$ × 100								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DCF only$_{i,j,t}$	4.75***	4.33***	4.26***	1.19***	2.53***	0.83***	0.53***	2.54***	0.58***
	(0.64)	(0.64)	(0.63)	(0.24)	(0.56)	(0.24)	(0.20)	(0.64)	(0.17)
Year FE	No	Yes	No	No	No	No	No	No	No
Industry FE	No	No	Yes	No	No	No	No	No	No
Firm FE	No	No	No	Yes	No	Yes	No	No	No
Analyst FE	No	No	No	No	Yes	Yes	No	No	No
Firm × Year FE	No	No	No	No	No	No	Yes	No	Yes
Analyst × Year FE	No	No	No	No	No	No	No	Yes	Yes
Observations	1,032,792	1,032,792	1,032,736	1,030,829	1,032,442	1,030,468	1,008,949	1,026,373	1,002,521
F statistic	55.01	46.25	46.09	24.58	20.06	11.54	7.09	15.67	11.64
R^2	0.002	0.010	0.019	0.561	0.178	0.594	0.808	0.279	0.841

Table III:
Valuation Methods and Forecast Accuracy: Firm Heterogeneity

This table examines heterogeneity in the association between valuation method usage and forecast accuracy across firm characteristics. Panel A considers a range of ex-ante (lagged) indicators for firm characteristics, including book leverage, firm size, R&D intensity, firm age, profitability, and growth. Panel B sorts firms into easy- and hard-to-value groups based on analysts' average lagged forecast errors for those firms in the prior year. We report results using either average raw absolute forecast errors or absolute forecast errors residualized with respect to the valuation method alone or the valuation method and the firm's industry. The regressions are estimated using ordinary least squares. Standard errors (in parentheses) are estimated using heteroskedastic-consistent estimators and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Ex-Ante Firm Characteristics

Dependent variable:	Absolute Forecast error×100					
	(1) High Leverage	(2) High Assets	(3) High R&D	(4) Young Firm	(5) High ROE	(6) High M/B
DCF (no Multiples)	1.20***	0.74***	0.64*	0.51**	0.84***	0.43*
	(0.26)	(0.26)	(0.35)	(0.21)	(0.25)	(0.26)
DCF × High book leverage	-0.77**					
	(0.30)					
DCF × High lnassets		-0.23				
		(0.29)				
DCF × High R&D to sales			-0.07			
			(0.48)			
DCF × Young firm				0.34		
				(0.28)		
DCF × High Profitability (ROE)					-0.11	
					(0.29)	
DCF × Growth Firm (High M/B)						0.11
						(0.29)
Firm×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	778,517	981,675	451,040	956,611	777,430	851,318
F-stat	10.716	6.207	2.501	7.931	7.976	3.943
R^2	0.839	0.840	0.838	0.842	0.839	0.832

Panel B: Hard-to-Value Firms

Dependent variable:	Absolute forecast error ×100					
Hard-to-value measurement:	Raw		Resid (⊥ DCF)		Resid (⊥ DCF+Ind)	
	(1)	(2)	(3)	(4)	(5)	(6)
DCF only	0.29***	0.20	0.27**	0.20	0.39***	0.24
	(0.11)	(0.18)	(0.11)	(0.18)	(0.12)	(0.19)
DCF × Hard-to-value	0.58	0.93***	0.64	0.95***	0.37	0.87**
	(0.43)	(0.32)	(0.43)	(0.32)	(0.44)	(0.34)
Firm × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst × Year FE	No	Yes	No	Yes	No	Yes
Observations	966,459	960,456	966,459	960,456	966,421	960,418
F statistic	4.98	7.72	4.63	7.81	6.48	7.33
R^2	0.801	0.835	0.801	0.835	0.801	0.835

Table IV:
Analyst Skill and Forecast Accuracy

This table examines heterogeneity in the association between valuation method usage and forecast accuracy across analyst characteristics, focusing on analyst skill. Panel A reports results for the full sample; Panel B examines the subsample of easy-to-value firms; and Panel C examines the subsample of hard-to-value firms. Analyst skill is measured using the analyst's average lagged absolute forecast errors in the prior year, based on raw absolute errors, or absolute errors residualized with respect to firm fixed effects. Easy- and hard-to-value firms are defined as in Table III. The regressions are estimated using ordinary least squares. Standard errors (in parentheses) are estimated using heteroskedastic-consistent estimators and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Analyst Skill and Forecast Accuracy

Dependent variable:	Absolute forecast error × 100			
Analyst skill measurement (t-1):	Raw		Residualized	
	(1)	(2)	(3)	(4)
DCF only	-0.14	1.08***	0.48**	1.42***
	(0.46)	(0.34)	(0.19)	(0.32)
More Skilled Analyst (continuous, raw)	-0.12***			
	(0.01)			
DCF × More Skilled Analyst (continuous, raw)	-0.01			
	(0.01)			
More Skilled analyst (dummy, raw)		-1.55***		
		(0.19)		
DCF × More Skilled analyst (dummy, raw)		-1.28***		
		(0.37)		
More Skilled Analyst (continuous, resid)			-0.46***	
			(0.05)	
DCF × More Skilled Analyst (continuous, resid)			-0.18***	
			(0.05)	
More Skilled analyst (dummy, resid)				-2.21***
				(0.18)
DCF × More Skilled analyst (dummy, resid)				-2.07***
				(0.40)
Observations	938,030	953,060	928,832	940,845
F-statistic	28.590	27.519	39.521	52.152
R^2	0.811	0.810	0.812	0.810
Firm×Year FE	Yes	Yes	Yes	Yes

Panel B: Analyst Skill and Forecast Accuracy: Easy-to-value firms

Dependent variable:	Absolute forecast error × 100					
Sample:	Easy-to-value firms					
Hard-to-value measure:	Raw		Resid (⊥ DCF)		Resid (⊥ DCF and Ind)	
	(1)	(2)	(3)	(4)	(5)	(6)
DCF only	0.20*	0.46***	0.19*	0.49***	0.32***	0.57***
	(0.11)	(0.15)	(0.11)	(0.15)	(0.12)	(0.15)
More Skilled Analyst (continuous, resid)	-0.08***		-0.07***		-0.08***	
	(0.01)		(0.01)		(0.01)	
DCF × More Skilled Analyst (continuous, resid)	-0.05**		-0.06**		-0.06**	
	(0.03)		(0.02)		(0.02)	
More Skilled analyst (dummy, resid)		-0.67***		-0.67***		-0.81***
		(0.09)		(0.09)		(0.10)
DCF × More Skilled analyst (dummy, resid)		-0.53***		-0.61***		-0.51***
		(0.17)		(0.17)		(0.17)
Observations	510,568	515,498	508,018	512,907	517,024	521,919
F-statistic	16.204	32.067	16.598	34.479	17.766	38.436
R^2	0.598	0.600	0.599	0.600	0.608	0.609
Firm×Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Analyst Skill and Forecast Accuracy: Hard-to-value firms

Dependent variable:	Absolute forecast error × 100					
Sample:	Hard-to-value firms					
Hard-to-value measure:	Raw		Resid (⊥ DCF)		Resid (⊥ DCF and Ind)	
	(1)	(2)	(3)	(4)	(5)	(6)
DCF only	1.00**	2.65***	1.02**	2.76***	0.88**	2.71***
	(0.40)	(0.70)	(0.41)	(0.72)	(0.41)	(0.73)
More Skilled Analyst (continuous, resid)	-0.71***		-0.71***		-0.74***	
	(0.07)		(0.07)		(0.07)	
DCF × More Skilled Analyst (continuous, resid)	-0.23***		-0.23***		-0.24***	
	(0.07)		(0.07)		(0.07)	
More Skilled Analyst (dummy, resid)		-4.53***		-4.45***		-4.34***
		(0.41)		(0.40)		(0.40)
DCF × More Skilled analyst (dummy, resid)		-4.01***		-4.18***		-4.45***
		(0.87)		(0.90)		(0.92)
Observations	386,742	391,718	389,292	394,309	380,255	385,266
F-statistic	48.778	42.450	48.792	42.367	49.945	40.361
R^2	0.807	0.802	0.807	0.802	0.814	0.808
Firm×Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table V:
Quasi-Experiment: Voluntary Vs. Forced Model Adoption

This table examines voluntary versus forced adoption of valuation models in a quasi-experiment. The regressions relate DCF-only usage to absolute forecast errors, i.e., forecast accuracy, splitting analysts by whether they predominantly used DCF methods in the prior year (DCF experts) or predominantly used other methods (DCF non-experts). Column 1 reports results for the full sample, in which switching to DCF methods is endogenous and thus voluntary. Column 2 restricts the sample to 2009, the Great Financial Recession, when multiple-based methods were often infeasible due to negative EPS forecasts, rendering switches to DCF methods plausibly exogenous. The regressions are estimated using ordinary least squares. Standard errors (in parentheses) are estimated using heteroskedastic-consistent estimators and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Dependent variable:	Absolute Forecast Error	
	Full sample	2009 only
	(1)	(2)
(1) DCF only × DCF expert	0.96***	0.34
	(0.24)	(2.03)
(2) DCF only × DCF non-expert	0.06	6.27**
	(0.25)	(2.84)
Difference in coefficients: (2) − (1):	-0.90***	5.93*
Firm*Year FE	Yes	Yes
Observations	937,533	6,704
F Statistics	8.29	2.48
R^2	0.84	0.87

Table VI:
Valuation Multiples and Theoretical Drivers

This table examines how valuation multiples relate to their key theoretical determinants: risk and long-term growth expectations. The analysis uses natural logarithm transformations for three variables of interest. The dependent variable (valuation multiple) is at the firm i, analyst j, and year t level. CAPM β (representing systematic risk) is at the firm i and year t level. Real GDP growth (representing growth expectations) is measured at the country c and year t level. The regressions are estimated using ordinary least squares. Standard errors (in parentheses) are estimated using heteroskedastic-consistent estimators and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Dependent variable:	$\text{Multiples}_{i,j,t}$			
	(1)	(2)	(3)	(4)
CAPM $\beta_{i,t}$	-0.27***	-0.27***	-0.28***	-0.28***
	(0.02)	(0.02)	(0.02)	(0.02)
Real $\text{GDP}_{c,t}$	1.62***	5.00***	0.75*	
	(0.27)	(0.75)	(0.42)	
Year FE	No	Yes	Yes	No
Country FE	No	No	Yes	No
Country × Year FE	No	No	No	Yes
No. Observations	43,355	43,355	43,355	43,269
F statistic	151.18	155.15	134.85	268.10
Adjusted R^2	0.04	0.06	0.10	0.10

Table VII:
Valuation Multiples and Theoretical Drivers

This table examines how analyst sentiment influences the distance between chosen valuation multiples and their corresponding reference points across three benchmarking approaches: historical, current sector, and peer comparisons. The variable of interest, Sentiment, is measured at the firm i, analyst j, and year t level. The dependent variables, distance to reference point and reference point selection, are similarly measured at the firm i, analyst j, and year t level. Distance to reference point is equal to $2 * [(\text{multiple} - \text{reference point})/(\text{multiples} + \text{reference point})]$. Sentiment denotes the average sentiment measured in the equity report as constructed in Bastianello, Decaire, and Guenzel (2025). The regressions are estimated using ordinary least squares. Standard errors (in parentheses) are estimated using heteroskedastic-consistent estimators and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Dependent variable:	Distance to Reference Point						Reference Points		
	Historical		Current		Peers		Hist.	Current.	Peers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{Sentiment}_{i,j,t}$	0.15***	0.07***	0.09***	0.11***	0.13***	0.06**	0.15	-0.42	-0.35
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.33)	(0.46)	(0.91)
Firm × Year FE	No	Yes	No	Yes	No	Yes	Yes	Yes	Yes
No. Observations	9,773	4,406	8,170	3,169	10,032	3,662	4,438	3,260	3,775
F statistic	344.41	26.48	278.84	62.34	168.77	5.81	0.21	0.81	0.15
Adjusted R^2	0.06	0.47	0.05	0.46	0.03	0.40	0.41	0.42	0.23

Table VIII:
Valuation Multiples and Forecast Outcomes

This table examines how the distance between analysts choice of multiples and their reference points related to their forecast levels and forecast accuracy. All variables are measured at the firm i, analyst j, and year t level. Distance to reference point is equal to $2 * [(\text{multiple} - \text{reference point})/(\text{multiples} + \text{reference point})]$. Forecast levels, denoted expected returns below, are defined as expected log returns, computed as the natural logarithm of the analyst's price target divided by the current price. Absolute forecast errors are defined as the absolute value of realized log returns, i.e., the natural logarithm of the 12-month realized price divided by the current price, minus expected log returns. The regressions are estimated using ordinary least squares. Standard errors (in parentheses) are estimated using heteroskedastic-consistent estimators and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Dependent variable:	Expected Return			Absolute Forecast Error		
	(1)	(2)	(3)	(4)	(5)	(6)
Distance to Reference Point (Hist.)$_{i,j,t}$	0.08***			0.01		
	(0.02)			(0.01)		
Distance to Reference Point (Current)$_{i,j,t}$		0.36***			0.03	
		(0.04)			(0.04)	
Distance to Reference Point (Peers)$_{i,j,t}$			0.03*			0.01
			(0.01)			(0.02)
Firm × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	4,406	3,169	3,662	3,946	2,839	3,381
F statistic	23.71	98.64	2.88	0.89	0.65	0.64
Adjusted R^2	0.51	0.72	0.55	0.84	0.91	0.89

Table IX:
Choice of Reference Points and Cross-Sectional Characteristics

This table presents adjusted R^2 values from ordinary least squares regressions examining the determinants of analysts' reference point choices. The dependent variable is a binary indicator equal to 1 if an analyst employs a specific reference point type in their report, and 0 otherwise. We decompose the variation in reference point usage by including three sets of fixed effects: (i) firm fixed effects, capturing firm-specific characteristics that influence reference point selection; (ii) analyst fixed effects, identifying individual analyst preferences and styles; and (iii) year fixed effects, accounting for temporal trends and market conditions. Panel A reports the decomposition for historical reference points (comparisons to past performance), Panel B for current reference points (comparisons to contemporaneous benchmarks), and Panel C for peer reference points (comparisons to industry competitors). The decomposition reveals the relative importance of firm characteristics, analyst heterogeneity, and time-varying factors in explaining reference point selection.

Dependent variable:	Partial Set of Fixed Effects			Complete Set of Fixed Effects
	(1)	(2)	(3)	(4)
Panel A: Historical	Firm + Year	Analyst + Year	Firm + Analyst	Firm + Analyst + Year
Adjusted R^2	0.18	0.28	0.33	0.33
No. Observations	58,512	58,602	58,506	58,506
Panel B: Current	Firm + Year	Analyst + Year	Firm + Analyst	Firm + Analyst + Year
Adjusted R^2	0.09	0.22	0.24	0.24
No. Observations	58,512	58,602	58,506	58,506
Panel C: Peers	Firm + Year	Analyst + Year	Firm + Analyst	Firm + Analyst + Year
Adjusted R^2	0.20	0.31	0.37	0.37
No. Observations	58,512	58,602	58,506	58,506

Appendix

Valuation Models

Francesca Bastianello, Paul H. Décaire, Marius Guenzel

Not for Publication

Appendix A Valuation Prompt

```
CONTEXT


You will be provided with:
(A) A list of valuation methods, in the format:
    List_Order : Valuation_Method
(B) The year in which the report was written.
(C) An excerpt from an equity analyst report that uses these methods to generate
    a price target.


-----


TASK
For each {List_Order} : {Valuation_Method} entry, output in this JSON format:


{
  "List_Order": null,
  "Recommendation": "",
  "Valuation_Method": "",
  "Numerical_Multiple": null,
  "Historical": null,
  "Historical Reference": "",
  "Historical Horizon": "",
  "Current": null,
  "Current Reference": "",
  "Forward": null,
  "Peers": null,
  "Peers Reference": "",
  "Peers Group": "",
```

```
  "Peers Ticker": "",
  "Multiple_Type": "",
  "Driver_Type": "",
  "Currency": "",
  "Numerical_Price_Bear": null,
  "Numerical_Price_Bull": null,
  "Numerical_Multiple_Bear": null,
  "Numerical_Multiple_Bull": null,
  "Driver_Bear": null,
  "Driver_Bull": null,
  "Forecast_Method_Bear": null,
  "Forecast_Method_Bull": null,
}

- Use null for missing numerical values (not 0)
- If there is more than 1 method provided, create separate entries for each method

-----

VARIABLE DEFINITIONS

List_Order:
- The number of methods for a specific report, if a report has 2 methods each
  of the two rows should have 2 as their value

Recommendation:
- The analyst's recommendation for the stock (e.g., Buy, Sell, Hold, Neutral)

Valuation_Method:
- The specific valuation method for this entry
```

Numerical_Multiple:

- The specific quantitative value (e.g., 12x, 20x) used for the multiple in the price target calculation. Do not provide anything else but the numerical value(s). If none is provided, enter "".

Historical:

- 1 if the multiple is justified by referring to historical valuation levels or past performance, 0 otherwise.
  Important: If the report refers to the numerical value the analyst previously used to generate the price target, this does not count as a historical reference point.
- Historical_Reference: The exact referenced historical numerical value (or its range), if any; if unavailable, include a percentage relating to the reference; if neither is present, include qualitative phrases such as "slightly above," "in line with," or "below" historical averages or values; else "".
- Historical_Horizon: Extract the historical horizon in years: if the reference horizon is a long term metric (e.g., "historical median", "long-term average", "long-run"), mark this as 100; if the horizon is uncertain leave as ""; output number only.

Current:

- 1 if the multiple is justified by current valuation or performance (explicit reference to present conditions), 0 otherwise.
  Important: Current should only count for the stock's current multiple, not peers or the broader market's current multiple. E.g., this snippet should be peers: "SBH is trading at a relatively attractive P/E multiple (15x) compared to its growth and to our coverage"
- Current_Reference: The exact referenced current numerical value (or its range), if any. If you cannot find a numerical value (or range) try to find a

percentage relating to the reference; else "".

Forward:

- 1 if the analyst justifies or adjusts a valuation multiple based on future-oriented expectations, including anticipated long-term growth, sustainability of future performance, ongoing momentum, or expected continuation of trends. This can be explicit ("we expect...") or implicit ("reflects..."). References to future metrics alone (e.g., "2024E EPS") do not count.
  Important: The rationale must link the multiple to forward-looking expectations, not merely to the use of a forward metric.
  Forward cues (non-exhaustive): expect, anticipate, projected, outlook for, improving/deteriorating future trends, long-term growth, growth trajectory, growth prospects, future margin expansion/contraction, sustainability of future performance, ongoing momentum, potential, potential for acceleration, concerns for future.

Note:

- Only assign a forward-looking code if the analyst's rationale for the value or adjustment of the multiple explicitly reflects future expectations (e.g., growth prospects, long-term growth, future outlook, projected industry changes, etc). Do not code as forward-looking merely because the multiple is applied to a forward metric such as next year's earnings or EBITDA. There must be clear evidence that the multiple itself is justified by expectations about future developments.

Peers:

- 1 if the stock or stock multiple is compared to peers or the industry, 0 otherwise.
- Peers_Reference: The referenced peer/industry numerical stock price (or its

range), if any; else "". Do not provide anything else but the numerical value(s) unless the value is a percentage discount or upgrade to its peers, in which case include that information as well.

- Peers_Group: Indicate if the compared group is "peers", the specific sector, "industry", "market", etc.
- Peers_Tickers: If stock tickers (e.g., ADP, IMG, RHI, etc.) or comparison stocks are present in the report or listed in tables in the report, include them here. Note that stock tickers are often presented in tables labeled similar to "Exhibit X: Comparables" or in coverage clusters at the end of reports with many companies in a table.

Bull/Bear Scenarios

- Extract values if the report presents any explicit alternative case (bull/bear, upside/downside, optimistic/pessimistic, floor/ceiling, blue-sky/stress, sensitivity, high/low case).
- Always map the most optimistic scenario to Bull and the most pessimistic scenario to Bear, regardless of the labels the report uses.
- Capture all available numerical values:
  -- Price targets
  -- Multiples
  -- Ranges
  -- Drivers (revenues, margins, growth rates, etc.)
  -- Currency (if multiple currencies are included, include all separated by "***")
- Capture qualitative drivers as well:
  -- Even if no number is given, statements like "higher estimated revenue" or "margin pressure" should still be coded.
  -- If a driver is expressed as a relative statement (e.g., "increase by 20%"), record it.
- Forecast_Method_Bear / Forecast_Method_Bull should be coded as:
  -- "Multiple only" if only the multiple changes

-- "Driver only" if only the driver changes

-- "Both" if both multiple and driver change

- If scenarios are absent, leave all Bull/Bear fields null.

ADDITIONAL INSTRUCTIONS

- **IMPORTANT**: Except for fields explicitly labeled as Bear/Bull (or their equivalents, such as pessimistic/optimistic scenarios), your efforts should be focused exclusively on extracting information related to the base case scenario (or its equivalent). If the report does not explicitly discuss multiple scenarios, assume that the scenario presented is the base case.
- Focus your analysis on the justification for the multiple used to generate the Price Target.
- Review the entire report for valuation-multiple reasoning, ensuring forward multiples are captured, as forward entries have previously been zero even when relevant reasoning exists.

Here are examples which would be counted as Forward Snippets:

1. We use a higher multiple to reflect anticipated market share gains.
2. We use this multiple higher than before due to solid earnings momentum.
3. We believe this multiple is appropriate based on the company's slower growth prospects.
4. This multiple reflects improving margin and growth outlook.
5. We raise our estimates, PT, and valuation multiple on increased visibility and confidence in WSM's long-term growth trajectory.
6. Our price target is based on c19x FY18E PE, ahead of our target sector multiple of 17x due to potential for growth.

7. It is likely that management will continue to beat Street estimates in the coming quarters, allowing estimates to increase in the out years. As such, we believe it is appropriate to use a 13x multiple.
8. We give the company a lot of credit for the inflection and expense discipline which we expect to continue, reflected in our higher multiple.
9. Our price target objective predicated on a 19x multiple of 2023E EPS, in line with VIVA's longer-term growth and higher-quality, and comparably-growing domestic peers.
10. Our price target is based on 25x multiple, which we believe better reflects our concerns regarding the sustainability of the growth and margin profile.

These are not Forward-Looking Snippet Examples:

1. We use a 15x multiple on 2015 EPS. (unless a forward-looking justification for the multiple is provided)
2. Our one-year price target of $100 is based on 10x our F2024 EV/sales estimate. (unless a forward-looking justification for the multiple is provided)
3. We are raising our price target to $41 from $38 prior as we raise our EPS and roll our valuation forward.
4. Based on forward earnings estimates, we use a 15x multiple. (needs explicit future-oriented rationale for the multiple value)
5. Our target price is predicated on our rolling one-year-forward target P/E. (unless a forward-looking justification for the multiple is provided)
6. We think a premium is merited given the business's consistent track record of execution. (unless a forward-looking justification for the multiple is provided)

Here are examples prior versions of the prompt have mislabeled, along with explanations on what they are supposed to be:

1. PT is 32$ (implying a 10x P/E ratio) - this would not count as a multiple, as 10x is not how they derived their Price Target, but it is instead a

separate multiple derived from their Price Target value. Only use a multiple that explicitly creates the Price Target and not the other way around.

2. Our price target is raised to $60 from $50, based on applying the current S&P 500 multiple (26 times) to our 2000 estimate. - this would not count as current, as the multiple is that of the S&P500 not of the stock. Instead, this would count as peer, as S&P500 is a group of Peers to the stock.
3. This is in-line with RVNC's peers, which trade, on average, at a forward EV/EBIT of 19x. This compares favorably to other companies that have been acquired in the industry for 20x EV/EBITDA, which means the EV/EBIT could be even higher - this snippet should be marked as peers not current, as the multiple is that of RVNC's peers not RVNC's current multiple
4. 8.0x EV/EBITDA, 2.3x EV/Sales, 11.0x EV/FCF: Generate 3 rows for this method, not one. When multiple methods are used in tandem, err on the side of creating more rather than fewer rows
5. Our new TP is based on 17.4x FY21F EPS of HKD2.19, equal to the mid-point of the long-term average and 1.0x standard deviation. The stock trades at 13.8x FY21F P/E, 5% below its long-term average of 14.5x, and more than 20% below our target multiple. - this example should mark the historical value as 14.5x as that's the historical, long-term average.
6. This stock trades at a 10.1x EV/ EBITDA 2024E multiple - Current, as it's what the stock is currently trading at
7. to which we apply a peer-derived average historical multiple - should be Peers

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(A) LIST OF VALUATION METHODS:

ListOrder_ValuationMethods

(B) THE REPORT WAS WRITTEN IN MonthReport OF YearReport.

```
(C) TEXT TO ANALYZE:

EquityReport

Return ONLY a JSON object with this structure -- no markdown or explanations:
{
  "Multiples": [ { ... non-DCF entries ... } ]
}
```