Dissecting Disagreement in Valuations: Inputs and Outcomes*

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Abstract

Using valuation models of financial analysts, we identify the drivers of disagreement in stock valuation. Disagreement in the discount rate is as important in explaining the variation in a stock's intrinsic value as the disagreement in expected cash flows. Analysts derive the discount rate by estimating the same return-generating model (CAPM) but over different trailing horizons and under different assumptions about the market risk premium. This approach produces large variation in betas and the discount rate. These methodological choices are specific to the analyst rather than their firm. Overall, we offer micro evidence on the inner workings of securities valuation.

JEL classification: G30, G31, G41, D25, D82, D83, O13, Q15, R14

Keywords: Disagreement, Security Valuation, Model Inputs, Subjective Beliefs

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1 Introduction

Finance theory postulates that investors trade securities primarily because they have different private valuations (Milgrom and Stokey, 1982; Karpoff, 1986). Consistent with these predictions, empirical work finds a surprisingly high amount of trading for U.S. stocks, given the relative information transparency in the U.S. market and a modest amount of portfolio rebalancing. In a survey of this literature, Hong and Stein (2007) conclude that the bulk of trading must come from differences in investors' valuation models "that lead traders to disagree about the value of a stock even when they have access to the same information sets" (p. 112).

While the divergence in investors' valuation models and private information inputs serves as a fundamental tenet in the theoretical literature on informed trading and a large body of empirical work on investor disagreement, the sources of disagreement in stock valuation remain elusive. In particular, it remains unclear to what extent the differences in private valuations are driven by the variation in methodology, information inputs, model assumptions, or temporal horizons. Answering this question is particularly important for asset valuations by sophisticated financial experts who serve as information leaders and represent large institutional investors—brokerage and investment firms commonly viewed as marginal investors.

To understand the sources of disagreement in securities valuation, we examine over 40,000 overlapping stock valuation models of financial analysts who represent most of the top brokerage firms worldwide. These data provide a rare perspective into the inner working of securities valuation, allowing us to observe the entire cash flow model, its inputs and outcomes, key assumptions and a qualitative discussion of the information sources and methodological choices.

In our first analyses, we decompose disagreement in securities valuation into that attributable to (1) expected cash flows and (2) the discount rate. This starting point follows the intuition of comparing the relative importance of the numerator and denominator in an analyst's discounted cash flow model as a driver of variation in its main outcome—the intrinsic value of a common share.

We find that the choice of the discount rate is as strong a driver of the variation in the estimated share price as cash flow growth is. We highlight several mechanisms that contribute to this effect and develop a simple analytical framework to formalize this intuition. First, while the average disagreement in estimated cash flows declines with a greater number of valuations that diversify away extreme estimates, we show that this pattern need not hold for the discount rate. The differences in the discount rate need not cancel out and may be augmented with a greater number of valuations due to the convexity in the discount rate's effect on the share price. Second, we show that the disagreement in the estimated share price depends on the joint distribution of the disagreement about the discount rate and the disagreement about cash flow growth rates.

We find that higher discount rates in valuation models are not offset by higher cash flow growth rates, whether in the explicit forecast or in the terminal growth rate, in contrast to what has been postulated in the literature (Cochrane, 2011). For example, in 45% of the valuation models, an above-consensus estimate of the discount rate is associated with a below-consensus estimate of the terminal growth rate (or vice versa), suggesting that they diverge in the opposite directions. Third, we find that financial analysts disagree more about the discount rate than they do about the cash flow growth rates (in absolute terms). For example, the cross-sectional mean of the disagreement in the estimated cost of capital for the average stock is 77 basis points, while the same average deviation for disagreement for terminal growth rates is only 61 basis points. The combination of these patterns highlights the discount rate as a pivotal driver of disagreement in stock valuation and motivates our primary focus on the discount rate.

A natural question is why critical valuation inputs vary so much across financial experts who work for similar financial firms and have comparable professional backgrounds. Does the variation in the modeling choices reflect the rules of the brokerage house, the institutional features of the firm or its industry, or the modeling preferences of an analyst?

To answer this question, we estimate the variance decomposition for the disagreement in WACC observed for a given firm-year into several components attributable to the brokerage house, financial analyst, or the focal firm. As expected, we find that WACC estimation varies significantly by the focal firm, likely reflecting a combination of industry-specific valuation rules and firm-specific events. Across firms, the disagreement in WACC is greater for younger firms, R&D intensive firms, and more complicated firms, consistent with prior definitions of hard-to-value stocks. Perhaps less expected, the analyst's identity has a significantly stronger effect in explaining the dispersion in WACC than the identity of the brokerage house. Interpreted broadly, these results suggest that methodological preferences in WACC estimation are specific to the analyst rather than dictated by the brokerage house, and these methodological choices move with the analyst across brokerage firms.

To better understand why financial experts disagree so much about a firm's discount rate, we focus on those that compute a weighted average cost of capital (WACC). We provide micro evidence on their inputs, assumptions, and methodological choices in estimating each of its components. We find that the primary source of the disagreement in WACC comes from the variation in the estimated cost of equity capital. This result is driven not by the differences the return-generating model, but by the variation in its inputs, assumptions, and estimation horizon.

When reported, the overwhelming majority of valuations (91%) use the Capital Asset Pricing Model (CAPM) but diverge sharply on its inputs. The largest sources of variation come from the differences in the estimation of betas and the market risk premium. The magnitude of this variation is surprisingly large. The cross-sectional standard deviation in the estimated beta for the average stock is 0.28 or 26% of the unconditional mean. The variation in the estimated market risk premium (MRP) is similarly large. During the median year in our sample (2000-2023), the 25th percentile of the MRP estimate is 5 percent per year, and the 75th percentile is 6.3 percent, indicating an interquartile range of 1.3 percentage points or 23% of the mean. Similarly, during the median sample year, the average standard deviation in the estimated MRP is 1.39 percentage points or 24% of the mean (5.7 percent per year).

To understand the mechanisms of disagreement in model inputs, we conduct a contextual analysis of valuation reports to extract the description of estimation procedures and data sources for the main inputs. We manually read a sample of reports to construct a training algorithm and develop a machine-learning procedure to extract key insights from analysts' qualitative discussions. We augment this approach with an advanced analysis that incorporates artificial intelligence and big-data contextual structures.

We find that the main driver of disagreement in beta for the same stock is the trailing estimation horizon. The estimation horizon varies from one to seven years, and the most common horizons use monthly stock returns over the trailing five years (47%), two years (26%), or three years (12%). We cross-validate these self-reported horizons by independently calculating betas using the stated estimation period and juxtaposing them against the reported values. We then expand our analyses by using the inferred estimation horizons.

The variation in the estimated beta horizon for the same stock produces large economic effects. For the average stock-year, an increase from using only one estimation horizon to two distinct horizons is associated with an absolute increase in beta disagreement by 18% of the unconditional mean.

In contrast to the large dispersion in beta and MRP estimates, analysts tend to converge on the other CAPM inputs—the risk-free rate. The overwhelming majority of stock valuations (87%) use the annual yield on a 10-year U.S. Treasury as a proxy for the risk-free rate, while a minority of reports use Treasury yields on the 30-year bond (12%) and none use the one-year T-bill (0%). When evaluating international firms, over 81% of the analysts use the firm headquarter's main national index as their proxy for the market portfolio, while the rest use the S&P 500. Décaire and Graham (2023) provide an in-depth review of these practices. Across the full sample, we find that the slight variation in these modeling choices has no material impact on the estimated WACC or the disagreement in the estimated share price.

Overall, our findings suggest that a large share of disagreement in stock valuation is attributable to modeling choices in estimating a firm's discount rate. Most of the variation results from estimating the same return-generating model but with different trailing horizons (beta estimates) and under different assumptions about the market risk premium. These methodological choices reside with the financial analyst and provide micro foundation for prior evidence on the importance of analyst identity in asset valuation.

The central contribution of this paper is to provide granular evidence on the inner workings of stock valuation and identify key determinants of disagreement in the financial models of sophisticated intermediaries. Our paper departs from most of the prior work on investor disagreement in three ways.

First, in complement to prior work that shows the consequences of investor disagreement on market outcomes, such as trading, pricing, and learning (e.g., Banerjee and Kremer, 2010; Carlin et al., 2014), we address a lingering question that predicates this logical chain: why do investors have different valuations in the first place? Second, while prior work infers investor disagreement from the outcomes of valuations, such as fund managers' active bets (Cremers and Petajisto, 2009), financial experts' forecasts (Patton and Timmermann, 2010), or analysts' recommendations (Sadka and Scherbina, 2007), our paper looks inside the valuation process that drives this variation in outcomes. Third, theory makes an important distinction between investor disagreement in information inputs and valuation methods (see Hong and Stein (2007) for a review), but this distinction has been difficult to test because it requires observing the valuation model, its inputs, and outcomes. Our paper is in a small set of research that dissects the valuation models of sophisticated financial experts and reveals the sources of disagreement in their models, information inputs, and estimation procedures.

Our paper contributes to an emerging literature that studies the sources of investor disagreement. So far, this research has focused mostly on retail investors. Using measures of disagreement from a social media platform, Cookson and Niessner (2020) find that investor disagreement is evenly split between a self-declared investment approach (technical vs. fundamental) and different information sets. Andrei et al. (2019) and Meeuwis et al. (2022) show that investors react differently in response to common information shocks. The authors attribute this disagreement to the variation in mental models. Using a survey, Giglio et al. (2021) find that investors disagree about both cash flows and expected returns and conclude that it is crucial to jointly model the disagreement about both objects and their co-movement. Our paper decomposes the disagreement in cash flow expectations and discount rates, identifies their drivers, and documents their co-movement. More broadly, we extend the scope by providing evidence on the disagreement among professional analysts tasked with information discovery and investor guidance. Rather than relying on indirect measures of disagreement in valuation, such as surveys, social media, or trades, we offer direct evidence from valuation reports that allows us to disentangle the disagreement in information inputs, financial models, and estimation methods.

This paper also expands our understanding of how key market agents determine the cost of capital and required rate of return. Since the discount rate is rarely observable to the econometrician, most research has inferred the discount rate from surveys (Graham and Harvey, 2001), observed investment actions (Kruger et al., 2015; Dessaint et al., 2021; Décaire, 2023), or select disclosures (Gormsen and Huber, 2023). While these approaches yield useful WACC measures, they remain silent about how agents arrive at their estimates and update them in response to market conditions. Our paper complements this work by providing evidence on the valuation processes in estimating each discount rate component. The discount rate estimates in analyst reports are economically important for both corporate managers and investors. For example, Décaire and Graham (2023) find that analysts' discount rates accurately predict realized returns with a near one-to-one magnitude and conclude that analyst discount rates approximate the investors' future required rate of return. Our paper shows that the discount rate is a dominant driver of disagreement in stock valuations.

2 Hypothesis Development

This section provides straightforward derivations in the dispersion of security valuations across analysts. Without loss of generality and for illustration purposes, we model a firm that generates a cash flow of $1 today, that is expected to grow at rate g next period, and has a discount rate r.

Then,

$$P = \frac{G}{R} \tag{1}$$

where $G = 1 + g$ and $R = 1 + r$. Now, let P_i represent the price target for analyst i, then

$$P_i = \frac{\tilde{G}_i}{\tilde{R}_i} \tag{2}$$

where $\tilde{G}_i$ is the total growth expectation of agent i and $\tilde{R}_i$ is the total discount rate used by agent i. Both measures are observed with noise, such that:

$$P_i = \frac{\tilde{G}_i}{\tilde{R}_i} = \frac{G + \tilde{\gamma}_i}{R + \tilde{\omega}_i} \tag{3}$$

where $\tilde{\gamma}_i$ and $\tilde{\omega}_i$ are each mean 0, with standard deviations $\sigma_{i,\tilde{\gamma}_i}$ and $\sigma_{i,\tilde{\omega}_i}$, respectively, and can be correlated for a specific valuation exercise (i.e., $\text{Cov}(\tilde{\omega}_i, \tilde{\gamma}_i) \neq 0$).

Taking natural logs on both sides gives

$$ln(P_i) = ln(\tilde{G}_i) - ln(\tilde{R}_i) \tag{4}$$

To identify disagreement in the cross-section, we can look at the dispersion of those measures across analysts following the same firm in the same year such that:

$$\text{Var}(P_i) = \text{Var}(ln(\tilde{G}_i)) + \text{Var}(ln(\tilde{R}_i)) - 2\text{Cov}(ln(\tilde{G}_i), ln(\tilde{R}_i)) \tag{5}$$

The equation tells us that for a given stock at a point in time, *cross-sectional* disagreement in prices depends on the disagreement about growth expectations, discount rates, and the relation between both variables. Given that we observe the price targets, and their associated inputs for each analyst-firm-year pair, we design an analysis to leverage the rich nature of this data. Thus, to transpose the intuition from the derivation above into our empirical framework, we adapt Equation (5) to obtain a measure of disagreement at the analyst-firm-year level, such that our measure of disagreement is the distance between the analyst estimates and the consensus for the stock at that point in time:

$$\begin{aligned} |ln(Price_{a,i,t}) - ln(\overline{Price}_{i,t})| = & |ln(1 + Discount\ Rate_{a,i,t}) - ln(1 + \overline{Discount\ Rate}_{i,t})| \\ & + |ln(1 + TGR_{a,i,t}) - ln(1 + \overline{TGR}_{i,t})| \end{aligned} \tag{6}$$

This strategy allows us to express an analyst's price target disagreement as a function of her disagreement in terms of discount rates and growth expectations. Two measures that we can directly measure in our data.

3 Institutional Details

The disclosure of DCF modeling details is done on a purely voluntary basis, which suggests that we have a selected sample. However, prior literature has found that the intensity of information disclosure of DCF modeling assumptions is positively associated with report accuracy (Asquith et al., 2005; Hashim and Strong, 2018), and more detailed information disclosure leads to larger market reactions following changes in recommendations (Huang et al., 2023). Moreover, by detailing their valuation theses, informed analysts have the opportunity to differentiate their work from their uninformed rivals, gaining credibility in the process.

In sum, these details suggest that our data differ in a favorable way from datasets that collect earnings forecasts unconditionally (e.g., I/B/E/S). That is, our data are more likely to be sampled from an informed subset of analysts. Moreover, such a selected sample of informed analysts helps narrow down the mechanism for disagreement. Prior work has shown that informational differences matter more than differences in investment models (Cookson and Niessner, 2020). Our data facilitate the study of disagreement across analysts that use the *same model* because we have the ability to identify how they parameterize and estimate each individual component. This allows us to distinguish whether differences in analysts' price targets come from the use of different sources of information or different ways to perform the analysis using the exact same model.

4 Methodology and Data

The bulk of our data is sourced from equity research reports (i.e., the original documents) published by sell-side analysts. We start with an initial batch of 157,549 equity reports with mentions of the keywords "DCF" or "discounted cash flow" from 55 major equity research firms. We restrict the time window to reports published in the first quarter of the calendar year (January 1^{st} to April 1^{st}) from 2000 to 2023. This ensures that our data are systematically measured at a similar time point in the year. In cases where analysts publish more than one report on the same firm during the first quarter, we systematically keep the earliest publication in that calendar year to avoid duplicates for a given analyst-firm-year pair. This procedure results in 42,720 equity reports that include at least one of our variable of interest, and for which each firm-year pair is covered by at least 2 analysts.

We collect numerical values for each of the inputs in four steps. First, documents are pre-processed using a Python program to identify sections of text, tables, and figures containing relevant information for the study (e.g., free cash flows, terminal growth rates, discount rates). Second, we convert each of these forms of publication into text snippets. Third, for each variable, we use artificial intelligence to extract the numerical value from the snippets. Fourth, we export the text snippets and the numerical values extracted by artificial intelligence to Excel – and our research team manually verifies every single number. This last step of the collection effort (manual verification) is crucial to ensure the integrity of the data used in the analysis. While artificial intelligence is an efficient tool for text extraction, error rates in the processing of complex sentences can be well above acceptable levels when AI is left unsupervised (Gilardi et al., 2023).

4.1 Firms and Coverage

The equity reports are produced by 42 of the largest equity research departments operating throughout the world. Because we aim to understand disagreement in the valuations of the same security during the same time period, we restrict our sample to firm-year observations with equity reports produced by at least two analysts. Panel A of Table 1 highlights the specific coverage for each of the DCF inputs in terms of number of firms and firm-year observations that meet this requirement. For example, in the discount rate sample, the 42,720 reports cover 3,971 firms located in 64 countries during the 2000-2023 period. Panel A also shows that as the DCF inputs increase in specificity, e.g., moving from discount rates to the components of a standard weighted average cost of capital (WACC) calculation, our sample sizes reduce as fewer equity reports include every such input.

Table 1 Panel A also reports on a limited set of firm characteristics for our discount rate sample. For example, the average firm is covered by 5.17 analysts and is included in the sample for 4.0 years. Moreover, the typical firm covered by our sample is 14 years old, has \$572.8 million in total assets, and spends 2.3% of total assets on research and development. As with standard commercial databases that report on analyst expectations (e.g., EPS forecasts via I/B/E/S), our sample skews older and larger than the full universe of publicly traded firms that could be downloaded from Compustat or CRSP. However, Décaire and Graham (2023) show that the characteristics of the firms in their sample (which closely matches out sample) are similar to the firms from I/B/E/S data in terms of size and investment intensity.

In terms of geographic coverage, 45% of firms have their headquarters located in Europe, 26% in North America, 15% in Oceania, 11% in Asia, 1% in South America, and 1% in Africa. The reports are produced by equity analysts located in Europe in 44% of the cases, 22% in North America, 18% in Oceania, 13% in Asia, 2% in South America, and 1% in Africa.

Two dozen NAICS industry sectors (2-digit) are represented in our sample, with the eight largest broad sectors accounting for 87% of the total coverage: 36% for manufacturing (NAICS 31-32-33), 19% for information (NAICS 51), 7% for professional services (NAICS 54), 7% for retail trades (NAICS 44-45), 6% for mining and oil & gas (NAICS 12), 5% for transportation (NAICS 48-49), 5% for utilities (NAICS 22), and 2% for finance and insurance (NAICS 52). Overall, these statistics suggest that our sample is comprehensive, representative, and comparable to its commercial counterparts.

4.2 Disagreement Measures Summary Statistics

Panel B of Table 1 reports the summary statistics for the analyst inputs to the DCF models in each respective equity report. For example, the average discount rate used by the analysts in our sample is 8.92% while the mean terminal growth rate is 2.23% (median of 2.0%). More important to us, however, Panel B reports the summary statistics for our measures of disagreement. We focus on two measures of disagreement: absolute and scaled. We define absolute disagreement as the absolute deviation of an individual analyst's estimate of a given input from the consensus (mean) estimate for a given firm-year. For example, the absolute discount rate disagreement for analyst a, covering firm i, during year t is $|Discount\ Rate_{a,i,t} - \overline{Discount\ Rate}_{i,t}|$. Scaled disagreement simply takes this absolute deviation and scales it by the consensus estimate for a given firm-year. One way to interpret these measures of disagreement is that the absolute disagreement gives the deviations in percentage points (pp.) while the scaled version gives the percentage deviation.

Table 1 Panel B highlights a few things. First, the means of the absolute deviations for each of the DCF inputs are on the same order of magnitude, ranging from 0.54 (for risk-free rate) to 0.77 (discount rate). Second, the magnitudes of the scaled disagreement measures differ more dramatically. For example, the means of the scaled disagreement measures for terminal growth rates and the risk free rate are 37.23% and 16.35%, respectively. Intuitively, the smaller the absolute value of the direct input, the larger the scaled disagreement. Finally, even within a given input disagreement measure, there is high variability. For example, the standard deviation for the absolute deviation in discount rates is 0.69, which is nearly as large as the mean. This suggests that disagreement in the analyst inputs vary significantly in the time-series and/or cross-section.

5 Results

5.1 Discount Rate vs. Terminal Growth Rate Disagreement

Section 2 highlights that cash flow disagreement, in isolation might not be sufficient to explain disagreement in expected prices. This section investigates the three terms of Equation (5) that, combined, generate overall disagreement in securities valuation: (i) disagreement in expected growth, (ii) disagreement in discount rates, and (iii) their relation in the cross-section.

Figure 1 presents cross-sectional distribution plots for both discount rate and terminal growth rate disagreement. Panel A focuses on absolute disagreement, and Panel B focuses on a relative measure of disagreement. The fat tail for discount rates in Panel A suggests that there is more disagreement in discount rates than there is for terminal growth rates in an absolute sense. However, once we scale the measure by their respective average size, we find that, in relative terms, analysts tend to disagree more about the terminal growth rate than they do about discount rates (Figure 1, Panel B). This reversal is not necessarily surprising, since the average value of discount rates in our samples is equal to 8.92 pp, compared to 2.23 pp for the terminal growth rate, making a 1% deviation from the consensus for discount rates almost 4 times larger than for terminal growth rates mechanically.[1] On its face, the fact that absolute disagreement in discount rates is larger than it is for terminal growth rates is rather surprising.

Figure 2 displays the time-series patterns of the annual mean disagreement measures for both discount rates and terminal growth rates. Panel A confirms both the summary statistics in Table 1 and the cross-sectional distributions in Figure 1 and shows that the absolute disagreement in discount rates is larger than the absolute disagreement in terminal growth rates in every year of our sample except one (the year 2014). In fact, for portions of the sample such as the financial crisis, the absolute disagreement in discount rates is nearly 60% larger than it is for terminal growth rates.

Figure 2 also reveals several interesting time-series patterns. For example, disagreement, particularly in discount rates, tends to spike during periods of economic turmoil. Panel C also suggests that in terms of forecasting long-term cash flow growth, the COVID-19 shock was unique. That is, while disagreement in terminal growth rates only increased during the recovery period *after* the financial crisis, it increased dramatically at the beginning of the year 2020 as the full impact of the Coronavirus was just becoming fully understood.

Figures 1 and 2 strongly suggest that forecasters disagree more in an absolute sense regarding firm discount rates than they do regarding long-term cash flow growth, both in the cross-section and the time-series. Importantly, however, Equation 6 highlights that disagreement in the overall valuation of a security also depends on the relationship *between* disagreement in growth and discount rates. In an extreme case in which cash flow growth and discount rate disagreement are highly positively correlated, the disagreement in the individual components could be completely cancelled, leaving no disagreement regarding overall valuation.

As a first step in understanding the covariance between the disagreement in discount rates and terminal growth rates, Figure 3 plots the absolute disagreements against each other. Panel A plots the within firm-year disagreement and shows a positive association between terminal growth rates and discount rate disagreement. We note, however, that the

[1] The spike in scaled disagreement at 1 for terminal growth rates is due to the fact that many terminal growth rates are set at *round* reference points.

coefficient of correlation, though significantly different than zero, is not overly positive at 12%. This is also highlighted in Panel A as the line of best fit is much flatter than the 45° line.

Panel B of Figure 3 shows the positive association between the disagreement in the discount rates and terminal growth rates also appears across firms within the same industry. There is, however, considerable variation across industries, suggesting a role for firm characteristics in the level of disagreement in both components. For example, the Professional Services and Information industries are in the upper right corner (high disagreement in both discount rates and terminal growth rates), which is consistent with such firms being more difficult to value, both in terms of growth but also discount rates.

The upshot of Figure 3 is that the covariance between is likely not positive enough for disagreement in the components to cancel out disagreement in price. The most egregious way in which such a mechanism would happen is through analyst fudging. That is, analysts following the same firms might roughly agree on a price target that *needs* to be reached by their valuation exercises, such that differences in their cash flow expectations must be offset by their chosen discount rates. In such a case, one would expect to measure a strong positive correlation between growth expectations and discount rates, which is not the case in our data.

The fact that we document cross-sectional expected price disagreement (12% of the price consensus), as well as a weak correlation between discount rates and growth expectation disagreement helps mitigate concerns concerns regarding this type of fudging. We also note that Décaire and Graham (2023) shows that the partial correlation between discount rates and growth expectations for an analyst tracking a specific firm over time is virtually zero. However, to further explore this, Table 2 reports the distribution of analyst estimates that are above and below consensus for both discount rates and terminal growth rates.

This table suggests that 55% of the time, analysts deviate from the consensus estimate for discount rates and terminal growth rates in the same direction, again minimizing the impact of either the growth rate estimate or discount rate estimate on overall valuation. However, this leaves nearly half of the cases in our sample (45%) that deviate in the opposite direction. Overall, we interpret the lack of discernible patterns in 2 as reasonable evidence that analysts do not systematically fudge their valuation models to reach the price target *consensus*.

5.2 Price Disagreement Decomposition

While the previous section provided visual evidence of the importance of discount rate disagreement in overall disagreement regarding securities valuation, this section aims to be more rigorous and precise. In particular, we aim to quantify the impact of both long-term cash flow disagreement and discount rate disagreement in overall price target disagreement for the analyst forecasts. To structure our quantification exercise, we

Table 3 reports the results of the price disagreement decomposition regression. We find that both growth expectations and discount rates are key drivers, consistent with Décaire and Graham's (2023) results showing that both variables are important determinants of expected price fluctuations. However, we find that disagreement in long-term growth expectations explains a greater share of disagreement in security valuations than does disagreement in discount rates. This difference can be attributed to multiple reasons, such as the fact that growth expectations, particularly at a long horizon, are challenging to produce Dessaint et al. (2023). The coefficient for terminal growth rate disagreement is 4.2 and is statistically significant at the 5% level. However, disagreement in discount rates has a similar impact (in terms of magnitude) on disagreement in price targets. The coefficient is also significant at the 5% level.

To further explore the impact of each on disagreement in valuations, we perform an R^2 Shapley decomposition. Consistent with the regression coefficients, the Shapley decomposition suggests that each component of disagreement (discount rate and terminal growth) impacts disagreement in overall valuation nearly equally, with discount rate disagreement accounting for 47% of the variation in price target disagreement. Our results draw parallels with Keloharju et al.'s (2021) findings. While analysts use a flat discount rate to evaluate cash flows at different horizons, in contrast to Keloharju et al. (2021) that studies how discount rate dispersion declines at different horizons in the aggregate, we show that discount rate disagreement is even persistent when evaluating a specific firm and at a point in time. This refines and more narrowly shows that discount rate dispersion is operating not only at the market or industry level, but also at the stock level.

5.3 Discount Rate Disagreement

Sections 5.1 and 5.2 highlight how important discount rate disagreement is to overall securities valuation disagreement. In this section, we look to dive deeper into the reasons why forecasts disagree about the firms' discount rates.

As a first step to better understand the sources of disagreement in discount rates, we perform a simple analysis of variance (ANOVA) decomposition. The explanatory variables in our model are indicators for specific brokerage houses, individual analysts, and the covered firms, respectively. We take several initial precautions to ensure the results from our ANOVA are not driven by idiosyncratic features of our data. First, because we do not (yet) have the full names for all the individual lead analaysts in our sample, we restrict the ANOVA sample to those forecasts where we cleanly observe and can identify the exact analyst producing the report. Second, to account for the fact that the sample used to conduct the analysis is unbalanced, as we do not observe a discount rate estimate for every analyst-firm-year pair during the entire sample period, we estimate the sequential partial sum of squares. When doing an ANOVA with sequential decomposition, the estimation is not indifferent to varying the order of included variables, and in unreported tables, we perform all potential permutations. Table 4 reports the most conservative estimate for the effect of analyst and firm indicators (i.e., the results for the ordering with the greatest importance placed upon the brokerage house indicators in the decomposition).[2]

Finally, because there is a high degree of overlap between individual analysts and the brokerage houses that employ them, we restrict the sample of brokerage houses to those that produce at least 10 equity reports from analysts that we observe providing forecasts for multiple brokerage houses over the course of our sample. Doing so ensures that indicators for brokerage houses and analysts are separable and estimated consistently.

Table 4 reports the results of the ANOVA decomposition. Perhaps surprisingly, the brokerage house indicators explain only 2% of the variation captured by the full model. Rather, analyst indicators and firm indicators explain 58% and 40% of the variation captured by

[2] The ordering of analyst and firm indicators behind the brokerage indicators does play a role in the SSE estimation. Over the course of all the permutations of variables included, the analyst indicators explain between 40-60% of the variation captured by the models.

the model, respectively. These are results are inconsistent with a mechanism that brokerage houses dictate modeling methodologies and inputs across all analysts they employ. Rather, the results suggest that individual analysts and the firms they cover play the most important role in why there is disagreement in discount rates.

5.3.1 Discount Rate Disagreement Decomposition

The prior sections show that there is substantial disagreement in the discount rate estimates and that the majority of the variation is explained by individual analysts and firms, rather than specific brokerage houses. It is important to note that though these discount rates are subjective, the overwhelming majority (>99% in our sample) are produced via straightforward weighted average cost of capital (WACC) calculations. For this reason, a natural next step is to hone in on how the disagreements in the inputs of the WACC impact overall disagreement in discount rates, much as we did earlier for discount rate disagreement and terminal growth rate disagreement.

Again, we start with simple figures of disagreement in equity betas and the equity risk premium for the following: (1) individually in the cross-section, and (2) individually in the time-series. Figures 4 and 5 show the cross-sectional distributions and the time-series patterns for the annual averages, respectively, for both equity beta and equity risk premium disagreement. Panel A of Figure 4 shows the cross-sectional distributions for absolute disagreement. Unsurprising due to sheer magnitude differences in the direct inputs for equity betas and the equity risk premium, absolute disagreement in equity betas is an order of magnitude larger than that for the ERP.

On the contrary, the distributions for scaled disagreement, both in the cross-section (Figure 4 Panel B) and the time-series (Figure 5 Panel A) are similar. Once again, interesting features of the time-series patterns are evident. Both equity beta and equity risk premium disagreement seem to spike in NBER recessions, and overall display significant variation through time.

Because the inputs to the WACC estimation enter linearly (as opposed to the nonlinear structure of cash flows and discount rates in price), we avoid the need to derive a formal decomposition to structure our empirical analysis. Rather, we simply regress the disagreement in each input to the WACC on overall discount rate discount agreement. Formally, our functional form for the regressions is

$$\begin{aligned} &|Discount\ Rate_{a,i,t} - \overline{Discount\ Rate}_{i,t}| = \\ &\qquad |BETA_{a,i,t} - \overline{BETA}_{i,t}| + |ERP_{a,i,t} - \overline{ERP}_{i,t}| + |Rf_{a,i,t} - \overline{Rf}_{i,t}| \end{aligned} \tag{7}$$

Table 5 reports the results of this discount rate disagreement decomposition. Disagreement in each WACC input (e.g., equity beta, equity risk premium, and the risk-free rate) significantly impact disagreement in the discount rate. For example, the coefficient for equity beta disagreement in Model (1) is 0.006 and is statistically significant at the 1% level. Moreover, both equity risk premium and risk-free rate disagreement display coefficients that are significant at least the 5% level.

Once again, to further explore the impact of each on disagreement in discount rates, we perform an R^2 Shapley decomposition. Consistent with the regression coefficients, the Shapley decomposition suggests that each component of disagreement (equity betas, equity risk premium, and risk-free rates) impacts disagreement in discount rates. However, unlike the equal split in the Shapley decomposition for price targets in Table 3, this decomposition suggests that disagreement in equity betas explains the bulk of the variation in discount rate disagreement.

This is particularly true for the U.S. sample in Model (2). In particular, in this sample of firms, disagreement in equity beta explains nearly 80% of the variation in discount rate disagreement. Moreover, consistent with nearly all analysts using treasury bill yields as a proxy for the risk-free rate in the U.S. sample, disagreement in the risk-free rate explains nearly none of the variation in discount rate disagreement. On the contrary, the disagreement in risk-free rate for foreign firms in Model (3) explains nearly a third of the total variation, consistent with analysts choosing different benchmarks for the risk-free rates in their WACC estimation. Overall, the results in Table 5 suggest disagreement regarding equity betas is more important than disagreement in the other two inputs, particularly for domestic firms.

5.3.2 Benchmark Equity Betas

It is fair to wonder why disagreement in equity betas is so substantial and why it is so important for disagreement in discount rates. In fact, through manual reading and textual analysis of the equity reports, the vast majority of equity betas are estimated using the same methodology: the Capital Asset Pricing Model (CAPM). Precisely, when analysts discuss their methodology to estimate betas, Décaire and Graham (2023) finds that in more than 96% of cases, analysts use the CAPM. There remains, however, subjectivity in the model inputs for CAPM. In particular, analysts must choose (a) the frequency of returns (e.g., weekly, monthly, etc.), and (b) the horizon over which beta is estimated from the regression analysis (e.g., 24 months, 36 months, etc.). That is, the analyst's choice of benchmark equity beta could potentially be an important source of disagreement for the discount rate calculation, and accordingly, securities valuation.

To investigate this, we focus on the discretion analysts exercise in the choice of horizon for their benchmark equity beta. We note that only a small number of equity reports directly publish the horizon of stock returns used to calculate their equity beta. For example, Table 6 shows the distributions of different horizons extracted via textual analysis by industry and (name redacted) brokerage house.

In order to utilize the entire sample of reported equity betas, not just those that directly report the horizon for the benchmark equity betas, we create what we term synthetic benchmark equity betas. In order to calculate such a synthetic beta, we make several assumptions. First, we assume that individual analysts use the same horizon of stock returns for all CAPM betas that they estimate. That is, we impose a time- and firm-invariant component to beta estimation within a specific analyst's reports through time. Second, we assume any differences between the CAPM equity betas we estimate using different horizons of returns and the reported analyst equity betas is due to noise and not some systematic bias.

Then, we estimate synthetic benchmark betas in the following way. First, using stock return data from Datastream, we estimate CAPM equity betas for each firm employing four different return horizons: 24 months, 36 months, 48 months, and 60 months. Second, for each analyst-firm pair, we calculate the sum of squared errors between the analyst equity beta and the CAPM equity betas for the firms across each different horizon. Finally, we classify the analyst equity beta as the horizon of the CAPM equity beta in which the sum of squared errors across all analyst-firm observations is minimized.

Figure 6 displays the time-series patterns for analyst and benchmark CAPM-estimated (synthetic) equity betas for different horizons. The blue lines depict annual average analyst equity betas that are classified as the corresponding horizon from the sum of squared errors approach. The red lines depict the annual average CAPM-estimated equity betas for the same firms using the corresponding horizon. Finally, the dashed gray and green lines depict the counterfactual annual average CAPM-estimated equity betas for the same firms, but using a horizon that does *not* correspond to the horizon classified using the sum of squared errors approach. Each panel of Figure 6 suggests that our synthetic equity betas track the overall CAPM-estimated equity betas for that horizon quite well. In particular, each panel shows substantial improvement in tracking the CAPM betas than an uninformed benchmark of a different horizon. All in all, Figure 6 provides reassurance that our synthetic equity beta estimation procedure yields valid results.

Next, we calculate the number of different benchmark betas (e.g., the number of different horizons in our synthetic beta approach) across all the different analyst forecasts for a given firm-year observation. Then we regress this number of benchmark betas on the absolute disagreement in reported analyst equity betas. The results appear in Table 7. The coefficient in Model (1) is 0.020 and is statistically significant at the 1% level. The economic magnitude of this effect is also significant as increasing the number of benchmark betas used in a firm-year by one increases the absolute disagreement in analyst equity betas by 18% relative to the unconditional mean.

To rule out a mechanical relationship between the number of benchmark betas and the number of total analyst forecasts in a firm-year, Model (2) adds fixed effects for the number of total forecasts. Moreover, Model (3) adds a control for the dispersion of the CAPM-estimated betas over the four horizons. The effect of the number of benchmark betas in Models (2) and (3) remains strong and significant. This suggests that the results are not driven simply by the number of analyst forecasts or the spread in CAPM-estimated betas over the different horizons. Finally, the results hold after adding fixed effects for industry and year, suggesting the impact is not driven but certain firms or time periods. Overall, these results suggest that even if all analysts employ the same methodology (e.g., textbook-based CAPM estimation for beta), subjective choices over the inputs can still lead to considerable disagreement in discount rates, and thus overall security valuation.

5.3.3 Firm Characteristics

Previous results in the above sections suggest that disagreement in discount rates may be impacted by certain firms and their characteristics. To investigate this more deeply, we directly analyze three salient firm characteristics that the prior literature has documented may lead to more difficulty in valuation. In particular, we focus on what the literature refers to as hard-to-value stocks: more complicated firms (Cohen and Lou, 2012), more R&D intense firms (Chan et al., 2001), and younger firms (Kumar, 2009).

Cohen and Lou's (2012) measure for complicated or complex firms is whether or not the firm is a conglomerate. Because of our selected sample, the overwhelming majority of our firms have multiple operating and geographic segments, making such a measure slightly less informative about the complexity of the firm. Moreover, due to data constraints for foreign firms, we only observe header variables for the number of segments each firm has at the last date this was measured for each firm in Refinitiv. Thus, to avoid these issues, we focus on a measure of complexity that is readily observable through time for our entire sample: firm size. Using textual analysis of firms' 10ks, Loughran and McDonald (2023) note that complexity is distinct from firm size, yet note the two remain positively correlated. We measure firm size using the log of total assets during each year.

On the contrary, measuring R&D intensity and firm age is relatively straightforward. First, we scale research and development by total assets as a proxy for R&D intensity, and second, we proxy for firm age using the number of years since the firm's initial public offering (IPO). Each of these data items is sourced from Refinitiv. We regress these proxies on the absolute disagreement in discount rates. The results appear in Table 8.

Model (1) in Table 8 only includes firm size as an explanatory variable and shows little effect in the full sample. When adding R&D intensity and firm age in Model (2), our sample drops to 25,170 observations as we only observe clean measures of IPO dates for part of the sample. However, when including all three measures of hard-to-value stocks, each enters with the hypothesized sign and is statistically significant at the 1% level. That is, consistent with previous work, the results in Model (2) suggest that bigger and more complex, more innovative, and younger firms yield more disagreement in discount rate estimates amongst the analysts that follow them.

Models (3) through (6) sequentially add fixed effects for industry, country, year, and industry $\times$ year. The coefficients for all three variables of interest remain stable and significant across each model.[3] These results suggest that the firm characteristics that play an important overall role in making firms hard to value do not impact only cash flow estimation, but also impact discount rate estimation.

6 Conclusion

This paper has studied the drivers of disagreement in securities valuation from the perspective of financial analysts. While prior work has focused mainly on the disagreement in analysts' cash flow forecasts, our findings suggest that the variation in the discount rate is at least as important for explaining the variation in a stock's intrinsic value. Our evidence highlights surprisingly high flexibility in the analysts' choice of estimation horizons and key inputs of standard asset pricing models. These methodological choices generate large cross-sectional dispersion in a firm's cost of capital and value per share. The pivotal role of the discount rate as a driver of analyst disagreement is somewhat unexpected, given the common tenet that analysts produce information mainly by estimating earnings and growth prospects rather than refining a firm's cost of capital.

Our study makes a step towards understanding the inner mechanisms of professional securities valuation. While most research has focused on valuation outcomes and their effects on market activity, our paper identifies key inputs and assumptions that produce the variation in these outcomes. Our evidence suggests that these methodological choices reside with individual analysts rather than the investment firm. It remains an open question why analysts with similar professional backgrounds at comparable investment firms make distinct

[3] Firm size becomes insignificant in just one model when including only country fixed effects.

methodological elections, a topic we hope to explore in a future draft.

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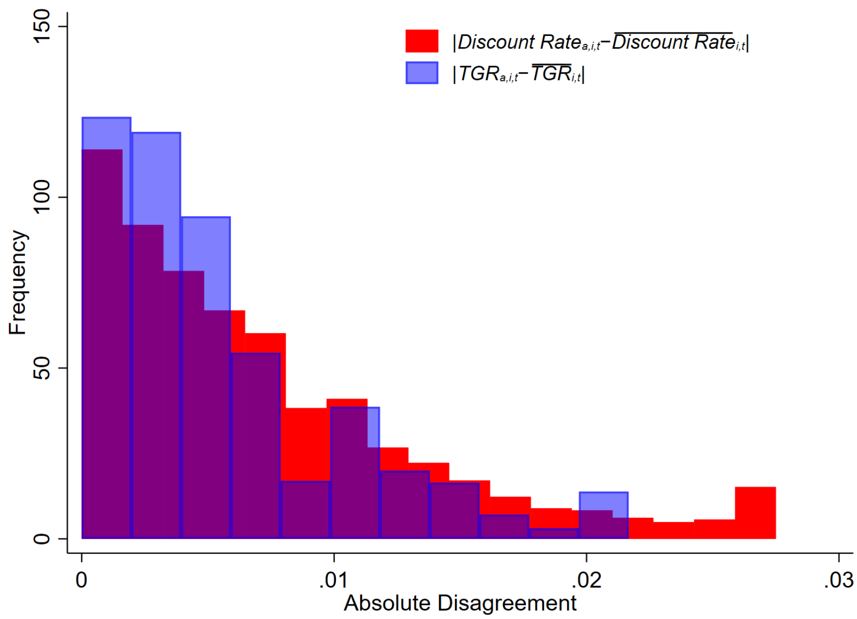
Figure 1: Cross-Sectional Densities for Disagreement in Analyst Discount Rates and Terminal Growth Rates. These figures display cross-sectional distributions for disagreement in analysts' estimates of a firm's discount rate and terminal growth rates (TGR). The sample period is 2000 through 2023. Panel (A) displays the cross-sectional distributions in *absolute* disagreement for analyst discount rate and TGR, where absolute disagreement is defined as the absolute deviation of an individual analyst's estimate from the consensus (mean) estimate for a given firm-year. Panel (B) displays the cross-sectional distributions in *scaled* disagreement for analyst discount rate and TGR, where scaled disagreement is defined as the absolute deviation of an individual analyst's estimate from the consensus (mean) estimate for a given firm-year divided by the consensus estimate. Data on individual analysts' estimates of discount rate and TGR are hand-collected from sell-side analyst equity research reports.

(A) Absolute Disagreement Densities



(B) Scaled Disagreement Densities

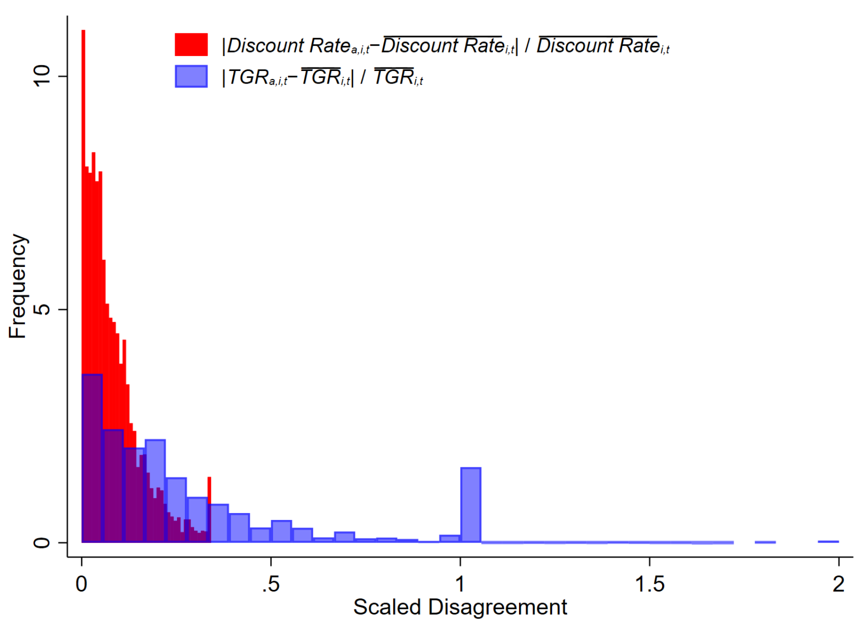
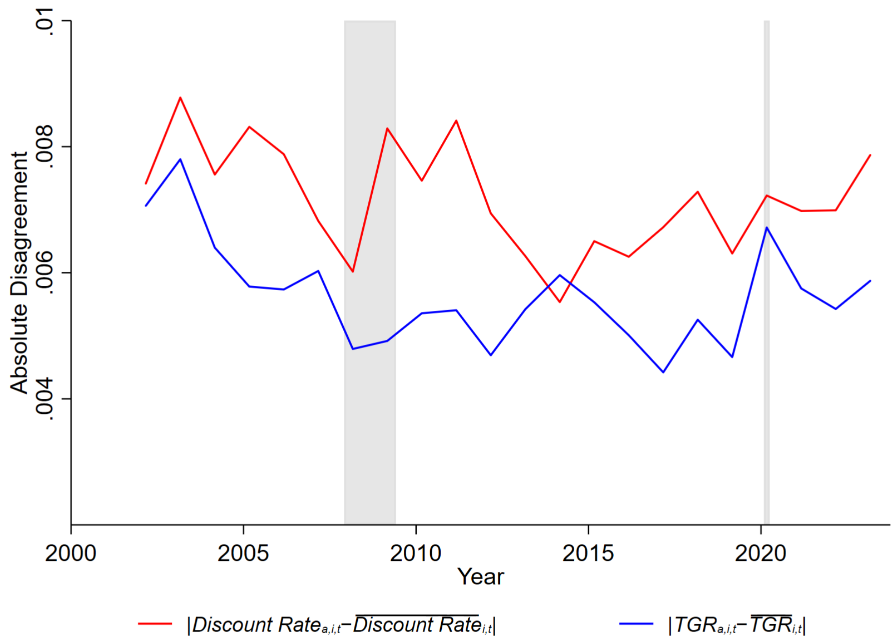
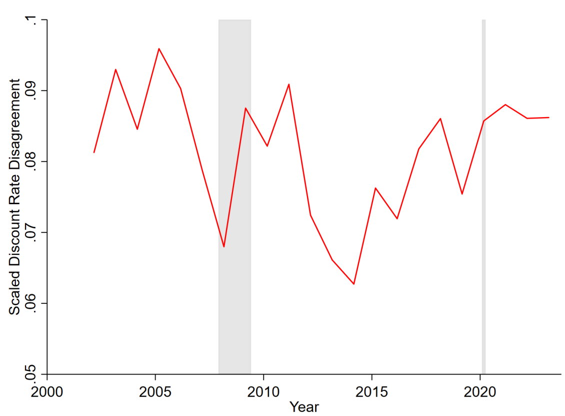


Figure 2: Disagreement in Analyst Discount Rates and Terminal Growth Rates in the Time-Series. These figures display time-series patterns for disagreement in analysts' estimates of a firm's discount rates and terminal growth rates (TGR). The sample period is 2000 through 2023. Panel (A) displays the time-series patterns in *absolute* disagreement for analyst discount rates and TGR, where absolute disagreement is defined as the absolute deviation of an individual analyst's estimate from the consensus (mean) estimate for a given firm-year. Panel (B) displays the time-series pattern in *scaled* disagreement for analyst discount rates, where scaled disagreement is defined as the absolute deviation of an individual analyst's estimate from the consensus (mean) estimate for a given firm-year divided by the consensus estimate. Finally, Panel (C) displays the time-series pattern in *scaled* disagreement for analyst TGRs. Gray bars represent NBER recessions using data from the St. Louis Federal Reserve Bank. Data on individual analysts' estimates of discount rates and TGRs are hand-collected from sell-side analyst equity research reports.

(A) Absolute Disagreement.



(B) Scaled Analyst Discount Rate Disagreement.



(C) Scaled Analyst TGR Disagreement

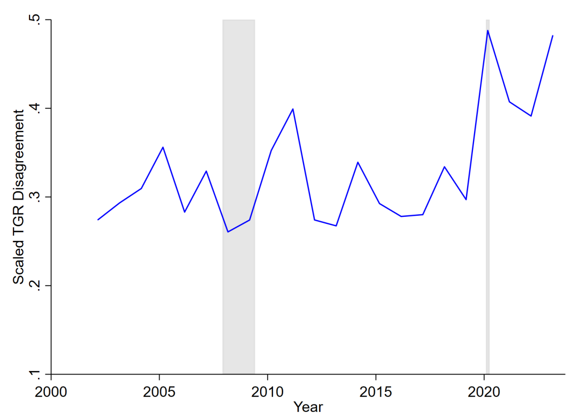
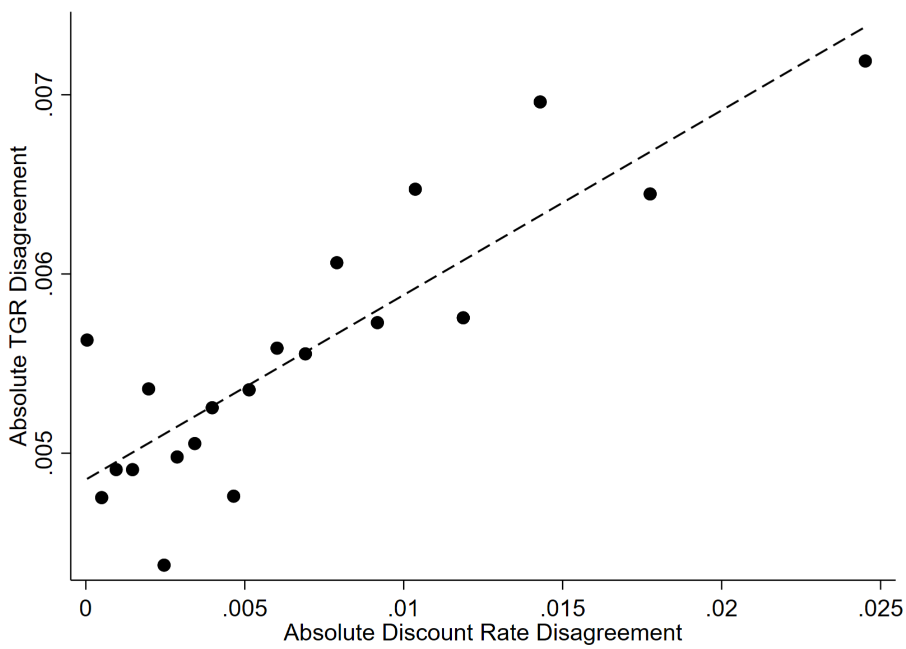


Figure 3: The Relationship between Analyst Discount Rate and Terminal Growth Rate Disagreement. These figures display scatter plots of disagreement in analysts' estimates of firms' discount rates relative to disagreement in estimates of terminal growth rates (TGR). The sample period is 2000 through 2023. Panel (A) displays the *absolute* disagreement for analyst discount rates and TGRs within a given firm-year observation, where absolute disagreement is defined as the absolute deviation of an individual analyst's estimate from the consensus (mean) estimate. Panel (B) displays the absolute disagreement calculated in the cross-section of different industries, defined at the two digit NAICS-level. Data on individual analysts' estimates of discount rates and TGRs are hand-collected from sell-side analyst equity research reports.

(A) Within Firm-Year Disagreement



(B) With-in Industry Disagreement

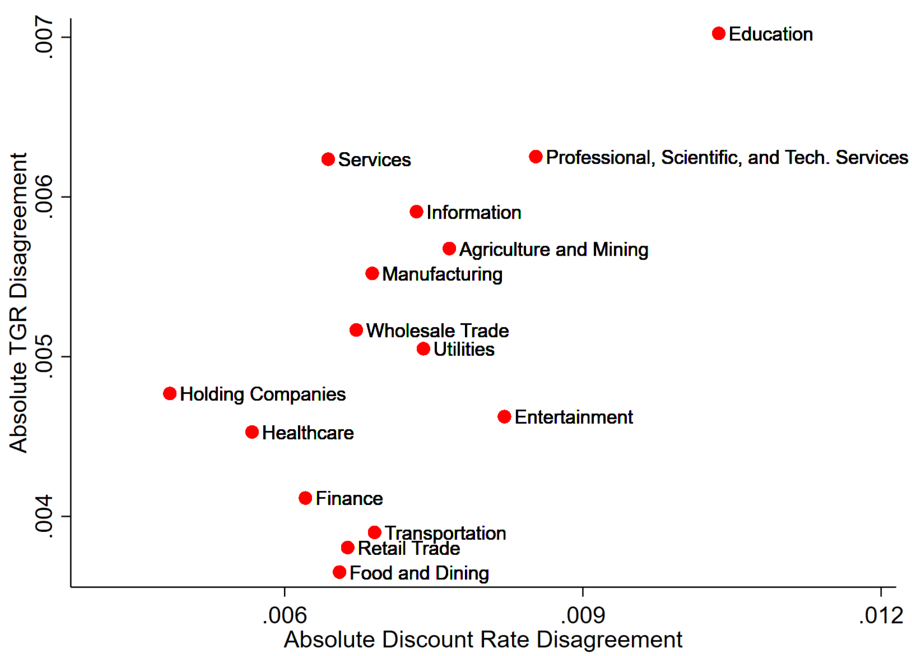
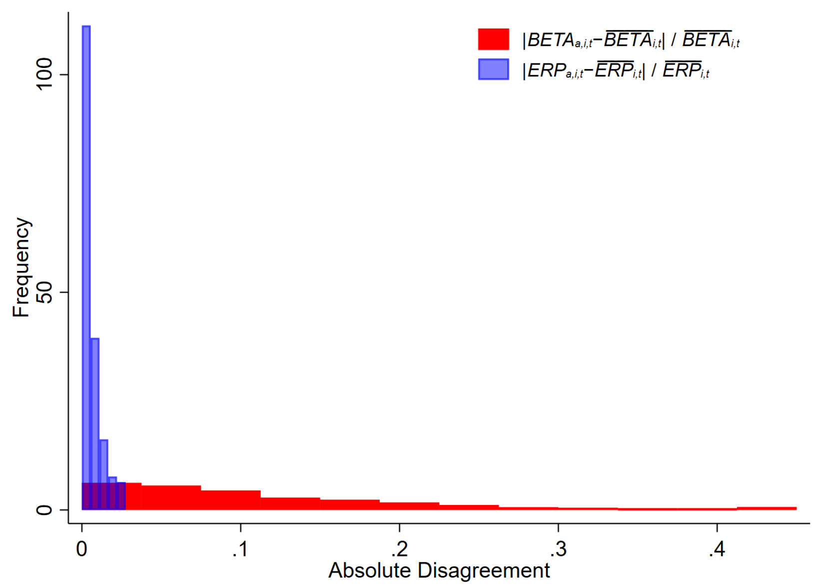


Figure 4: Cross-Sectional Densities for Disagreement in Analyst Equity Betas and Equity Risk Premiums. These figures display cross-sectional distributions for disagreement in analysts' estimates of a firm's equity beta and equity risk premium (ERP). The sample period is 2000 through 2023. Panel (A) displays the cross-sectional distributions in *absolute* disagreement for equity beta and ERP, where absolute disagreement is defined as the absolute deviation of an individual analyst's estimate from the consensus (mean) estimate for a given firm-year. Panel (B) displays the cross-sectional distributions in *scaled* disagreement for analyst equity beta and ERP, where scaled disagreement is defined as the absolute deviation of an individual analyst's estimate from the consensus (mean) estimate for a given firm-year divided by the consensus estimate. Data on individual analysts' estimates of equity beta and ERP are hand-collected from sell-side analyst equity research reports.

(A) Absolute Disagreement Densities



(B) Scaled Disagreement Densities

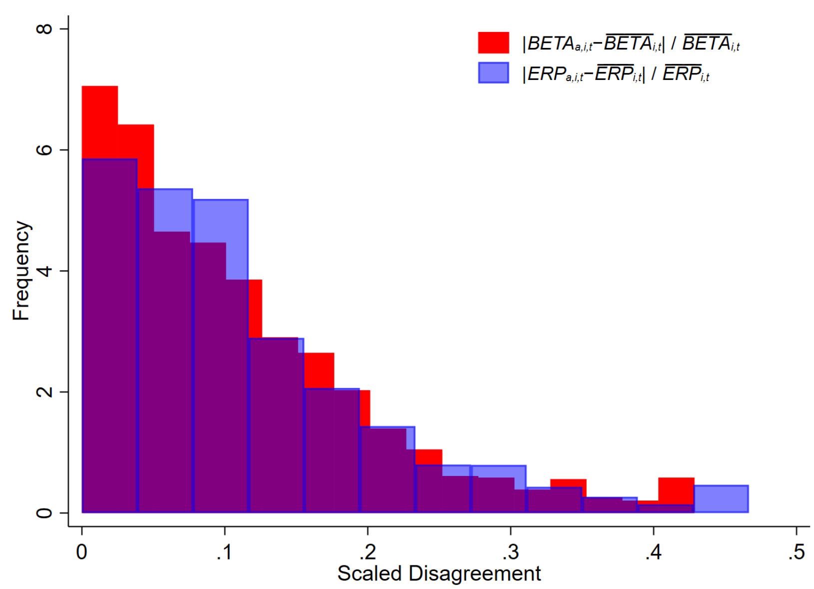
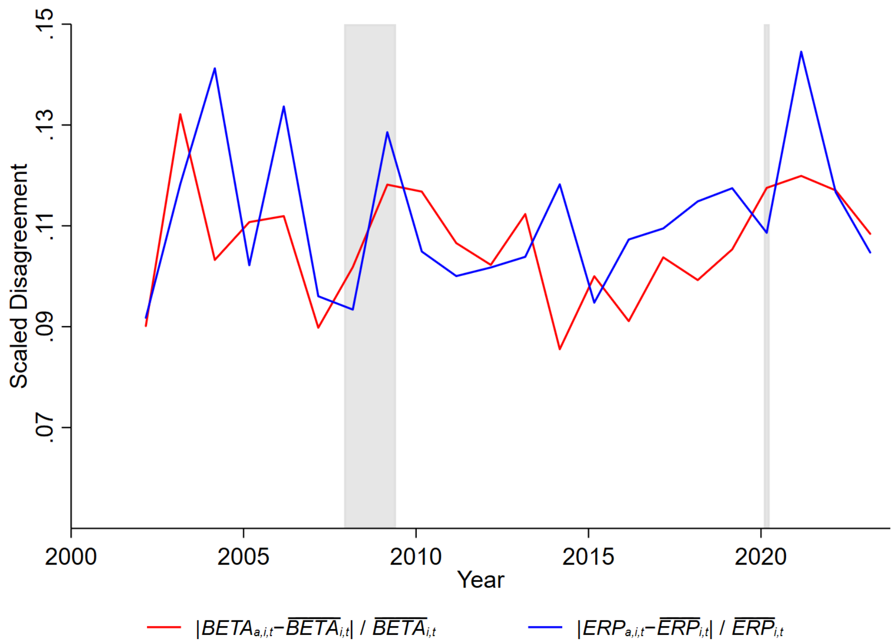
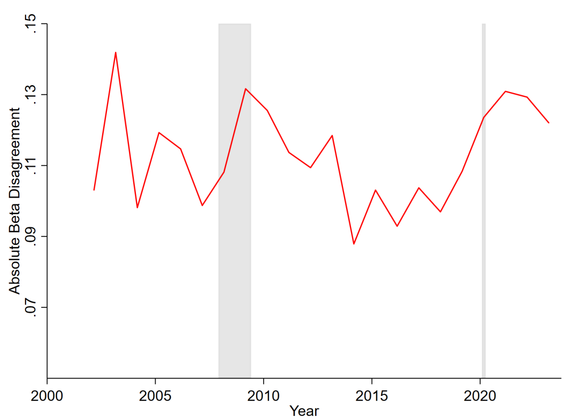


Figure 5: Disagreement in Analyst Equity Beta and Equity Risk Premium in the Time-Series. These figures display time-series patterns for disagreement in analysts' estimates of firms' equity betas and equity risk premiums (ERP). The sample period is 2000 through 2023. Panel (A) displays the time-series patterns in *scaled* disagreement for analyst equity betas and ERPs, where absolute disagreement is defined as the absolute deviation of an individual analyst's estimate from the consensus (mean) estimate for a given firm-year divided by the consensus estimate. Panel (B) displays the time-series pattern in *absolute* disagreement for analyst equity betas, where scaled disagreement is defined as the absolute deviation of an individual analyst's estimate from the consensus (mean) estimate for a given firm-year. Finally, Panel (C) displays the time-series pattern in in *absolute* disagreement for analyst ERPs. Gray bars represent NBER recessions using data from the St. Loius Federal Reserve Bank. Data on individual analysts' estimates of equity beta and ERP are hand-collected from sell-side analyst equity research reports.

(A) Scaled Disagreement.



(B) Absolute Equity Beta Disagreement.



(C) Absolute ERP Disagreement

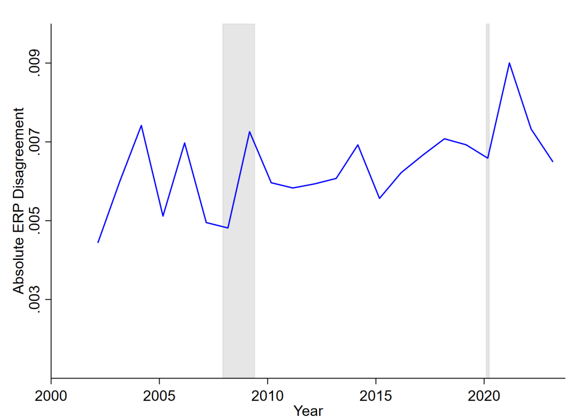


Figure 6: Classified Horizons and Analyst Equity Betas Versus CAPM Equity Betas. These figures display time-series patterns for analyst and benchmark CAPM-estimated equity betas for different horizons. The horizons are estimated using a minimized sum of squared errors approach. In particular, for each analyst-firm pair, we calculate the sum of squared errors between the analyst equity beta and the CAPM estimated equity betas for each of four horizons: 24 months, 36 months, 48 months, and 60 months. We classify the analyst equity beta as the horizon of the CAPM equity beta in which the sum of squared errors are minimized. The overall sample period is 2000 through 2023, though the figures are presented with data only from 2005-2023 due to sparse coverage from the early 2000s. The blue lines depict annual average analyst equity betas that are classified as the corresponding horizon from the sum of squared errors approach. The red lines depict the annual average CAPM-estimated equity betas for the same firm-analyst pairs using the corresponding horizon. Finally, the dashed gray and green lines depict the counterfactual annual average CAPM-estimated equity betas for the same firm-analyst pairs, but using a horizon that does *not* correspond to the horizon classified using the sum of squared errors approach. Data on security returns to estimate CAPM equity betas is taken from Datastream. Data on individual analysts' estimates of equity beta are hand-collected from sell-side analyst equity research reports.

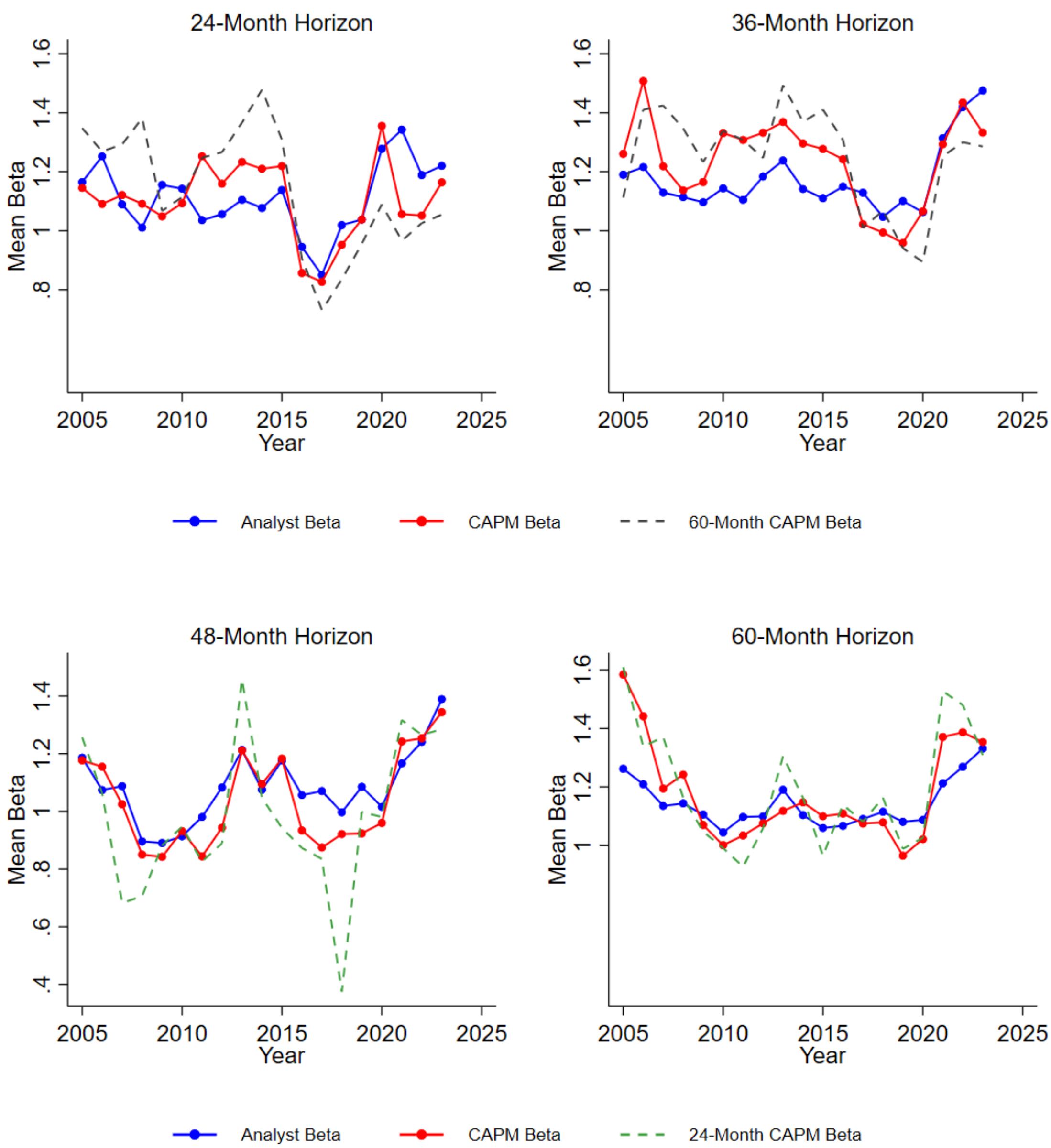


Table 1: Summary Statistics. This table reports summary statistics. The full sample (discount rate sample) consists of 3,971 firms with observations from 42,720 equity reports covering the years 2000 through 2023. Panel A describes the sample coverage and firm characteristics. Panel B focuses on variables associated with equity reports. Data on firm characteristics is taken from Refinitiv. Data on individual analysts' estimates of DCF inputs are hand-collected from sell-side analyst equity research reports. Subscript a identifies a specific analyst, subscript i a specific firm, and subscript t the year. Variable definitions appear in Appendix B.

Panel A: Firms and Coverage						
	No. Firm			No. Obs		
Discount rate sample	3,971			42,720		
Terminal growth rate sample	2,993			25,182		
Analysts equity beta sample	1,116			5,797		
Analysts equity risk premium sample	942			4,344		
Analysts risk-free rate sample	956			4,565		
Price target sample	1,073			8,292		
	Mean	25^{th} Pct.	Median	75^{th} Pct.	Std. Dev.	No. Obs.
Firm Variables						
Analyst coverage$_i$ (No. of analysts)	5.17	2.00	3.00	6.00	5.08	3,971
Years in sample$_i$ (in years)	4.01	1.00	2.00	5.00	4.17	3,971
Total assets$_i$ (in Billions USD)	572.8	1.0	3.9	18.4	6270.0	3,971
R&D expense/total assets$_i$(%)	2.3	0.0	0.0	1.1	5.8	3,971
Firm age$_i$ (in years)	14.3	4.7	10	19.2	14.9	2,249
Panel B: Equity Reports	Mean	25^{th} Pct.	Median	75^{th} Pct.	Std. Dev.	No. Obs.
DCF Inputs						
Analyst discount rate$_{a,i,t}$ (%)	8.92	7.60	8.70	10.00	1.93	42,720
Analyst terminal growth rate$_{a,i,t}$ (%)	2.23	1.50	2.00	3.00	1.31	51,016
Analyst equity beta$_{a,i,t}$	1.09	0.90	1.05	1.20	0.28	11,563
Analyst equity risk premium$_{a,i,t}$ (%)	5.70	5.00	5.50	6.30	1.39	10,262
Analyst risk-free rate$_{a,i,t}$ (%)	3.98	2.90	4.00	5.00	1.73	10,129
Disagreement Measures						
$\lvert Discount\ Rate_{a,i,t} - \overline{Discount\ Rate}_{i,t}\rvert$ (pp.)	0.77	0.25	0.59	1.09	0.69	42,720
$\lvert Discount\ Rate_{a,i,t} - \overline{Discount\ Rate}_{i,t}\rvert / \overline{Discount\ Rate}_{i,t}$ (%)	8.77	3.02	6.70	12.28	7.67	42,720
$\lvert TGR_{a,i,t} - \overline{TGR}_{i,t}\rvert$ (pp.)	0.61	0.25	0.50	0.86	0.54	25,182
$\lvert TGR_{a,i,t} - \overline{TGR}_{i,t}\rvert / \overline{TGR}_{i,t}$ (%)	37.23	9.09	20.00	48.28	45.73	24,860
$\lvert Beta_{a,i,t} - \overline{Beta}_{i,t}\rvert$	0.11	0.04	0.09	0.16	0.10	5,797
$\lvert Beta_{a,i,t} - \overline{Beta}_{i,t}\rvert / \overline{Beta}_{i,t}$ (%)	10.70	3.91	8.55	15.38	9.35	5,797
$\lvert ERP_{a,i,t} - \overline{ERP}_{i,t}\rvert$ (pp.)	0.64	0.25	0.50	0.83	0.60	4,344
$\lvert ERP_{a,i,t} - \overline{ERP}_{i,t}\rvert / \overline{ERP}_{i,t}$ (%)	11.02	4.00	9.09	15.09	9.79	4,344
$\lvert Rf_{a,i,t} - \overline{Rf}_{i,t}\rvert$ (pp.)	0.54	0.20	0.40	0.75	0.52	4,565
$\lvert Rf_{a,i,t} - \overline{Rf}_{i,t}\rvert / \overline{Rf}_{i,t}$ (%)	16.35	4.76	10.00	20.00	18.89	4,565

Table 2: Frequency of Above and Below Consensus Estimates of Analyst Discount Rates and Terminal Growth Rates. This table reports the frequency of analyst estimates for discount rates and terminal growth rates (TGR) that are above and below the consensus (mean) estimate for a given firm-year pair. Data on individual analysts' estimates of discount rates and TGRs are hand-collected from sell-side analyst equity research reports.

		Discount $Rate_{a,i,t}$		
		Above Consensus	Below Consensus	Total
$TGR_{a,i,t}$	Above Consensus	29.9% 1,418	25.4% 1,205	55.3% 2,623
	Below Consensus	19.0% 902	25.6% 1,216	44.7% 2,118
	Total	48.9% 2,320	51.1% 2,421	100.0% 4,741

Table 3: Decomposition of Disagreement in Analyst Price Target Estimates. This table reports the results of a linear regression model and the corresponding Shapley decomposition of the R-squared. The sample period is 2000 through 2023. The dependent variable is the absolute disagreement in the log of analyst price targets, which is defined as the absolute deviation of the log of an individual analyst's estimate of price target from the consensus (mean) estimate for a given firm-year. The independent variables of interest are the absolute disagreement in the log of one plus the analyst discount rate and the log of one plus the analyst terminal growth rate (TGR), respectively. The absolute disagreement in these variables is defined in similar manner as the absolute disagreement in the analyst price target. Data on individual analysts' estimates of price targets, discount rate, and TGR are hand-collected from sell-side analyst equity research reports. Robust standard errors, clustered at the firm level, are reported in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\lvert ln(Price_{a,i,t}) - ln(\overline{Price}_{i,t})\rvert$
	(1)
$\lvert ln(1+TGR_{a,i,t}) - ln(1+\overline{TGR}_{i,t})\rvert$	4.241**
	(1.714)
$\lvert ln(1+Discount\ Rate_{a,i,t}) - ln(1+\overline{Discount\ Rate}_{i,t})\rvert$	3.477**
	(1.612)
Observations	4,740
F Statistic	5.33
R^2	0.01
R^2 Shapley Decomposition	
$\lvert ln(1+TGR_{a,i,t}) - ln(1+\overline{TGR}_{i,t})\rvert$	52.81%
$\lvert ln(1+Discount\ Rate_{a,i,t}) - ln(1+\overline{Discount\ Rate}_{i,t})\rvert$	47.19%

Table 4: ANOVA Variance Decomposition of the Disagreement in Analyst Discount Rates. This table reports the results of an analysis of variance (ANOVA) for the absolute disagreement in analyst discount rates, which is defined as the absolute deviation of an individual analyst's estimate of discount rate from the consensus (mean) estimate for a given firm-year. The independent variables of interest are indicator variables for firm, the brokerage house covering the firm, and for the analyst completing the equity report. Data on individual analysts' estimates of discount rates are hand-collected from sell-side analyst equity research reports.

ANOVA Variance Decomposition

	Percentage	Partial Adjusted R^2
Brokerage Indicators	2%	0.01
Analyst Indicators	58%	0.12
Firm Indicators	40%	0.06
R^2	0.44	
Adjusted R^2	0.23	

Table 5: Decomposition of Disagreement in Analyst Discount Rate Estimates. This table reports the results of linear regression models and the corresponding Shapley decompositions of the R-squareds. The sample period is 2000 through 2023. The dependent variable is the absolute disagreement in analyst discount rates, which is defined as the absolute deviation of an individual analyst's estimate of discount rate from the consensus (mean) estimate for a given firm-year. The independent variables of interest are the absolute disagreement in the analysts' estimates of equity beta, the risk-free rate (Rf), and the equity risk premium (ERP), respectively. The absolute disagreement in these variables is defined in similar manner as the absolute disagreement in analyst discount rates. Data on individual analysts' estimates of discount rates, equity betas, Rfs, and ERPs are hand-collected from sell-side analyst equity research reports. Robust standard errors, clustered at the firm level, are reported in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\lvert Discount\ Rate_{a,i,t} - \overline{Discount\ Rate}_{i,t}\rvert$		
Sample =	All	U.S. Only	Foreign Only
	(1)	(2)	(3)
$\lvert Beta_{a,i,t} - \overline{Beta}_{i,t}\rvert$	0.006***	0.008*	0.005**
	(0.002)	(0.004)	(0.002)
$\lvert ERP_{a,i,t} - \overline{ERP}_{i,t}\rvert$	0.083***	0.051	0.075**
	(0.028)	(0.062)	(0.032)
$\lvert Rf_{a,i,t} - \overline{Rf}_{i,t}\rvert$	0.070**	0.022	0.077**
	(0.035)	(0.106)	(0.037)
Observations	2,618	382	2,236
F Statistic	9.09	1.91	5.51
R^2	0.02	0.02	0.01
R^2 Shapley Decomposition			
$\lvert Beta_{a,i,t} - \overline{Beta}_{i,t}\rvert$	47.37%	79.59%	37.59%
$\lvert ERP_{a,i,t} - \overline{ERP}_{i,t}\rvert$	36.22%	19.22%	35.31%
$\lvert Rf_{a,i,t} - \overline{Rf}_{i,t}\rvert$	16.40%	1.19%	27.10%

Table 6: Distribution of Benchmark Betas Across Industry and Brokerage House. This table reports .

	Horizon 2	Horizon 3	Horizon 4	Horizon 5	Horizon 6 to 9	Total
Panel A: Industry Dispersion via Textual Analysis						
Information (51)	35 (25%)	28 (20%)	3 (2%)	58 (41%)	21 (15%)	140
Mining / Oil & Gas (21)	43 (49%)	9 (10%)	2 (2%)	31 (36%)	3 (3%)	87
Professional Services (54)	9 (13%)	13 (18%)	1 (1%)	44 (62%)	6 (8%)	71
Retail Trade (44, 45)	21 (38%)	8 (15%)	0 (0%)	27 (49%)	1 (2%)	55
Transportation (48, 49)	12 (22%)	5 (9%)	2 (4%)	32 (58%)	4 (7%)	55
Wholesale Trade (42)	12 (38%)	1 (3%)	1 (3%)	13 (41%)	5 (16%)	32
Utilities (22)	7 (26%)	7 (26%)	1 (4%)	12 (44%)	1 (4%)	27
Finance and Insurance (52)	11 (42%)	1 (4%)	1 (4%)	13 (50%)	0 (0%)	26
Real Estate (53)	5 (25%)	3 (15%)	0 (0%)	13 (65%)	0 (0%)	20
Panel B: Brokerage House Dispersion via Textual Analysis						
Brokerage House 1	113 (66%)	15 (9%)	0 (0%)	45 (26%)	6 (4%)	171
Brokerage House 2	5 (4%)	8 (7%)	2 (2%)	83 (72%)	21 (18%)	116
Brokerage House 3	53 (60%)	2 (2%)	0 (0%)	29 (33%)	9 (10%)	88
Brokerage House 4	27 (40%)	10 (15%)	0 (0%)	36 (53%)	2 (3%)	68
Brokerage House 5	4 (6%)	4 (6%)	5 (7%)	46 (69%)	8 (12%)	67
Brokerage House 6	17 (26%)	18 (27%)	0 (0%)	34 (52%)	3 (5%)	66
Brokerage House 7	3 (5%)	11 (20%)	0 (0%)	39 (70%)	5 (9%)	56
Brokerage House 8	20 (36%)	22 (40%)	2 (4%)	12 (22%)	10 (18%)	55
Brokerage House 9	12 (26%)	10 (22%)	1 (2%)	24 (52%)	2 (4%)	46
Brokerage House 10	0 (0%)	24 (57%)	0 (0%)	16 (38%)	4 (10%)	42

Table 7: Disagreement in Equity Betas and the Use of Different Benchmark Equity Betas. This table reports the results of linear regression models in which the dependent variable is the absolute disagreement in analyst equity beta, which is defined as the absolute deviation of an individual analyst's estimate of equity beta from the consensus (mean) estimate for a given firm-year. The sample period is 2000 through 2023. The independent variable of interest is the number different benchmark (horizon) CAPM equity betas used by analysts covering the same firm in the same year. Benchmark CAPM equity betas are estimated using a minimized sum of squared errors approach. In particular, for each analyst-firm pair, we calculate the sum of squared errors between the analyst equity beta and the CAPM estimated equity betas for each of four horizons: 24 months, 36 months, 48 months, and 60 months. We classify the analyst equity beta as the horizon of the CAPM equity beta in which the sum of squared errors are minimized. Data on securities returns to estimate CAPM equity betas is taken from Datastream. Data on individual analysts' estimates of discount rates, equity betas, Rsf, and ERPs are hand-collected from sell-side analyst equity research reports. Robust standard errors, clustered at the firm level, are reported in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dependent variable =	$\lvert Beta_{a,i,t} - \overline{Beta}_{i,t} \rvert$				
	(1)	(2)	(3)	(4)	(5)
Number of Benchmark Betas$_{i,t}$	0.020***	0.019***	0.020***	0.021***	0.021***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Std.(Benchmark Betas$_{i,t}$)			0.024*	0.022	0.069***
			(0.014)	(0.014)	(0.016)
Number of Forecasts FE		✓	✓	✓	✓
Industry FE				✓	✓
Year FE					✓
Observations	5,117	5,117	5,117	5,117	5,117
F Statistic	28.98	20.33	11.72	13.39	21.45
R^2	0.02	0.02	0.02	0.04	0.06

Table 8: Disagreement in Analyst Discount Rates and Firm Characteristics. This table reports the results of linear regression models in which the dependent variable is the absolute disagreement in analyst discount rates, which is defined as the absolute deviation of an individual analyst's estimate of discount rate from the consensus (mean) estimate for a given firm-year. The sample period is 2000 through 2023. The independent variables of interest are the log of total assets, research and development (R&D) expense scaled by total assets, firm age. Data on firm characteristics is taken from Refinitiv. Data on individual analysts' estimates of discount rates are hand-collected from sell-side analyst equity research reports. Robust standard errors, clustered at the firm level, are reported in parentheses. *,**, and *** denote significance at the 10%, 5%, and 1% level, respectively

Dependent variable =	$\lvert Discount\ Rate_{a,i,t} - \overline{Discount\ Rate}_{i,t}\rvert$					
	(1)	(2)	(3)	(4)	(5)	(6)
log(Total Assets$_{i,t}$)/10	0.000	0.001***	0.001***	-0.000	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D Expense / Total Assets$_{i,t}$		0.009***	0.009***	0.006***	0.011***	0.012***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Firm Age$_{i,t}$ (100 years)		-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry FE			✓			
Country FE				✓		
Year FE					✓	
Industry × Year FE						✓
Observations	42,720	25,170	25,170	25,170	25,170	25,170
F Statistic	1.51	18.47	16.66	13.17	20.18	20.27
R^2	0.00	0.01	0.01	0.03	0.02	0.06

Appendix A: Variable Definitions

Table A1: Variable Definitions

Subscript a indicates a specific analyst, i indicates a specific firm, and t indicates a year. This table includes only the definitions for the absolute disagreement measures. The scaled disagreement measures are defined as the absolute measures divided by the consensus estimate for that given measure in each respective firm-year observation.

Variable	Definition
Analysts' discount rate$_{a,i,t}$	The discount rate used by analysts to evaluate firm cash flow in equity reports.
Analysts' terminal growth rate$_{a,i,t}$ (TGR)	The terminal growth rate used by equity analysts in their DCF models, measured from the equity reports.
Analysts' equity beta$_{a,i,t}$	The equity beta used by analysts when computing their discount rate in equity reports.
Analysts' equity risk premium$_{a,i,t}$ (ERP)	The equity risk premium used by analysts when computing their discount rate in equity reports.
Analysts' risk-free rate$_{a,i,t}$ (Rf)	The risk-free rate used by analysts when computing their discount rate in equity reports.
$\lvert Discount\ Rate_{a,i,t} - \overline{Discount\ Rate}_{i,t}\rvert$	The absolute deviation of an individual analyst's estimate of the discount rate from the consensus (mean) estimate of the discount rate across all analysts for a given firm-year.
$\lvert TGR_{a,i,t} - \overline{TGR}_{i,t}\rvert$	The absolute deviation of an individual analyst's estimate of the terminal growth rate from the consensus (mean) estimate of the terminal growth rate across all analysts for a given firm-year.
$\lvert Beta_{a,i,t} - \overline{Beta}_{i,t}\rvert$	The absolute deviation of an individual analyst's estimate of the equity beta from the consensus (mean) estimate of the equity beta across all analysts for a given firm-year.
$\lvert ERP_{a,i,t} - \overline{ERP}_{i,t}\rvert$	The absolute deviation of an individual analyst's estimate of the equity risk premium from the consensus (mean) estimate of the equity risk premium across all analysts for a given firm-year.
$\lvert Rf_{a,i,t} - \overline{Rf}_{i,t}\rvert$	The absolute deviation of an individual analyst's estimate of the risk-free rate from the consensus (mean) estimate of the risk-free rate across all analysts for a given firm-year.