Valuation Fundamentals*

November 17, 2023

Abstract

We investigate a comprehensive sample of 78,509 equity reports to understand how professionals perform valuations. By directly observing measures of short- and medium-term growth expectations, terminal growth expectations, and discount rates, we study the drivers of fluctuations in expected valuations. We find that both growth expectations and discount rates play crucial roles. Our analysis reveals that discount rate calculations align with theoretical recommendations, track other professionals' estimates, and vary substantially over time, both in the aggregate and within firms. Equity betas explain four times more of the discount rate process than equity risk premia. The slope of the security market line obtained using analyst equity beta is equal to 7.9%. The partial correlation between discount rates and growth expectations is small, at 0.03. Lastly, terminal growth rates respond to macroeconomic factors, such as monetary policies and GDP growth, but not to inflation.

JEL classification: D24, D25, D46, D84, G17, G31, G41

Keywords: valuation, horizon, expectations, discount rates, behavioral finance, analyst

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1 Introduction

Asset prices are determined by both future cash flows and discount rates. There is, however, limited consensus on which of these factors explains most of the variation in prices. Spurred by the fact that changes in dividends are insufficient to explain changes in prices (Shiller, 1981), a vibrant literature investigates how subjective expectations can help reconcile this puzzle. By refining belief formation mechanisms, De Bondt and Thaler (1985), Hirshleifer et al. (2015), and Bordalo et al. (2023b) argue that price fluctuations are primarily driven by expectations. These conclusions, however, contrast with other research (Campbell and Cochrane, 1999; Bansal and Yaron, 2004; Barro, 2006) that argues that time-varying stochastic discount factors are the main source of price variation Cochrane (2011).

We explore these issues from a complementary but new angle, by looking at the drivers of *expected* valuation. Our strategy combines key elements from both literatures: our sample contains the complete term structure of expectations, expanding beyond the analyst expectation measures used in previous studies (La Porta, 1996; De La O and Myers, 2021; Nagel and Xu, 2022; Bordalo et al., 2023a), and we *directly observe* the discount rates of valuation professionals. This allows us to work within the subjective expectation literature's empirical framework, but to precisely account for the effect of discount rates (Shiller, 1981; Cochrane, 2011). By decomposing expected valuations into their components and studying each component in depth, we provide new evidence on how real-world valuation aligns with academic theory and textbook recommendations.

To conduct our analysis, we introduce one of the largest and most comprehensive datasets of equity analyst models: 78,509 reports from 94 countries over 24 years. Directly collecting data from original documents offers several advantages over mainstream commercial databases. First, we observe the complete term structure of growth expectations from year one through the terminal period. For example, IBES and Value Line provide "long-term" forecast estimates[1], which correspond to a blend of analysts' 3- to 5-year forecasts, whereas we are able to examine the long-term growth rates by analyst by year. This refinement

[1] IBES provides a standard "LTG" variable, and Value Line highlights the cumulative expected growth rate over years 3 to 5 of the forecast horizon.

allows us to document effective long-term growth forecasts that are an order of magnitude (10 percentage points) smaller than those from IBES and Value Line. Consistent with this large difference, Décaire and Guenzel (2023) show that the information and methods used by analysts to generate the long-term forecasts have little overlap with those used to form IBES long-term growth rates.

A second advantage of our analysis is that we examine the growth expectations of each company's free cash flows, the effective source of value creation. Previous research instead examines dividends, which are lumpy and sticky, or earnings, a measure more affected by accounting norms than are free cash flows. Third, while extant research has explored some elements of what we study, we jointly observe all of the inputs used in valuations, such as growth expectations at all time horizons, discount rates—separately observing equity betas and equity risk premia—as well as the underlying assumptions and modeling choices upon which they are based. These features allow us to quantify each valuation input's relative importance and investigate how these variables are jointly determined. Lastly, because our data are taken directly from equity reports, we can link the numerical inputs to *how* analysts motivate their decisions, allowing us to determine more directly the relation between professional valuations and academic recommendations.

We start our analysis by decomposing valuations into fundamental components: short- and medium-term growth expectations, terminal growth rates, discount rates, and initial cash flow. When comparing the combined effect of growth expectations at all horizons with discount rates, we find that both sets of variables explain a large share of expected valuation fluctuations. Taking into account the fact that analyst discount rates vary substantially over time, in the aggregate and within firms, our evidence aligns with arguments in the rational expectation literature that highlight the importance of discount rates Cochrane (2011). Then, comparing the effect of growth expectations over its entire term structure, we find that growth expectations at longer horizons are associated with most of the fluctuation in expected valuations, consistent with Bordalo et al.' (2023b) results. Combined, these results suggest that no single input explains all the variation in expected valuations. Rather, our evidence points toward an intermediate scenario where the effect of expectations is less dominant than argued in the subjective expectation literature, but where discount rates are important and exhibit significant variation over time.

In a related exercise, we investigate how analyst subjective discount rates and terminal growth rates relate to ex-post one-year realized returns. Our results confirm and complement Bordalo et al.' (2023a) findings. Consistent with their evidence, we find that terminal growth rates are negatively associated with ex post realized returns, even when studying its relation to firm-level returns. We add to this evidence by showing that the regression coefficient associated with analyst subjective discount rates is close to 1 (0.85)[2], and we fail to reject the null hypothesis that the intercept coefficient is statistically different from zero. We interpret this result as suggestive evidence that analyst discount rates likely capture inherent features associated with market participants' required rate of return for the firms included in our sample.

We structure the rest of our analysis around three discounted cash flow (DCF) components that have received limited attention in the existing literature due to data challenges. Our findings highlight these as critical to understanding variation in prices:

- Discount rates: How do analysts select equity betas, equity risk premia, and risk-free rates? How do professionals update their discount rate estimates over time? What inputs account for most of the variation in discount rates? Do discount rates change with economic conditions over time or across economic environments? How are growth expectations related to discount rates?
- Terminal growth rates: What economic variables drive the chosen value of the terminal growth rate? How much do terminal values contribute to the total valuation?
- DCF design: How many years of cash flows are forecasted year-by-year? Do growth expectations taper toward a long-term growth rate by the end of the year-by-year (discrete) period?

The data that we use to investigate these issues are comprehensive in that they allow us to explore these questions across industries and across countries, as well as through time and in changing economic circumstances.

To validate our data, we start by benchmarking analyst discount rates to comparable series produced by managers of the firms covered in our sample; and then we investigate

[2] The value of one is included in the coefficient 95^{th} confidence interval.

how the methods used to determine inputs (e.g., risk-free rate, equity beta) align with theoretical recommendations. We find that the yearly average of analyst discount rates has similar trends and levels to those used by corporate executives (Gormsen and Huber, 2022), suggesting that managers and analysts generally agree on the cost of capital. The average discount rate decreased substantially from 2000 to 2021 across all regions and industries in our sample, consistent with the secular downward trend in the risk-free rate; then, there was a sharp uptick in the discount rate starting in 2022.

Next, we show that analysts' choice of discount rate inputs aligns with academic recommendations (Berk and DeMarzo, 2019; Brealey et al., 2022). The analysts' report discussions indicate that they discount with the weighted average cost of capital (WACC) in 99.2% of cases, and the discount rate tends to be constant over the forecast horizon. The fact that analysts do not simply use the risk-free rate to discount expected cash flows directly supports Adam et al.' (2021) tests and casts doubt on the idea that analysts report risk-neutral expectations (Cochrane, 2011).

We find that the capital asset pricing model (CAPM) is the dominant cost of equity model used by analysts (96.8%), and note that Decaire et al. (2023) show that there is cross-sectional disagreement among analysts regarding beta estimation choices related to the return horizon used in its calculation (e.g., 2 years versus 5 years of monthly returns). By studying the effective betas used by analysts in their calculations, we confirm Andrei et al.' (2023) evidence, showing that analyst betas produce a substantially steeper security market line than those produced by *econometricians*, the implication being that the CAPM might perform better than previously documented. Based on our analysis, we argue that this improvement occurs because analysts account for estimation noise when updating their CAPM beta estimates.

Regarding the choice of risk-free rate, most analysts use long-term Treasuries: the 10- and 30-year maturities are used in 87.62% and 11.2% of cases, respectively. Our analysis also reveals that the sovereign government bond yield associated with the firm's headquarters country is the most common benchmark for risk-free rates. In addition, we document that discount rates barely respond to short-term measures of inflation, although we find a strong relation with long-term expectations of inflation, highlighting which horizon of inflation expectations most likely impacts valuation through the discount rate channel.

Lastly, we find a small but positive wedge between analyst discount rate inputs and some of their stated benchmarks, such as the risk-free rate. To investigate whether this wedge is due to analysts systematically inflating discount rates to offset "optimistic" growth expectations (Cochrane, 2011; Adam et al., 2021), we study how changes in terminal growth rates relate to discount rate fluctuations. The partial correlation coefficient between long-term growth expectations and discount rates is 0.03, a magnitude too small to support the optimism hypothesis. As further evidence that analyst discount rates and growth expectations do not move in tandem, we document that their difference—r minus g—ranges from 6.1% to 7.7% over the sample period, in the aggregate.

Having explored beta estimations and the choice of risk-free rates, we next evaluate discount rate fluctuations. We find that, over a 5-year horizon, the volatility of discount rates used by analysts to evaluate a specific firm is equal to 0.78 pp (8.8% of the 5-year average). To identify the main drivers of fluctuation, we decompose discount rates into analysts' choice of risk-free rates, equity betas, and equity risk premia. We find that equity betas explain 4 times more of discount rate fluctuations. We also note that the equity risk premia used by analysts exhibit less volatility than the series generated by rational expectation models (e.g., Martin (2017)). By studying similar analysts to those included in previous behavioral studies, our work highlights that those analysts perform significant adjustments to their discount rates when evaluating firms, and that changes in both the quantity and the price of risk drive this process.

Combined, our tests of analyst discount rates show that the measure (i) is disciplined by simple theoretical models, (ii) tracks other professionals' estimates, and (iii) is not inflated to offset the potential optimistic biases present in cash flows expectations. Lastly, the aggregate time series variation in discount rates coincides with the secular decline in the Treasury yield, as well as with fluctuations in the price and quantity of systematic risk.

Having explored discount rates in detail, we next focus on the terminal growth rate: the long-run steady-state growth rate that follows the discrete forecasts, and analysts assume that a firm can maintain indefinitely. By studying the text of equity reports, we learn that analysts motivate their terminal growth rate choice based on their long-term expectations of two economic variables: (i) the GDP growth rate and (ii) the inflation rate (Appendix A). In practice, bounding terminal growth rates between the magnitudes of these two variables helps discipline the valuation exercise. Among other considerations, it is not feasible for a firm to outperform the economy in the long run for two reasons: (i) the average growth rate of *surviving* Compustat firms aged 10 years and older is 5.67%, and (ii), historically, 22.1% of public firms experience bankruptcy or liquidation after operating for 9.4 years[3]. Taken together, these magnitudes suggest that it is unlikely for the average firm to systematically outperform the average nominal GDP growth rate of 5.1% (4.7% in the US) measured in our sample. Further, Décaire and Guenzel (2023) shows that analysts reduce long-term growth estimates for older firms and those facing high long-term default probability. Lastly, DCF models are measured in nominal terms; thus, using the inflation rate implicitly assumes a zero real growth rate as a lower bound. Consistent with this evidence, we find that the average nominal terminal growth rate has steadily declined over the past 24 years, from a high of 3.11 pp to a low of 2.02 pp. However, we document markedly different patterns across regions and industries.

To then evaluate how professionals account for macroeconomic series when producing their terminal forecasts, we start by noting that in reports, analysts often refer to recent realizations of macroeconomic variables and forward-looking arguments based on strategists' forecasts. To systematically investigate which approach ultimately dominates, we run a horse-race between three measurement strategies: (i) contemporaneous measures, (ii) 10-year historical averages, and (iii) 10-year forecasts from the Survey of Professional Forecasters. By using historical averages and strategists' forecasts, our goal is to distinctively capture the backward- and forward-looking dimensions of the data, to match discussions from equity reports. Using this measurement strategy, we consider three macroeconomic variables to perform the horse-race: (i) real GDP growth, (ii) inflation, and (iii) the 10-year treasury yield.

We find that historical averages (backward-looking variables) best explain the terminal growth rate choices made by analysts. This evidence aligns with Nagel and Xu' (2022)

[3]To obtain this statistic, we restrict our sample to firms that experienced bankruptcy, liquidation, or that are still active in Compustat as of August 28, 2023. For example, M&A targets and firms involved in going-private transactions were excluded from our sample for this calculation

findings, which shows that long-term growth expectations are anchored in recent historical realizations. However, our findings contrast with some of their arguments that analysts' subjective equity premia are flat in the time series. In our data, the standard deviation of the equity risk premium used by an analyst to evaluate a specific firm over a 5-year period is equal to 0.31 pp, a 5.4% dispersion compared to their respective 5-year averages.

Next, we investigate which macroeconomic variables best explain the aggregate variation in terminal growth rates. Using a variance decomposition, we find that inflation measures are the least important factors in explaining fluctuations in terminal growth rates. On the contrary, both real GDP growth rates and 10-year treasury yields explain a sizable share of the terminal growth rate process. Standard macroeconomic models help put into context the importance of the long-term Treasury yield as a driver of long-term growth expectations: the risk-free rate bounds from above the expected GDP growth in the long run (Abel et al., 1989; Barro, 2023). Overall, the textual information collected in equity reports combined with our empirical analysis align with some of Bordalo et al.' (2023b) conclusions, showing that expectations at longer horizons are intricately related to macroeconomic variables. However, our analysis shows that the three macroeconomic variables used in our analysis Granger cause analysts' choice of terminal growth rate, consistent with the textual evidence collected from equity reports. This discrepancy with Bordalo et al.' (2023b) findings might be attributable to the fact that the terminal growth rate captures growth expectations at a longer horizon than the IBES LTG variable Décaire and Guenzel (2023). We also find that DCF terminal values—a function of discount rates and terminal growth rates—account for 67.2-75.6% of equity valuations throughout the sample period, highlighting an important and direct channel through which recent economic conditions affect valuations.

Finally, we note three DCF design features that have methodological implications for researchers extracting variables (e.g., implied cost of capital (Gebhardt et al., 2001)) from analysts' short- and medium-term forecasts. First, the average explicit forecast horizon is equal to 6.24 years, with the modal horizon being equal to 3 years. Second, we do not find that the growth rates in the discrete year-by-year forecast period gradually decline to the chosen terminal growth rate; in contrast, we document a significant drop (7.1 pp) from the last explicit expected growth rate to the terminal growth rate. Third, we find that analysts adjust the horizon of their discrete forecast period over time. Combined, these three facts suggest that estimation approaches relying on strategies similar to Gebhardt et al.' (2001) implied cost of capital can be biased in non-trivial ways because the data from mainstream providers do not allow researchers to observe these features, violating some of those methods' implicit assumptions.

Our paper makes contributions to several areas of the literature. First, we add to an expanding and dynamic stream of studies that use analysts' survey data to investigate asset prices dynamics (Brav and Lehavy, 2003; Sadka and Scherbina, 2007; Bouchaud et al., 2019; Derrien et al., 2022; Nagel and Xu, 2023), and market participants' beliefs (La Porta, 1996; De La O and Myers, 2021; Nagel and Xu, 2022; Bordalo et al., 2023a,b; Decaire, 2023). By directly collecting our data from original documents, we can jointly observe short-, medium-, and long-term expectations, discount rates, and target values. This allows us to venture beyond short- and medium-term growth expectations and instead study the joint dynamic between all variables used in valuation models.

Second, by studying how financial professionals perform fundamental valuation, we add to the existing literature focused on understanding the innermost mechanisms of resource allocation (Graham and Harvey, 2001; Duchin and Sosyura, 2013; Decaire and Sosyura, 2022; Décaire and Sosyura, 2022; Graham et al., 2015). In addition, we complement the body of knowledge related to how financial professionals determine discount rates (Graham and Harvey, 2001; Kruger et al., 2015; Decaire and Bessembinder, 2021; Gormsen and Huber, 2022; Decaire et al., 2023; **?**).

Section 2 discusses institutional details, Section 3 introduces the data collection methodology and summary statistics, and examines trends in our key variables, Section 4 discusses the paper's results, and Section 5 concludes.

2 Institutional Details

Among the methods used to perform valuation, financial textbooks (Berk and DeMarzo, 2019; Brealey et al., 2022), and business school curricula emphasize discounted cash flow models (DCF) and valuation multiples methods, a preference echoed by their dominant use among professionals (Graham and Harvey, 2001; Mukhlynina and Nyborg, 2018). Our data allow us to document a time trend, with the number of equity reports using DCF models has steadily increased over the past 20 years. In total, approximately 40% of all reports including DCF analysis over the past 15 years[4] (Appendix Figure A1). Although DCFs and multiples have similarities, we favor studying DCFs for three reasons. First, DCF models nest multiple valuation models into a more general structure:

$$\mathrm{P}_0 = \underbrace{\sum_{i=1}^{H} \frac{CF_i(1+g_{\mathrm{i}})}{(1+r)^i}}_{\text{Explicit Forecast}} + \underbrace{\frac{1}{(r-g_{\mathrm{T}})}}_{\substack{\text{Terminal}\\ \text{Value}\\ \text{Multiple}}} * \frac{CF_H(1+g_{\mathrm{T}})}{(1+r)^H} \tag{1}$$

Second, in contrast to valuation multiples that only disclose a single metric—the multiple—DCFs require analysts to report detailed modeling assumptions, thus making DCFs a richer setting for conducting our empirical analysis. Specifically, the data that we collect from each analyst report contains, among other things, the analyst's personal information (i.e., name and location), price targets over a 6- to 18-month forecast horizon, and the discount rate used in the DCF analysis. When observing the entire model, we are also able to extract their short- and long-term growth expectations, as well as other DCF features. Appendix Figure A2 presents an example of a complete DCF model from an equity report[5]. The richness of the data means that we do not have to estimate or "back out" any of the variables. Our analysis is conducted entirely with data directly observed in analyst reports.

Third, many past studies using analyst data have relied on commercial databases, such as the Institutional Brokers' Estimate System (IBES) or Value Line, which collect or provide mainly short- and medium-term expectations, price targets, and recommendations. The long-term growth estimates reported in these databases (e.g., LTG) do not reflect the actual long-term expectations provided by analysts. That is, LTG from IBES and Value line reflect forecasts made over a three- to five-year horizon, while our data include the actual terminal growth rate expectations. Appendix Figure A3 contrasts how the long-term expectation measure used in our analysis compares to those provided by IBES. The interquartile range

[4]The SEC approval of NASD Rule 2711 in 2002 requires equity analysts to disclose the valuation model(s) used in equity reports.

[5]For copyright reasons, we redacted the numbers used in the model.

of the LTG from IBES is between 5.5% and 17.0%, in contrast to 1.5% to 3% for the effective terminal growth rates used by equity analysts.

We note that disclosure of DCF modeling details is done on a voluntary basis. Studies have found that the intensity of information disclosure of the DCF model 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). By detailing their valuation thesis, informed analysts have the opportunity to differentiate their work from their uninformed rivals, gaining credibility in the process. In total, this suggests that our data differ in a favorable way from datasets that unconditionally collect earnings forecasts: our data are more likely to be sampled from an informed subset of analysts.

Also noteworthy, equity research firms mandate that analysts produce valuation targets over a 6 to 18-month horizon[6], standardizing horizon in analysts' objective functions. This allows us to compare analysts' predictions with the realized outcomes at those forecast horizons. Although optimistic, consistent with the literature (Adam and Nagel, 2022), aggregate expected returns are reasonably accurate (Figure 1), falling within the range of forecast horizon realized returns— the 6, 12, and 18-month realized returns—for every year of our sample except for periods that coincide with recessions[7].

3 Methodology and Data

We collect our data from equity reports (i.e., the original documents) published by analysts. We initially downloaded 157,549 equity reports with mentions of DCF from 55 major equity research firms. We restricted the time window to reports published in the first months of the calendar year (January 1^{st} to April 1^{st}) from 2000 to 2023. This ensured that our data were systematically measured at a similar time point in the year. In cases where analysts published more than one report on the same firm during those months, we systematically kept the earliest publication of that calendar year to avoid duplicates for a given analyst-firm-year pair. This resulted in 78,509 reports, each containing at least one variable used in

[6]This compares to IBES data in which 99.5% of price targets are done over a 6, 12, or 18-month horizon.
[7]i.e., Dot-com crash, 2008 financial crisis, and the Covid pandemic.

our analysis.

For each variable contained in the analysis, we collected numerical values in four steps. First, documents were pre-processed using a Python program to identify sections of text, tables, and figures containing relevant information for the study. Second, we converted these different media into text snippets. Third, for each variable collected, we used artificial intelligence to extract the numerical value from these snippets. Fourth, we exported to Excel the text snippets and the numerical values extracted by artificial intelligence – and our research team manually verified each number. This last step of the collection effort is crucial for the integrity of the data used in the analysis. Although artificial intelligence is an efficient tool for text extraction Gilardi et al. (2023) and processes complex sentences with a high success rate, error rates are above acceptable levels when left unsupervised.

We augment the sample with country-level data on inflation rates and the 10-year treasury yield from Refinitiv and the real gross domestic product (GDP) growth rate from the World Bank. For American firms, we add 10-year-horizon forecasts of inflation, 10-year treasury yield, and real GDP growth rate from the Philadelphia Federal Reserve Survey of Professional Forecasters (SPF). Finally, we also gather measures of company accounting variables, realized stock prices, industry (NAICS), and country of headquarters using Refinitiv.

3.1 Firms and Coverage

The equity reports come from 55 of the largest equity research departments operating throughout the world. The 78,509 reports in our sample cover 11,171 firms located in 94 countries during the 2000-2023 period. Panel A in Table 1 reports summary statistics for our sample firms. The average firm (median) owns assets with a book value of \$13.0 (\$2.2) billion and has an investment rate of 5.7% (4.0%). These magnitudes are comparable to firms covered in IBES, where the average (median) IBES firm has assets with a book value of \$ 15.2 (\$0.8) billion, and has an investment rate of 5.3% (2.9%). Overall, this implies that the firms in our sample are of comparable size and invest with similar intensity as those included in other broadly distributed commercial analyst datasets.

The average firm is covered by 2.9 analysts and is included in the sample for 4.4 years. In terms of geographic coverage, 38% of firms have their headquarters located in Europe, 29%

in North America (25% in the US), 17% in Asia, 12% in Oceania, 3% 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 84% of the total coverage: 35% for manufacturing (NAICS 31-32-33), 16% for information (NAICS 51), 8% for professional services (NAICS 54), 6% 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 3% for finance and insurance (NAICS 52). Overall, these statistics suggest that our sample is comprehensive, representative, and comparable to its commercial counterparts.

3.2 Discount Rates and Inputs

Panel B in Table 1 reports summary statistics on the discount rates used by analysts. The average (median) discount rate is 9.1% (8.9%). Panel A of Figure 2 presents the aggregate time trend for the discount rate used by analysts. Consistent with the secular decline in the risk-free rate in recent decades, we find that the discount rates used by analysts steadily declined over the period, reaching a low of 8.2% during the worst of the COVID pandemic before bouncing back in the most recent two years. The maximum average discount rate of 9.9% occurred following the 2008 Great Financial Recession (Panel A of Figure 2).

We benchmark our cost of capital estimates against those used internally by companies. To verify this pattern, we directly matched our analyst discount rates with the raw cost of capital data used in Gormsen and Huber (2022). In total, we matched 751 firm-year pairs, for which we have both managers and analysts estimates in a given year. As shown in Panel B of Figure 2, for the average firm, the time trends of discount rates used by analysts and those used by managers have similar magnitudes and trends. The two time series exhibit a correlation of 0.89. We interpret these similarities as suggestive evidence that firm managers and equity analysts measure the cost of capital with comparable methods.

The downward trend in discount rates is not specific to particular regions (Appendix Figure A4) or major industries (Appendix Figure A5). We document a steady, although shrinking, gap between discount rates used to evaluate North American firms and their European counterparts, with gap values ranging from 0.4 to 2.2 pp during the sample period. Finally, we note significant and persistent differences between industry-level discount rates, consistent with industries facing different levels of systematic risk.

We now explore the summary statistics of discount rate inputs. These statistics provide the basis for our empirical analysis later in the paper.

3.2.1 Equity Betas

Panel A of Appendix Table A1 reports the results of our textual analysis on analyst equity betas. 938 of the reports (4.3% of the 21,973 reports that provide a beta estimate) explicitly mention the asset pricing model employed. Among this group, the Capital Asset Pricing Model (CAPM) is used pervasively by analysts (96.8%). We also note that while some analysts do not directly mention the asset pricing model used to calculate the cost of equity, they specify the data provider from which their betas are sourced in 645 additional reports. These 645 reports rely on Bloomberg (85.9%), as well as Refinitiv (5.9%), and FactSet (5.3%). The default asset pricing model used by these data providers is also the CAPM.

We also collect information on two key features of beta estimation: (1) return horizon and (2) market benchmark. Most analysts use 5 years of return data (44.9%), or 2 years (30.1%). When cross-referencing return horizons with returns frequencies, two strategies appear to dominate: (i) using two years of returns at a weekly frequency and (ii) using five years of returns at a monthly frequency. Second, there is a lack of consensus in the academic literature on the market benchmark to use when estimating betas. Focusing on international firms, we find that analysts tend to use major stock indices associated with the country of a firm's headquarters (80.9%), rather than using international indexes (MSCI World) or the S&P 500 (19.1%). Finally, the average beta used by analysts is equal to 1.10, and the 25-75^{th} percentile range includes values between 0.9 and 1.25. Panel C of Figure 2 plots the average equity beta used by analysts. These betas suggest that the firms in our sample face a reasonable range of exposure to systematic risk, as measured by the CAPM beta.

To corroborate the just-reported stylized facts obtained with the textual analysis, we regress the numeric value of beta reported by analysts on 6 different CAPM betas that we calculate with monthly returns; these 6 betas are for a 2, 3, 4, 5, 6, and 7-year horizon. Panel A of Table 2 reports the results. Consistent with the textual analysis in the previous paragraph, our regression decomposition indicates that analysts rely primarily on 5 years of returns in the calculation of their CAPM betas.

3.2.2 Analysts' Equity Risk Premia

Analysts explicitly mention their equity risk premia in 19,812 reports (25.2% of the sample). Panel B of Table 1 shows that the average (median) equity risk premium used by analysts is equal to 5.5% (5.7%). Panel D of Figure 2 shows the average equity risk premium over time. The measure used by analysts has increased over the past 23 years, from a low of 4.5% in 2000, to a high of about 6.0 over the years 2013 to 2023, casting doubt on the idea that professionals use a fixed value as their estimate.

Lastly, Panels A to D of Appendix Figure A6 plot the equity risk premium across the four main regions included in our sample. While we find that the measures have remained elevated since the 2008 crisis in most regions, we document differing patterns in all four regions. We interpret these distinct patterns as indicating that analysts use different prices of systematic risk across regions over time. We also note that, while the patterns are different across regions, the measure displays volatility in most regions, relative to existing evidence suggesting that subjective risk premia are relatively flat Nagel and Xu (2023).

3.2.3 Analysts' Risk-Free Rate

Analysts explicitly mention their risk-free rate in 19,448 reports (24.8% of the sample), and in 2,018 of these cases, they explicitly discuss the maturity of their measure. When discussed, the 10- and 30-year maturities are used in 87.6% and 11.2% of cases (Panel B of Appendix Table A1). Looking at firms located in Asia, Europe, and Oceania respectively, Appendix Table A2 expands the textual results and shows that the region-specific 10-year treasury yield better tracks analysts' choices of the risk-free rate than that of the US. Panel B in Table 1 shows that the average (median) risk-free rate used by analysts is 4.0% (4.0%), while Panel C in Table 1 shows the average 10-year treasury yield associated with firm headquarters countries is 4.5% (4.0%). Finally, the 10-year US Treasury yield is 3.2% (3.1%).

Panel E of Figure 2 plots the risk-free rate used by analysts and the corresponding 10-year Treasury yield. Both the risk-free rate used by analysts and the treasury yield follow the same pattern over the sample period, but we note that analysts' risk-free rate process is more persistent and tends to be greater than the 10-year treasury yield throughout the sample. Appendix Figure A7 plots analysts' risk-free rates, regional 10-year treasury yields, and the US 10-year treasury yield, showing that similar patterns apply for most regions.

3.3 Terminal Growth Rates

More than 51,000 equity reports (65.0% of the sample) provide numerical values for the terminal growth rate. Panel B of Table 1 presents summary statistics. The average (median) terminal growth rate is 2.2% (2.0%). Figure 3 displays the trend of the average terminal growth rate; from a peak of 3.11 pp in 2001, the measure has steadily declined to a low of 2.02 pp in 2020. Appendix Figure A8 presents regional trends for terminal growth rates across continents. We find that all regions experienced a sustained decline in long-term growth rate over the sample period.

Finally, Appendix Figure A9 presents the time series patterns for the eight largest industries in our sample. Most industries experienced a sustained decline in the average terminal growth rate in the first decade of the sample, to stabilize at an average of approximately a 2% in the second half of the 2010s. The information and the oil & gas industries faced the sharpest average declines, while the transportation and finance industries experienced the smallest reductions.

4 Analysis and Discussion

4.1 Firm Expected Valuation Decomposition

The previous section provides descriptive statistics on the key inputs that analysts use in valuation. Now, in this section, we explore how these various inputs affect valuations, and which inputs play the most important role. We start our analysis by expressing DCFs in a way that highlights the key inputs whose roles we will examine in detail. To structure our decomposition exercise with how analysts perform valuation in practice, we set the explicit forecast horizon to be equal to three years: the modal forecast horizon in our sample (Panel A of Figure 4). We note that such a horizon has also been used in other contemporaneous studies (e.g., Hommel et al. (2023)) facing similar challenges as ours. In addition to our choice of horizon, our DCF decomposition reflects several key features of the practice of valuation discussed in the previous sections: (i) the required rate of return—the discount rate—is constant over the forecast horizon of a given valuation, (ii) analysts evaluating the same firm can have different subjective discount rates Decaire et al. (2023), and (iii) cash flows are the basis of the valuation, instead of earnings or dividends:

$$\mathrm{E}_0^*[P_0] = \frac{E_0^*[CF_1]}{1+E_0^*[r]^1} + \frac{E_0^*[CF_2]}{(1+E_0^*[r])^2} + \frac{E_0^*[CF_3]}{(1+E_0^*[r])^3} + \underbrace{\sum_{i=4}^{\infty} \frac{E_0^*[CF_3] * (1+E_0^*[g_T])^{i-3}}{(1+E_0^*[r])^i}}_{\text{Terminal value}} \tag{2}$$

$$\Rightarrow \text{Terminal value multiple} = \frac{1}{(E_0^*[r]) - E_0^*[g_T])} \tag{3}$$

Where $\mathrm{E}_0[\mathrm{P}_0]$ is the analyst's price expectation for the 12-month forecast horizon at the time of the forecast, CF_i is the analyst's expectation of the firm cash flows in i years at the time of the forecast, H is the explicit forecast horizon, $E_0^*[r]$ is the analyst subjective discount rate, and g_T denotes the terminal growth rate. The forecast horizon, H, corresponds to the number of years over which analysts explicitly model cash flows year by year. For the period following H, they then use a terminal value to represent all future cash flows to be received until infinity. In DCFs, the terminal value directly accounts for the no-bubble condition, such that $(E_0^*[r] - E_0^*[g_T]) > 0$. We apply the Campbell-Shiler decomposition and linearize the DCF models:

$$1 + \mathrm{E}_0^*[r] = \frac{\mathrm{E}_0^*[CF_1] + \mathrm{E}_0^*[P_1]}{P_0} \tag{4}$$

$$ln(1 + \mathrm{E}_0^*[r]) = k - ln(\mathrm{E}_0^*[P_0]) + ln(CF_0) + ln(\frac{E_0^*[FCF_1]}{FCF_0}) + \rho ln(\frac{\mathrm{E}_0^*[P_1]}{\mathrm{E}_0^*[CF_1]}) \tag{5}$$

By reorganizing the equation as a function of $ln(\mathrm{E}_0^*[P_0])$, we get:

$$ln(\mathrm{E}_0^*[P_0]) = k + ln(CF_0) - ln(1 + \mathrm{E}_0^*[r]) + ln(\frac{E_0^*[FCF_1]}{FCF_0}) + \rho ln(\frac{\mathrm{E}_0^*[P_1]}{\mathrm{E}_0^*[FCF_1]}) \tag{6}$$

In the last step of the derivation, we iterate forward the expression and we make use of the terminal growth rate assumption imposed by DCF models:

$$
\begin{aligned}
ln(\mathrm{E}_0^*[P_0]) =& k + ln(CF_0) + ln(1 + E_0^*[g_1]) + \rho ln(1 + E_0^*[g_2]) + \rho^2 ln(1 + E_0^*[g_3]) \\
&+ \frac{\rho^3}{1-\rho} ln(1 + \mathrm{E}_0^*[g_T]) - \frac{1}{1-\rho} ln(1 + E_0^*[r])
\end{aligned}
\tag{7}
$$

This allows us to express DCFs, as a function of variables that are all determined and observable at the time of the forecast: (i) the growth expectations, (ii) the discount rate, and (iii) ρ, a normalizing constant smaller than 1. This decomposition allows us to match the expected growth horizon that has been explored in existing work in our empirical specifications, such as defining the short-term horizon using the 1-year growth forecast (De La O and Myers, 2021), medium-term horizon as the expected growth at the 2- and 3-year horizons, and the long-term growth horizon as the terminal growth rate used in the DCF model (g_T) to capture the effect of longer-term expectations explored in Bordalo et al.' (2023a) and Bordalo et al.' (2023b). Ultimately, the empirical design used in this section shares several features with the strategy used in Bordalo et al. (2023b).

The results of this test are reported in Panel A of Table 3. We find that the combined effect of a one standard deviation increase in the expected growth variables is associated with a 16.8% increase in analysts' expected valuation, a magnitude that compares to the effect of a one standard deviation increase in discount rates (-27.5%). The fact that we finding that growth expectations is an important channel through which analysts adjusts expected prices is consistent with the current consensus in the literature (De La O and Myers, 2021; Bordalo et al., 2023a). However, our results contrast with that subjective expectation consensus, since we simultaneously find that the discount rate is an equally important driver of variation in expected prices. In a final exercise, we decompose the regression R^2. This confirms our findings, showing that discount rates explain 43.83% of the regression R^2, whereas the combined effect of cash flow expectations explains 24.7% of the R^2.

Focusing on the three variables capturing growth expectations at different horizons in the model, we find that medium- and long-term expectations explain 98.8% of the effect associated with expectations, such that a one standard deviation increase in longer-term variables is associated with a 16.7% increase in expected valuations. We note that while we are studying expected valuations, instead of aggregate market prices, this evidence aligns with Bordalo et al.' (2023a) finding showing that long-term expectations are more important than short-term expectations to explain aggregate market prices fluctuation.

Turning to the effect of discount rates, our results highlight that it is associated with the greatest amount of variations in expected prices, making it the single most important input to understand expected prices. This contrasts with the existing consensus in the literature. A few factors can help explain this difference. First, our study is the first to include the exact discount rate used by financial professionals, instead of indirect proxies. This provides us with the ability to properly account for changes in discount rates in the valuation exercise. Second, we study expected valuation of single firms, instead of aggregate market prices, which allows us to establish a more direct link between DCF inputs and prices, instead of making the assumption that our explanatory variables proxy for the subjective beliefs of the marginal investor. Differences aside, this set of evidence suggests that when professionals determine expected firm prices, it appears that no single variable can explain the entire source of variation in prices.

Columns 5 to 7 replicate the analysis for the subset of younger firms in our sample, those whose post-IPO age is below the sample median. Consistent with economic intuition, we find that, for younger firms, growth expectations, especially longer-term expectations, explain a larger share of the expected price process than does the discount rate. Precisely, cash flow growth expectations at medium- and long-horizons are explain 41.33% of the regression R^2, compared to 33.31% for discount rates.

Last, we note that cash flows can sometimes be negative, making the computation of annual growth rates impossible mechanically excluding some observations from our analysis. To ensure that our results are not driven by sample selection from a subset of DCF models in which all expected cash flows are positive, Column 7 replicates the Table 3 main specification, Columns 3 and 6, but replaces expected free cash flows with expected sales—a variable that only takes positive values—for each affected variables. Our broad conclusions remain unchanged.

In the final part of this section, we decompose the terminal value multiple (TVM), $\frac{1}{r-g}$.

This multiple shapes a large share of equity valuation, as the terminal value accounts for 67.2% to 75.6% of the total equity valuation during our sample period (Figure 5). To perform the decomposition using a linear regression framework, we log-linearize the terminal multiple. To make it easier to read the following, we drop the $E_0^*[.]$ from the notation:

$$TVM_0 = \frac{1}{r - g_T} \tag{8}$$

$$TVM_0 = \frac{1}{(1+g_T)(e^{ln(\frac{(1+r)}{(1+g_T)}-1)})} \tag{9}$$

$$ln(TVM_0) \approx -ln(1+g_T) - ln(e^{ln(\frac{(1+r)}{(1+g_T)}} - 1) \tag{10}$$

$$ln(TVM_0) \approx k + (\theta - 1) * ln(1+g_T) - \theta ln(1+r) \tag{11}$$

Where we perform a first-order Taylor expansion for the term $ln(e^{ln(\frac{(1+r)}{(1+g_T))}} - 1)$. Panel B of Table 3 presents the results of the decomposition for the two inputs used in its construction: (i) the discount rate, and (ii) the terminal growth rate. In line with the above discussion, we find that both variables are important drivers of change in the terminal multiple. To be precise, a one standard deviation in the discount rates is associated with a 34.4% reduction in the terminal multiple, whereas a one standard deviation in the terminal growth rate results with a 18.35% increase in the terminal multiple.

Lastly, we look at the relation between these variables and one-year realized returns. Combined, our evidence confirms and complements Bordalo et al.' (2023a) results. Consistent with their findings, Table 4 shows a negative relation between one-year realized returns and long-term growth expectations. However, we add to this set of evidence by (i) showing that the regression coefficient of analyst sujective discount rates is close to one, (0.85 with the value of one included in the 95^{th} coefficient's confidence interval), and (ii) after including analyst sujective discount rates as an explanatory variables, the intercept becomes statistically indistinguishable from zero. We interpret this second result as suggestive evidence that analyst subjective discount rates capture reasonable features of market participant required rate of returns.

Ultimatemaly, the results of this section emphasize three key facts: (i) the combined effect of subjective expectation is large, (ii) long-term expectations explain a larger share of price fluctuation than do short-term expectations, and (iii) discount rates are equally important in explaining how professionals form their beliefs about assets value.

4.2 Discount Rates

Given their importance in driving valuation, we now study analysts' discount rates in detail, to better understand the underlying inputs and trends that influence discount rates. This section has four parts in which we (i) investigate the time series properties of discount rates, (ii) decompose the discount rate into its components collected from equity reports, as well as their relation to macroeconomic variables, (iii) look at the relation between discount rates and growth expectations, and (iv) deepen our analysis by directly studying how analysts determine discount rate inputs.

Panel A in Table 5 investigates how analysts estimate corporate discount rates. To determine which inputs drive discount rates, we perform linear regressions, where the dependent variable is the *Discount Rate* used by analysts, and the unit of observation is at the firm-analyst-year level. Column 1 shows that the analyst-firm level discount rate autocorrelation at the yearly frequency is equal to 0.73, a magnitude similar to the autocorrelation of the 10-year treasury yield in our data (0.86), suggesting that discount rates are not substantially more persistent than their readily observable inputs. We also note that analysts update firms' discount rates by 0.81 pp in absolute terms from their previous year estimates. Looking at the time-series volatility of the discount rate process in the aggregates (firm-analyst level), we find that over 5-year periods the average standard deviation is equal to 0.25 pp (0.78 pp), a deviation 2.7% (8.8%) from the 5-year window average. Repeating this exercise for the equity risk premium, we document similar magnitudes in the aggregate 0.15 (2.7%) and at the firm-analyst level 0.31 pp (5.4%). In total, these results suggest that discount rates used by equity analysts exhibit variation over time.

Next, we decompose the discount rate into the effects of its key determinants (in Columns 2 to 6 of Table 5 Panel A). We first present univariate regressions evaluating the effect on the discount rate of the *Risk-free rate*, *Equity beta*, and *Equity premium* in Columns 2 to 4. All three regressors are scaled by their sample standard deviation, enabling us to directly compare their relative effect on the discount rate. Taken alone, each variable is positively correlated with the discount rate, consistent with economic theory. Column 5 examines the relative importance of the three regressors in a multivariate setting, and Column 6 includes firm*analyst fixed effects to evaluate the relation for a given analyst-firm pair over time. Comparing the three regressors' coefficients from columns 5 and 6, we find that the risk-free rate and the equity beta are responsible for most of the discount rate variation, explaining 45.7% and 43.4% of regression R^2, respectively. Ultimately, our decomposition shows that the quantity of systematic risk explains 4x more of the discount rate process than the price of risk at the firm level. Combined, this analysis indicates the importance of risk-free rates and equity betas in explaining discount rates, motivating our deeper analysis of these inputs in sections 4.2.1 and 4.2.2.

Next, we explore the relation between discount rates and key macroeconomic variables. Panel B of Table 5 reports the results of linear regressions of the discount rate on market measures of inflation and the risk-free rate. In this Panel, the unit of observation is at the country-year level. Columns 1-2 examine whether and how analysts account for inflation. Our results show that current inflation measures have limited explanatory power on the discount rate process. In contrast, the 10-year inflation forecast of the Survey of Professional Forecasters explains 3x more of the process than current inflation, as shown by the R^2 decomposition. This helps shed light on which inflation expectation horizon likely affects valuation through the discount rate channel. Lastly, Columns 3 and 4 show that the risk-free rate measures used by analysts have a similar passthrough than the 10-year Treasury yield benchmark (0.29 versus 0.20), suggesting that changes in monetary policies are readily reflected in the discount rate produced by equity analysts.

Finally, we investigate the relation between discount rates and growth expectations to determine if equity analysts adjust the two variables in tandem. It would be of note (and potentially concerning) if, for example, analysts specifically increased discount rates to offset *optimistic* growth expectations. Table 6 shows that the relation between discount rates and growth expectations is statistically significant at the 5% level, but the economic magnitude is negligible: The estimated coefficient of 0.03 suggests that a 1 pp increase in the terminal growth rate is associated with a 0.03 pp increase in discount rates. Because of the inclusion of firm∗analyst fixed effects, this implication is within-analyst (that is, how a given analyst jointly updates both components over time). This small magnitude suggests that analysts do not simply adjust their discount rates to offset changes in growth expectations. Another lens of this issue can be provided by plotting the difference between discount rates and terminal growth rates—r minus g—over time (Figure 6). If this relation is flat through time, it would suggest that discount rates are chosen to offset growth expectations. On the contrary, the difference ranges from 6.05 to 7.69 pp throughout the sample period, around an average of 6.85 pp, implying a reasonable amount of variation in the average terminal value multiple ($13.0\text{x} \leq \frac{1}{r-g} \leq 16.5\text{x}$).

Overall, our analysis of the discount rate suggests (i) that discount rates exhibit significant variation over time, both in the aggregate and at the firm level, and (ii) that changes in growth expectations are not systematically offset by adjustments in discount rates. To better our understanding of the discount rate process, we next focus our analysis on how analysts update their measures of risk-free rates and equity betas, which our earlier analysis suggested are the two components as the most important drivers of discount rate fluctuations.

4.2.1 The Risk-Free Rate

Our data provide the unique opportunity to study the numeric risk-free rate used by analysts and its market counterpart in real-time without the need to perform any estimation. In addition, analysts often describe their choice of risk-free rate in equity reports, allowing us to combine qualitative and quantitative evidence. Also, the risk-free rate is continuously discussed in financial news, and obtaining accurate and current measures can be easily done using any financial platform. This helps us to rule out alternative behavioral channels, such as rational inattention and salience.

In addition to the patterns documented in Section 3.2.1, textual discussion in equity reports indicates that analysts use information from their brokerage firms' strategists to think about whether (at the time) spot market treasury yields are likely to persist over their 12-month forecast horizon. Such discussions tend to involve a combination of (i) backward- and (ii) forward-looking arguments (Appendix B). Backward-looking arguments tend to compare the treasury yield with historical averages, sometimes raising doubt that current levels might deviate too much from what their strategists perceive as sustainable: "**We note**

that our risk-free rate of 3.5% is higher than current levels, but representative of a longer-term view as we do not expect current low interest rates to be sustained in perpetuity."[8] Similarly, forward-looking arguments compare the treasury yield with the rate they expect to realize at the end of the forecast horizon: "We realigned our risk-free rate assumption to 7.3% based on our newly revised end-2017 10-year government bond yield forecast (previously 6.5%)."[9] We interpret the content of those discussions as suggestive evidence that analysts perceive the treasury yield as an imperfect measure of the risk-free rate that they believe will be realized over the forecast horizon. To test this interpretation, we borrow from the noisy information empirical literature (e.g., Coibion and Gorodnichenko (2015)) and formalize the dynamic as:

$$rf_{i,j,t}^{Market} = rf_{j,t}^{Sustainable} + \omega_{j,i,t} \tag{12}$$

Where i is a particular analyst, j denotes a firm, t represents a year, $rf_{i,t}^{Market}$ is the signal that analysts receive from the market to inform them about what the national 10-year treasury yield will be over the forecast horizon, $rf_{j,t}^{Sustainable}$ is the sustainable risk-free rate over the forecast horizon, and $\omega_{j,i,t}$ represents normally distributed mean-zero noise, which is assumed to be i.i.d. across time and across agents. Then, we can model analysts' risk-free rate expectations as:

$$F_{i,j,t} rf_{j,t}^{Sustainable} = G rf_{i,j,t}^{Market} + (1 - G) F_{j,i,t-1} rf_{j,t}^{Sustainable} \tag{13}$$

$F_{j,t} rf_{j,t}^{Sustainable}$ is the analyst's subjective expectation of the forecast horizon sustainable risk-free rate at the time of the forecast and $F_{j,i,t-1} rf_{j,t}^{Sustainable}$ is the analyst's subjective expectation of the sustainable risk-free rate for the previous year. In these models, 1-G can be interpreted as the degree of information rigidity. If $rf_{i,j,t}^{Market}$ were to be perfectly informative about the sustainable risk-free rate, then "G" would take the value of one.

Panel A in Table 7 presents the results of this test. The regression is estimated as a linear model, where the dependent variable is *Analysts' Risk-free Rate*, the risk-free rate

[8] Contributor: Macquarie Research, Ticker: GPK.N, Report date: 2015-03-13
[9] Contributor: Auerbach Grayson, Ticker: GGRM.JK, Report date: 2017-02-24

taken from equity reports. The unit of observation is at the firm-analyst-year level to track the granularity of the Coibion and Gorodnichenko' (2015) model. We use the 10-year national Treasury yield as our proxy of $rf_{j,i,t}^{Market}$, the risk-free rate market benchmark that analysts commonly reference in reports. Column 1 presents the results based on Equation (6). We obtain an OLS coefficient for the variable $rf_{j,i,t}^{Market}$ (i.e., G) that is equal to 0.19. This suggests that changes in 10-year Treasury yields are not directly reflected in analysts' choice of risk-free rate. Instead, we find that analysts heavily weigh their previous measure of risk-free rates, where the coefficient of $F_{j,i,t-1}rf_{j,t}^{Sustainable}$ is equal to 0.67.

To directly investigate the role of noise in the treasury yield process, we interact $rf_{i,j,t}^{Market}$ with a measure of volatility for the national treasury yield. Specifically, $Volatility_{j,t}^{Rf}$ is equal to the monthly standard deviation of the 10-year Treasury yield during the previous year, scaled by the sample standard deviation to facilitate the interpretation of its regression coefficient. Intuitively, higher values are associated with greater uncertainty about the exact level that will be reached by the 10-year Treasury yield. Panel B in Table 7 examines this relation. Consistent with the role of signal noise in Bayesian updating, we find that an increase in $Volatility_{j,t}^{Rf}$ is associated with a reduction in the weight analysts put on the market signal: the 10-year Treasury yield.

Then, we study how the size of the 10-year treasury yield innovation impacts analysts' decisions on the extensive margin: the decision to adjust or not their measure from the previous year. For extensive margin adjustments in the presence of uncertainty, large changes in the Treasury yield are more likely to trigger adjustments. Panel C of Table 7 reports the results of this test. Regressions are estimated as a probit model, where the dependent variable *Analysts' Adjust Risk-free Rate* is a binary variable equal to one if the analyst updates the previous measure, and zero otherwise. The regressor is *Treasury yield* Δ *(pp)*, measured as the absolute difference in the 10-year treasury yield year-over-year. Column 1's regression coefficient of 0.15 (p-value 0.00) supports this intuition, suggesting that larger changes in the treasury yield are more likely to be associated with analysts adjusting the risk-free rate used in their DCFs.

For completeness, and to mitigate measurement concerns regarding analysts' effective choice of the risk-free rate benchmark, columns 2 and 3 of each panel replicate the regression from column 1 using subsets of the data where analysts explicitly mention using the 10-year Treasury yield or using only firms headquartered in the United States, respectively. We note that for all three panels, our results remain unchanged using those alternative subsamples.

Lastly, in Panel D, we study the relation of analysts' risk-free rate with measures of inflation. We find that contemporaneous measures and historical averages fail to explain a significant share of analysts' risk-free rates (within $R^2 = 0.00$). In contrast, the 10-year horizon forecast from the Survey of Professional Forecasts performs substantially better ($R^2 = 0.68$). This is consistent with the results from Panel B in Table 5, showing that discount rates respond to inflation long-horizon expectations, but not short-term measures.

The results of this section yield two key insights. First, our quantitative and qualitative results suggest that when determining their risk-free rate, analysts view the Treasury yield as an imperfect proxy of what they believe the risk-free rate should be over their forecast horizon. Second, this requires analysts to filter out short-term noise from the Treasury yield measure, making analysts' choice of risk-free rate (1) less responsive to the Treasury yield and (2) more persistent in periods of high uncertainty.

4.2.2 Equity Betas

As discussed above, equity betas are a key component in discount rate estimation; therefore, in this section we explore beta estimation in detail. We orient our analysis around the fact that many analysts tend to use the 60-month CAPM (Panel A of Table 2 and Appendix Table 1). As additional confirmation, Panel A of Figure 7 shows that analyst betas track the CAPM beta estimate reasonably well, on average, but the relation becomes weaker with larger values of betas.

We first look at the relation between analyst betas and realized 1-year returns. Panel B (C) of Figure 7 plots the security market line for analyst betas (60-month CAPM betas). Both estimates share similar patterns for small values of betas, but the pattern becomes increasingly noisier with larger values of betas when looking at the 60-month econometrician betas (Panel C). This noise is not as prevalent in the analyst sample, resulting in a sharper and steeper relation between analysts' estimates and realized returns. This can help explain why security market line regressions using econometrician betas generate smaller slope coefficients. Panel B of Table 2 formalizes this intuition using an OLS regression. Column 1 presents the results for regressing the 1-year realized returns on analysts' betas. As a comparison benchmark, we replicate the exercise for CAPM betas measured using 2 to 6 years of monthly returns in Columns 2-6. The coefficient obtained for analyst betas suggests a markedly steeper slope (7.89) than those obtained with the econometrician's beta estimates (2.07-4.29). Further, the intercept in Column 1 is marginally insignificant (t-stat = 1.64), but its magnitude is more reasonable (0.69) than those obtained by using the econometrician CAPM betas (5.54-7.52). These results support and complement the findings presented in Andrei et al. (2023), showing that analysts' use of the CAPM model appears to contain additional information missed in standard tests of the CAPM.

In a second step, we study how and when analysts decide to update their beta estimates. Comparing the patterns in Panel D and E of Figure 7, we first note that analysts adjust their betas more aggressively when the new CAPM estimates are statistically different from their previous year estimates. We interpret these patterns as suggestive evidence that analysts consider the precision of the CAPM estimate when deciding to update their betas. Panel C of Table 3 presents the regression of a test that directly tests this hypothesis. In Columns 1 and 2, the estimated coefficients indicate that analysts tend to put significant weight on their previous estimates, resulting in the persistency of the betas they use. We also find that the intensity at which new CAPM estimates are incorporated into analysts' betas is negatively associated with the quantity of estimation noise. Then, in Columns 3-5, we show that an analyst's decision to update the equity betas depends both on the estimation noise and on the gap between the equity beta and the current CAPM estimate. Beta adjustments tend to occur when the gaps are large compared to estimation noise (i.e., large t-statistics).

Taken together, these results help partially explain why analysts' betas produce a steeper security market line than betas generated by the econometrician. Analysts appear to filter out estimation noise, updating their estimates only when the change is "statistically significant", in contrast to econometricians who systematically update the measure. This, in turn, has the potential to increase the quantity of measurement noise in econometricians' estimates, leading to attenuation bias.

4.3 The Terminal Growth Rate

We next examine a second important determinant of the terminal value—-the terminal growth rate. This section investigates the economic factors shaping analysts' choice in the aggregates.

Looking at the discussions from the equity reports, we note that analysts generally base their decisions on two economic series: long-term inflation expectations and the expected long-term GDP growth rate. When referring to inflation, analysts tend to conceive it as a lower bound value for firms' terminal growth rate: "We have assumed a 3.0% perpetual growth rate, somewhat above the current rate of inflation, reflecting longer-term growth prospects."[10] Alternatively, GDP growth rate references generally relate to a potential upper bound: "[We use a] terminal growth rate of 2.75% (21% discount to long-term forecast Australian GDP 3.5%) [...]."[11] Mathematically, it makes sense that in the very long run any given firm can not outgrow the overall economy, else the firm's size would rival or surpass the economy itself. Moreover, in the medium term, we note that among U.S. firms (1) public firms aged 10 years and older grow at a 5.67% rate (Appendix Figure A10), and (2) historically 22.1% of public firms experience bankruptcy or liquidation after operating for an average of 9.4 years[12]. Given that GDP growth averaged 5.1% (4.7% in the US) over the period 2000-2023, after accounting for the probability of bankruptcy, estimating medium-term (and infinite-horizon) expected growth below the long-run expected GDP growth is sensible.

We perform regression analyses to determine the relation between chosen terminal growth rates, inflation, and GDP growth rate. For completeness, we also consider a third variable: the long-term risk-free rate. There is a close connection between long-term GDP growth rates and long-term interest rates in empirical studies (Piketty, 2011; Blanchard, 2019) and practitioner guides **?**. Conceptually, the dynamic efficiency condition of macroeconomic theory formalizes this relation because, in the long run, the risk-free rate caps the growth

[10]Equity Firm: Credit Suisse, Ticker: DTEGn.DE, Report date: 2023-01-22

[11]Equity Firm: Credit Suisse, Ticker: ORI.AX, Report date: 2002-01-18

[12]To obtain this statistic, we restrict our sample to firms that experienced bankruptcy, liquidation, or that are still active in Compustat as of August 28, 2023. For example, M&A targets, and firms involved in going-private transactions were excluded from our sample for this calculation.

rate of the economy (Cass, 1965; Phelps, 1961), making it an intuitive reference variable in our test.

Table 8 examines the effect of these three variables on analysts' long-run expectations, based on linear regression model, in which the dependent variable is *Analysts' terminal growth rates* averaged at the country-year level. We perform these regressions at the economy-wide level because the explanatory variables are economy-wide. We consider three methods to measure our regressors: (1) the current estimate, (2) the 10-year historical average, (3) and the 10-year forecast provided by the Survey of Professional Forecasters (SPF). We note that the SPF is only available for the subset of firms located in the United States. Using historical averages and long-term forecasts for these variables aligns with the descriptions made by analysts in equity reports (Appendix B).

To determine which economy-wide economy variables best explain the terminal growth rate process, we report the results of a horse race between the three variables, measured in various ways for each country included in our sample (see Table 8). Columns 1-3 analyze the subsample of firms headquartered in the US. For all three specifications, the 10-year Treasury yield and, to a lesser extent, Real GDP growth explain terminal growth rates. Comparing across columns, historical averages explain a greater share ($R^2 = 0.92$) of the terminal growth rate process than do current measures ($R^2 = 0.74$) or the SPF 10-year forecasts ($R^2 = 0.83$). Turning to the full set of countries in Columns 4 and 5, we document a similar pattern where the explanatory power of historical averages (Within $R^2 = 0.07$) dominates that of the current measures (within $R^2 = 0.03$). These results square with Nagel and Xu (2022), who show that analysts long-term expectations are anchored on recent macroeconomic realizations. Our results however contrast with some of their other findings, as we also document significant variation in analyst equity risk premia, and discount rates.

We note that, in most specifications, the inflation rate coefficient is not statistically significant, and that the variable explains the smallest share of the regression R^2, 0.29% to 23.99%. To ensure that this lack of significance is not driven by multicollinearity between our three regressors, we verify the variance inflation factor (vif) and find values below conventional thresholds (i.e., maximum vif is equal to 2.47 in the full sample regressions). Last, we find that, combined, these three macroeconomic variables Granger cause analysts' terminal growth rate, highlighting a channel through which macroeconomic variables directly enter the price formation process.

Overall, the results of this section help refine our understanding of how financial professionals conceptualize long-term growth expectations in the aggregate. While inflation and GDP growth are discussed in official communications, our analysis suggests that long-run historical measures of the risk-free rate and GDP growth better explain patterns from the data.

4.4 DCF Design

We begin our analysis by studying how financial professionals determine their explicit forecast horizon. Discounted cash flow models are, in their simplest form, the combination of two parts: (1) a near-future explicit forecast over a few years and (2) a measure that captures all remaining years— the terminal value. Combined, these two parts allow financial professionals to value every cash flow that a firm is expected to generate until infinity. We find that the average explicit forecast is modeled over a 6.24-year horizon, with 3 and 10 years being the most common horizons (39.9% of cases), in line with heuristics discussed in financial textbooks and previous surveys (Mukhlynina and Nyborg, 2018).

Although our evidence suggests that analysts generally adopt textbooks' rule-of-thumb, forecast horizon fluctuate over time, with annual averages ranging between 5.2 and 7.9 years (Panel B of Figure 4). Next, we study how analysts link both parts of their valuation model, focusing on the relation between growth rates in the last year of the explicit forecast section and terminal growth rates. In principle, expected growth rates should converge toward their steady-state target—the terminal growth rate—by the end of the discrete period. However, Appendix Figure A11 shows a significant gap (average = 7.11 pp, p-value = 0.00) between both time series. We interpret this pattern as suggestive evidence that heuristic rules implicitly impose relatively short discrete period horizons when performing valuation, cutting short explicit forecasts before cash flows reach a steady state.

These facts that (i) explicit forecast horizons are not constant over time, and (ii) there is a significant and discrete drop between the growth rate used in the near- and far-future parts of their models, making DCFs a juxtaposition of two related but disjointed sections, have important research implications. These facts highlight potential methodological challenges for researchers applying methods such as the *implied cost of capital* to analysts' short-term earnings forecasts. Ultimately, these facts suggest that those methods might yield estimates that may be biased in nontrivial ways because mainstream datasets do not allow researchers to directly observe terminal growth rates and the complete horizon of explicit forecasts.

5 Conclusion

In this paper, we introduce one of the largest and most comprehensive datasets collected from equity analyst reports where we directly observe most of the DCF inputs used in the valuation calculation. In contrast to existing results, we show that both subjective expectations and discount rates explain expected valuation fluctuations. Our results highlight that analyst subjective discount rates as well as equity risk premia exhibit significant variation over time, both in the aggregate and at the firm-analyst level. This calls for additional work to be done, in order to reconcile theories focused on subjective beliefs with the work done on time-varying stochastic discount factors.

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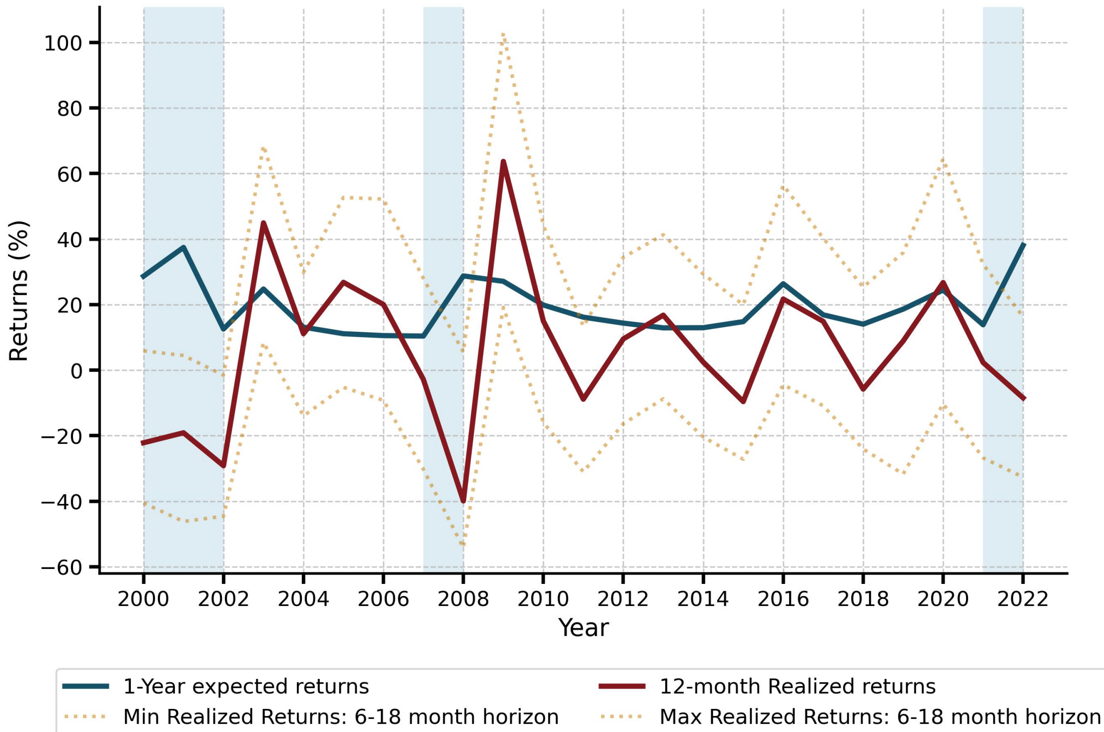


Figure 1: Expected Versus Realized Returns This figure plots analysts' expected stock returns over their 6 to 18-month forecast horizon and compares them with realized returns for 2000-2022. The x-axis is expressed in years, and the y-axis denotes realized 1-year returns measured in percentages. The sample includes all firms for which we observe realized stock prices over the full forecast horizon and valuation targets. The solid blue line represents the expected return to be realized over the forecast horizon at the time of making the prediction. The solid red line represents the 12-month realized return from the forecast date. The yellow dotted line indicates the average minimum and maximum returns over the full 6 to 18-month forecast horizon. Shaded regions identify periods where average analysts' forecasts lie outside of the realized min/max range.

Figure 2: **Dispersion of Long-Horizon Variables** This figure plots the time trends for discount rates, and its key components over the sample period, 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages, with the exception of Panel C where the y-axis denotes numerical values. In Panel A, the sample includes all firms for which we have a measure of the discount rate. The solid blue line represents the full sample discount rate pattern (78,509 observations), while the solid red plot is constructed using only American firms. In Panel B, we match our sample with Gormsen and Huber' (2022) firm-level raw data and only use the overlapping observations (751 firm-year pairs). The solid blue line is generated from our sample, while the solid red line is provided directly by Kilian Huber and Niels Gormsen. Panel C plots trends in equity betas used by equity analysts. Panel D presents the subjective equity risk premia used over the sample period. Panel D plots the risk-free rate used by analysts, and compares it to the 10-year treasury yield associated with firms' country.

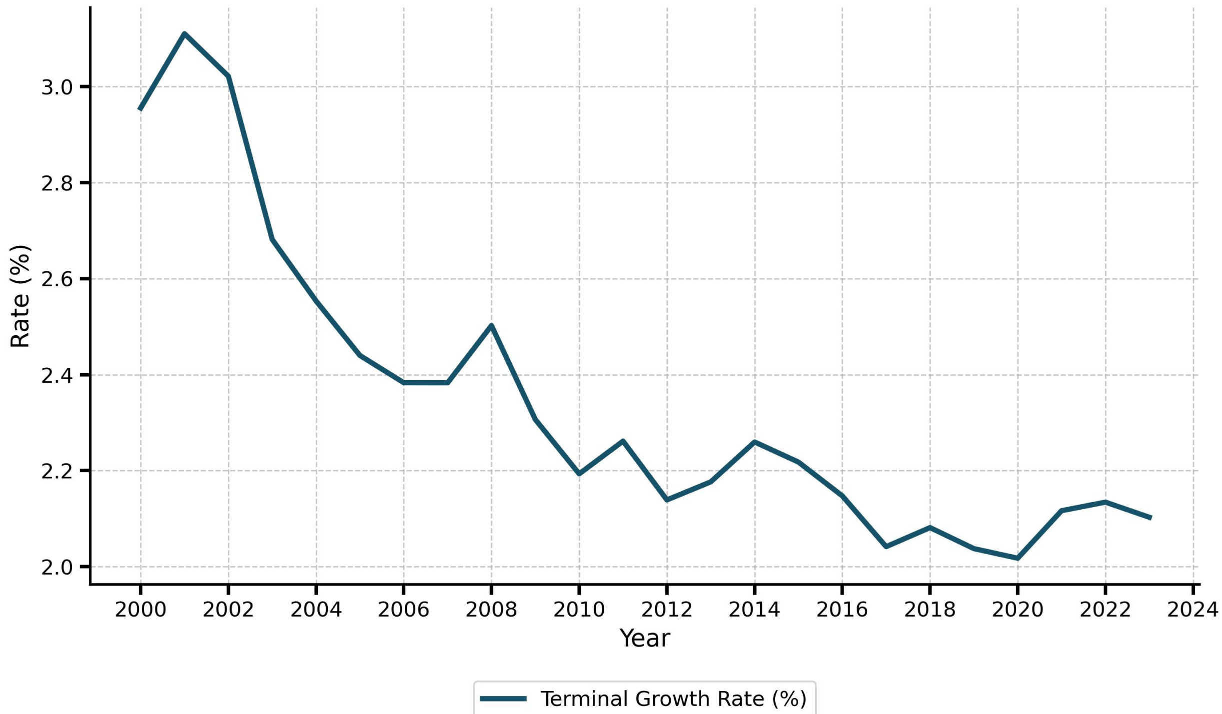
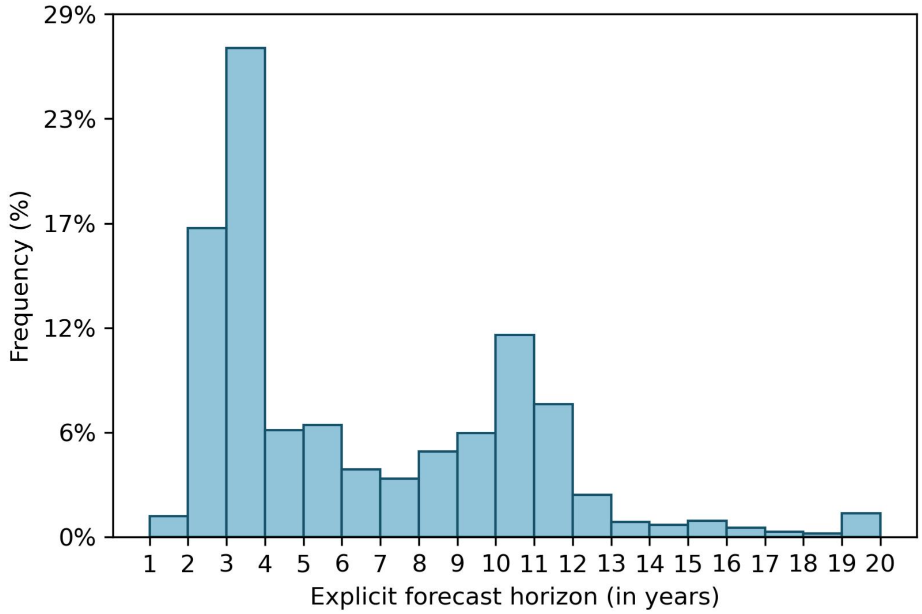


Figure 3: Analysts' Terminal Growth Rate Trend This figure plots analysts' terminal growth rates over the sample period, 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which we have a measure of analysts' terminal growth rates. The solid blue line represents analysts' terminal growth rate patterns (51,016 observations).

(A) Explicit Forecast Horizon Histogram.



(B) Explicit Forecast Horizon Trend.

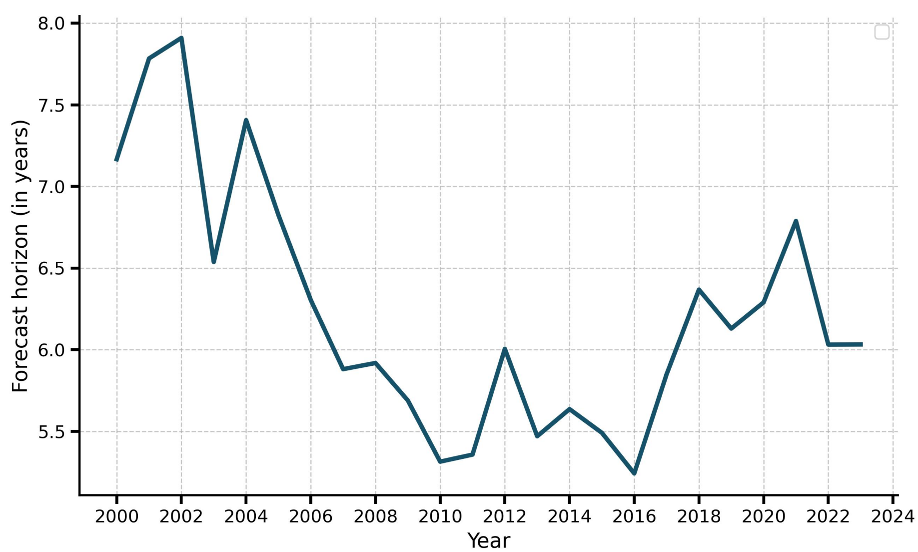


Figure 4: **Forecast Horizon** This figure plots the explicit forecast horizon patterns for the period 2000–2023. Panel A presents the histogram of DCFs forecast horizon in our sample. The x-axis represents the explicit forecast horizon (in years), and the y-axis indicates sample frequencies. Panel B shows the time trend. The x-axis is expressed in years, and the y-axis denotes the average number of years used in analysts' explicit forecasts. The sample includes all firms for which we have information on the explicit forecast part of the DCF.

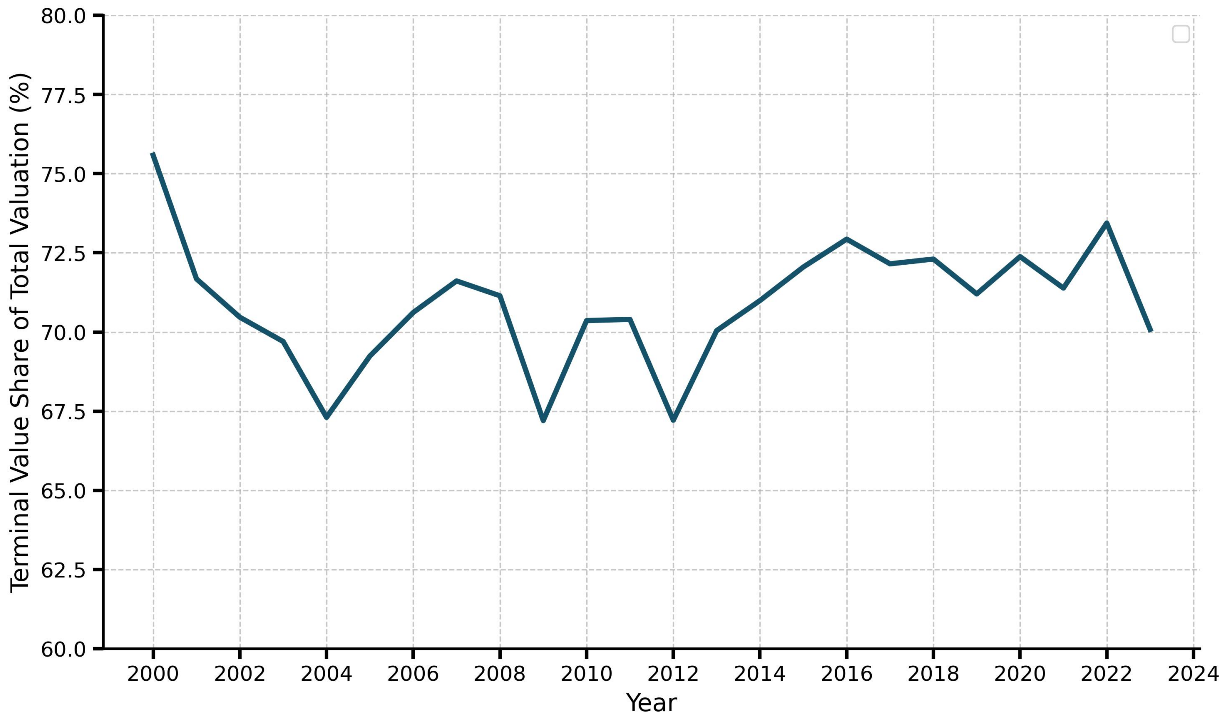


Figure 5: Terminal Value Share of Total Equity This figure plots the share of equity valuation that is associated with DCF (Discounted Cash Flow) terminal values for the period 2000–2023. The x-axis is expressed in years, and the y-axis denotes the proportion of the firm valuation derived from the terminal value. The sample includes all firms for which we have both the terminal growth rate, the discount rate, and the explicit cash flows prediction.

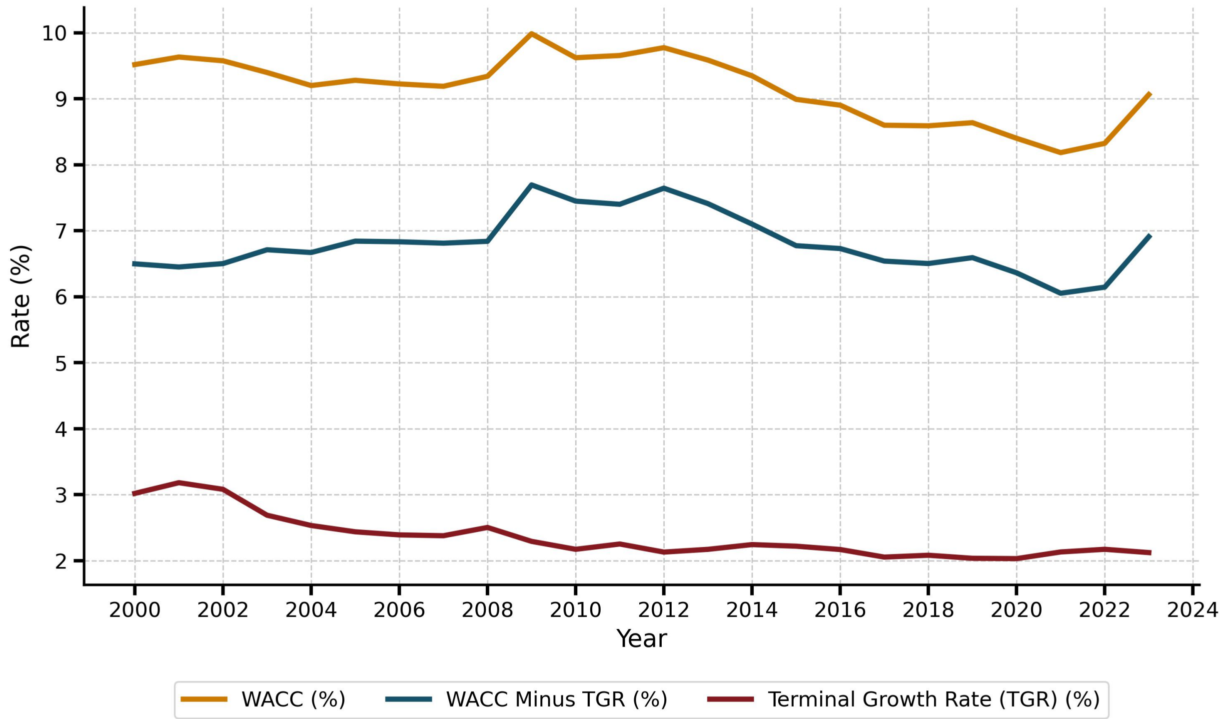


Figure 6: Discount Rate Minus Terminal Growth Rate Trend This figure plots the difference between the discount rate and the terminal growth rate for the period 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which we have both the terminal growth rate and the discount rate. The solid blue line shows the difference between the discount rate and the terminal growth rate, the solid red line plots the terminal growth rate, and the solid yellow line corresponds to the discount rate.

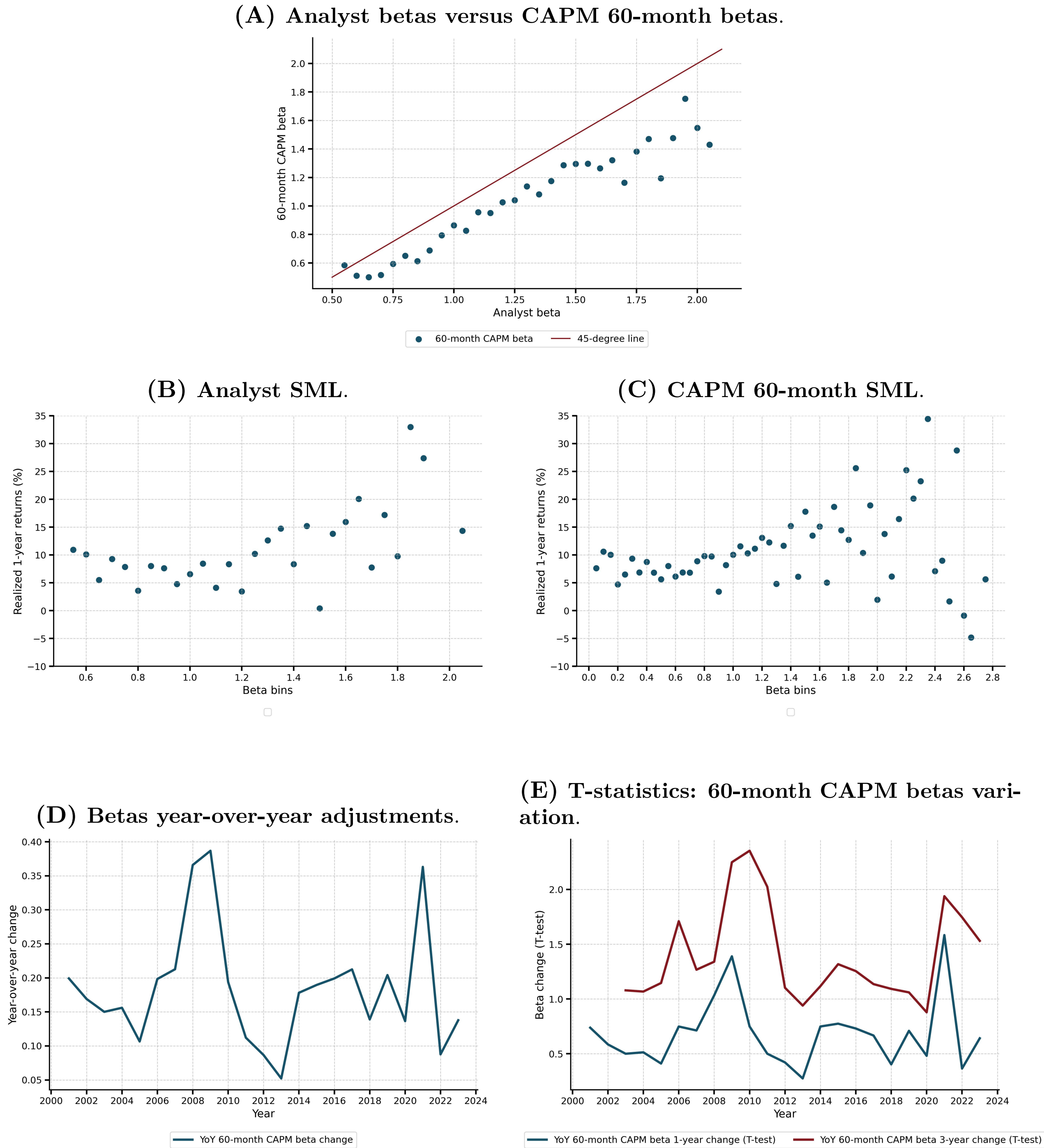


Figure 7: **Analyst betas and adjustments** This figure plots analyst betas patterns in the cross-section and time-series for the period 2000-2023. The x-axis in Panels A, B, and C denotes beta bins in 0.05 increments. In Panel A, the y-axis denotes the average 60-month beta estimates. In Panels B and C, the y-axis corresponds to the 1-year realized returns. Panel D plots the average adjustment of analysts' beta in percentage points over time for the period 2000-2023. Panel E plots the average t-statistics between the 60-month CAPM current estimates and the measure estimated by the econometrician in the previous year in blue, and 3 years prior in red, over the period 2000-2023.

Table 1: Summary Statistics This table reports summary statistics. The sample consists of 11,171 firms with observations from 78,509 equity reports in 2000–2023. Panel A describes the sample coverage and firm characteristics. Panel B focuses on variables associated with equity reports, and Panel C examines economic data series. Variable definitions appear in Appendix C.

Panel A: Firm and Coverage

	No. Firm	No. Obs
Discount rate sample	11,171	78,509
Terminal growth rate sample	9,173	51,016
Analysts risk-free rate sample	5,594	19,448
Analysts equity beta sample	6,006	21,973
Analysts equity risk premium sample	5,700	19,812

	Mean	25^{th} Pct.	Median	75^{th} Pct.	Std. Dev.	No. Obs.
Firm Variables						
Analysts coverage$_i$ (Nb. of analysts)	2.90	1.00	2.00	4.00	2.94	11,171
Years in sample$_i$ (in Years)	4.41	1.00	2.00	6.00	4.65	11,171
Assets book value$_{i,t}$ ($ Mil.)	13,041.31	632.90	2,221.62	7,778.20	55,256.50	43,742
Investment - (capex/assets)$_{i,t}$ (%)	5.69	1.95	3.97	7.26	6.21	42,772
Worldscope data for IBES firms						
Assets book value$_{i,t}$ ($ Mil.)	15,226.79	178.26	802.10	3,687.42	11,0443.76	101,064
Investment - (capex/assets)$_{i,t}$ (%)	5.25	0.95	2.91	6.46	8.63	101,064

Panel B: Equity Reports	Mean	25^{th} Pct.	Median	75^{th} Pct.	Std. Dev.	No. Obs.
DCF Structure						
Forecast horizon$_{i,j,t}$ (in years)	6.24	3.00	4.00	10.00	6.22	8,685
Terminal value share of total valuation$_{i,j,t}$(%)	70.87	61.22	75.14	82.21	15.14	8,685
DCF Inputs						
Discount rate$_{i,j,t}$(%)	9.11	7.70	8.90	10.20	2.09	78,509
Analyst risk-free rate$_{i,j,t}$(%)	4.02	3.00	4.00	5.00	1.81	19,448
Analyst equity beta$_{i,j,t}$	1.10	0.90	1.07	1.25	0.29	21,973
Analyst equity risk premium$_{i,j,t}$(%)	5.70	5.00	5.50	6.50	1.39	19,812
Analyst terminal growth rate$_{i,j,t}$(%)	2.23	1.50	2.00	3.00	1.31	51,016
Discount rate *minus* terminal growth rate$_{i,j,t}$(%)	6.83	5.40	6.60	8.00	2.13	48,934
DCF Cash Flow Inputs						
Expected returns over 6-18 month horizon$_{i,j,t}$(%)	19.32	1.00	12.64	25.98	56.24	23,946
Realized 12-month returns$_{i,j,t}$(%)	7.99	-19.71	2.55	24.84	94.67	23,946
Forecast horizon min. realized returns (6 to 18-mth)$_{i,j,t}$(%)	-19.89	-41.24	-18.75	-1.05	48.60	23,946
Forecast horizon max. realized returns (6 to 18-mth)$_{i,j,t}$(%)	37.57	2.38	21.82	48.63	128.65	23,946

Panel C: Economic Data Series	Mean	25^{th} Pct.	Median	75^{th} Pct.	Std. Dev.	No. Obs.
Current Variables						
10-year treasury yield$_{c,t}$(%)	4.51	2.09	4.04	5.98	3.44	834
US 10-year treasury yield$_{c,t}$(%)	3.23	1.96	3.11	4.13	1.38	24
Inflation$_{c,t}$(%)	2.93	1.11	2.20	3.85	3.26	834
Real GDP growth$_{c,t}$(%)	5.39	-1.35	5.45	11.44	10.34	834
10-Year Historical Averages						
10-Year hist. avg. risk-free rate$_{c,t}$(%)	4.47	2.79	4.20	5.61	2.40	587
Nominal GDP growth$_{c,t}$(%)	2.47	1.54	2.05	2.76	1.76	587
Inflation$_{c,t}$(%)	5.07	1.77	4.64	7.55	4.03	587
Survey of Professional Forecasters						
SPF 10-Year forecast 10-year treasury yield$_{c,t}$ (%)	3.11	2.47	2.84	3.78	0.84	24
SPF 10-Year forecast inflation$_{c,t}$ (%)	2.36	2.27	2.36	2.50	0.13	24
SPF 10-Year forecast GDP growth$_{c,t}$ (%)	5.09	4.59	5.04	5.66	0.56	24

Table 2: Analyst Equity Betas This table presents the properties of analysts' equity betas. The sample period is 2000–2023. In Panel A, the dependent variable, *Analyst beta*, is the analysts' equity beta used to compute the discount rate, measured at the firm *i*, analyst *j*, and year *t* levels. The variables of interest in Panel A correspond to the monthly CAPM beta estimates produced when using 2 to 6 years of returns. In Panel B, the dependent variable is the 1-year realized return at the firm *i*, analyst *j*, and year *t* levels. The variable of interest, beta, is the beta associated with the subtitle of each column in Panel B. In Panel C, the dependent variable in Columns 1-2 is the beta used by analysts to compute their discount rate. In columns 3-5, it is equal to an indicator variable that takes the value of 1 if the analysts updated the beta used in the DCF from the previous year's estimates, and 0 otherwise. Standard errors (in parentheses) are heteroskedastic-consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Decomposition	Analyst beta$_{i,j,t}$
	(1)
24-month CAPM beta$_{i,j,t}$	-0.01**
	(0.01)
36-month CAPM beta$_{i,j,t}$	0.04***
	(0.01)
48-month CAPM beta$_{i,j,t}$	0.04***
	(0.01)
60-month CAPM beta$_{i,j,t}$	0.11***
	(0.01)
72-month CAPM beta$_{i,j,t}$	0.02***
	(0.01)
Observations	15,934
F Statistics	607.50
R^2	0.16
R^2 Shapley Decomposition	
24-month CAPM beta$_{i,j,t}$	11.79%
36-month CAPM beta$_{i,j,t}$	19.37%
48-month CAPM beta$_{i,j,t}$	23.68%
60-month CAPM beta$_{i,j,t}$	27.59%
72-month CAPM beta$_{i,j,t}$	17.57%

Panel B: SML regression:	1-year realized return$_{i,j,t}$					
	(1) Analyst beta	(2) 24-month	(3) 36-month	(4) 48-month	(5) 60-month	(6) 72-month
Beta$_{i,j,t}$	7.89***	2.65***	2.07**	4.29***	3.05***	2.43***
	(1.57)	(0.72)	(0.81)	(0.83)	(0.87)	(0.76)
Constant	0.69	7.12***	7.52***	5.54***	6.53***	6.78***
	(1.64)	(0.68)	(0.75)	(0.76)	(0.79)	(0.73)
Observations	15,143	13,749	13,212	12,650	12,083	11,584
F Statistics	25.12	13.75	6.59	26.79	12.32	10.30
R^2	0.00	0.00	0.00	0.00	0.00	0.00

Panel C: Beta adjustments	Analyst beta$_{i,j,t}$		Adjusted beta (Indicator) $_{i,j,t}$		
	(1)	(2)	(3)	(4) $\frac{\lvert\beta^{60}-\beta^{A}\rvert}{SE^{\beta^{60}}} >= 1.64$	(5) $\frac{\lvert\beta^{60}-\beta^{A}\rvert}{SE^{\beta^{60}}} < 1.64$
Analyst beta$_{i,j,t-1}$	0.76***	0.75***			
	(0.01)	(0.01)			
CAPM beta$^{60}_{i,j,t}$	0.06***	0.08***			
	(0.01)	(0.01)			
CAPM beta$^{60}_{i,j,t}$ * Std. Error beta$_{i,j,t}$		-0.06***			
		(0.02)			
Std. Error beta$_{i,j,t}$		0.14***	-0.22**	-0.92***	-0.07
		(0.04)	(0.10)	(0.33)	(0.14)
|CAPM beta$^{60}_{i,j,t}$ - Analyst beta$_{i,j,t-1}$|			0.06*	0.14*	-0.06
			(0.03)	(0.07)	(0.08)
Year FE	No	No	Yes	Yes	Yes
Analyst*Firm FE	No	No	Yes	Yes	Yes
Observations	6,015	6,015	4,674	1,894	2,175
F Statistics	2716.20	1450.57	3.29	4.78	0.47
R^2	0.65	0.65	0.47	0.48	0.52

Table 3: Valuation Decomposition In Panel A, this table decomposes DCF valuations into its core component following Equation (4). The unit of observation is at the firm i, analyst j, and forecast year t levels. The sample period is 2000–2023. The dependent variable, $Valuation_{i,j,t}$, is equal to the natural logarithm of the analyst's price target, $\ln(\text{Price target}_{i,j,t})$. *Terminal growth rate*$_{i,j,t}$ is equal to the natural logarithm of the terminal growth used by the analyst, $\ln(1 + \text{TGR}_{i,j,t})$. The discount rate corresponds to the natural logarithm of the discount rate used to evaluate firm cash flows, $\ln(1+\text{Discount rate}_{i,j,t})$. *Initial cash flow* denotes the natural logarithm of the last annual cash flow generated by the firm at the time of producing the equity report, $\ln(\text{FCF}_0)$. *FCF short-term growth rate*$_{i,j,t}$ is the natural logarithm of the explicit forecast for the first year, $\ln(1 + \text{FCF growth rate}^{Year=1}_{i,j,t})$. *FCF medium-term growth rate*$_{i,j,t}$ is the natural logarithm of the average explicit forecast for the second and third year, $\ln(1 + \text{FCF growth rate}^{Year=2+3}_{i,j,t})$. In Panel B, the dependent variable is equal to the natural logarithm of the terminal multiple, as shown in equation (1). Variable definitions appear in Appendix C. The regressions are estimated using ordinary least squares, and the standard errors (in parentheses) are heteroskedastic-consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: DCF	$\ln(\text{Valuation}_{i,j,t})$						
	All sample			Younger firms			All sample
	Free cash flows						Sales
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Terminal growth$_{i,j,t}$	10.48***	4.88***	6.90**	9.50***	8.45***	18.83***	11.39**
	(1.74)	(1.27)	(3.22)	(2.71)	(1.83)	(6.55)	(4.84)
Discount rate$_{i,j,t}$	-20.16***	-13.22***	-16.47***	-13.75***	-14.48***	-19.91***	-19.13***
	(1.35)	(1.06)	(3.51)	(2.00)	(1.70)	(5.39)	(3.95)
Initial value$_{i,j,t}$			0.06**			0.07	0.09
			(0.03)			(0.04)	(0.08)
Short-term growth$^{\text{Year = 1}}_{i,j,t}$			0.00			0.08	-0.02
			(0.05)			(0.09)	(0.09)
Medium-term growth$^{\text{Year = 2-3}}_{i,j,t}$			0.22***			0.34**	0.15
			(0.08)			(0.14)	(0.12)
Contibutor*Firm FE	No	Yes	Yes	No	Yes	Yes	Yes
Observations	18,578	12,058	413	5,934	3,507	143	384
F Statistics	120.83	83.55	5.75	28.09	53.11	6.39	6.74
R^2	0.04	0.93	0.92	0.02	0.94	0.94	0.92
R^2 Decomposition							
Initial value$^{\text{Year = 0}}_{i,j,t}$			8.15 %			6.32 %	8.15 %
Discount rate (DR)$_{i,j,t}$	90.07 %	81.82 %	71.04 %	83.09 %	51.59 %	42.17 %	71.04%
Short-term growth$^{\text{Year = 1}}_{i,j,t}$			3.32 %			10.91%	3.32 %
Medium-term growth$^{\text{Year = 2-3}}_{i,j,t}$			6.10 %			8.66 %	6.10 %
Terminal growth (TGR)$_{i,j,t}$	9.93 %	18.18 %	11.39 %	16.91 %	48.41 %	31.94 %	11.39%

Panel B: Terminal Multiple	$\ln(1/(\text{DR}_{i,j,t}$ - $\text{TGR}_{i,j,t}))$	
	(1)	(2)
Terminal growth$_{i,j,t}$	10.48***	14.01***
	(1.38)	(0.92)
Discount rate$_{i,j,t}$	-15.37***	-16.38***
	(0.21)	(0.18)
Contibutor*Firm FE	No	Yes
Observations	48,857	37,617
F Statistics	15,641.63	4,868.67
R^2	0.81	0.95
R^2 Decomposition		
Discount rate$_{i,j,t}$ (%)	72.79 %	59.47 %
Terminal growth rate$_{i,j,t}$ (%)	27.21 %	40.53 %

Table 4: Ex-post realized returns and analyst discount rates This table studies the relation between analyst discount rates and one-year realized returns. The dependent variable, *Realized returns*, is a firm realized return from year t to t+1. The sample period is 2000–2022. The unit of observation is at the firm i, analyst j, and forecast year t level. For the regression coefficient associated with the explanatory variable, *Discount rate*, we fail to reject that it is statistically different from the value of 1 at the 95% confidence level. The regressions are estimated using ordinary least squares. In Panel A, standard errors (in parentheses) are heteroskedastic-consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Dependent variable	Realized return$_{i,t+1}$		
	(1)	(2)	(3)
Terminal growth rate$_{i,j,t}$	-0.80***		-1.12***
	(0.29)		(0.31)
Discount rate$_{i,j,t}$		0.62***	0.85***
		(0.16)	(0.22)
Constant	5.58***	-0.96	-1.36
	(0.72)	(1.40)	(1.85)
Observations	16,717	26,726	16,024
F Statistics	7.39	14.59	11.89
R^2	0.00	0.00	0.00

Table 5: Discount rates This table presents the properties of analysts' discount rates. The dependent variable, *Discount rate*, is the analysts' discount rate used to evaluate the firm's cash flows. The sample period is 2000–2023. In Panel A, we look at the persistence of the discount rate process, and we decompose the discount rate into the core inputs used by analysts. The unit of observation is at the firm i, analyst j, and forecast year t level. *Analysts' risk-free rate*$_{i,j,t}$ is equal to the analysts' choice of risk-free rate. *Analysts' equity beta*$_{i,j,t}$ is equal to the analysts' choice of equity beta. *Analysts' equity risk premium*$_{i,j,t}$ is equal to the analysts' choice of equity risk premium. In Panel B, the unit of observation is at the country c and forecast year t levels. *Inflation rate*$_{c,t}$ denotes the firm headquarters country's current inflation measure. *10-year inflation expectations*$_{c,t}$ correspond to the Survey of Professional Forecasters' 10-year forecasts consensus for the 10-year treasury yield in the United States. *10-year treasury yield*$_{c,t}$ indicates the current measure associated with the firm headquarter country's 10-year treasury yield. Variable definitions appear in Appendix C. The regressions are estimated using ordinary least squares. In Panel A, standard errors (in parentheses) are heteroskedastic-consistent and clustered at the firm level. In Panel B, standard errors (in parentheses) are heteroskedastic-consistent and clustered at the country level when regressions include all countries; otherwise, standard errors are estimated using heteroskedastic-consistent jackknife estimators. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Discount rate	Discount rate$_{i,j,t}$ (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Discount rate$_{i,j,t}$ (%)	0.73***					
	(0.01)					
Analysts' risk-free rate$_{i,j,t}$ (%)		0.46***			0.58***	0.48***
		(0.01)			(0.02)	(0.03)
Analysts' equity beta$_{i,j,t}$ (%)			2.56***		3.12***	2.52***
			(0.07)		(0.08)	(0.14)
Analysts' equity risk premium$_{i,j,t}$ (%)				0.18***	0.41***	0.35***
				(0.02)	(0.02)	(0.03)
Contibutor*Firm FE	No	No	No	No	No	Yes
Observations	32,798	18,466	20,966	18,868	13,328	8,789
F Statistics	3,930.60	1,238.49	1,171.29	132.75	787.38	190.76
R^2	0.52	0.15	0.13	0.02	0.39	0.82
R^2 Shapley Decomposition						
Analysts' risk-free rate$_{i,j,t}$ (%)					47.86 %	45.74 %
Analysts' equity beta$_{i,j,t}$ (%)					40.55 %	42.37 %
Analysts' equity risk premium$_{i,j,t}$(%)					11.58 %	11.89 %

Panel B: Inflation & Treasury yield	Discount rate$_{c,t}$ (%)			
	(1)	(2)	(3)	(4)
		US Only		
Inflation rate$_{c,t}$ (%)	0.02	-0.22***		
	(0.02)	(0.04)		
10-Year inflation expectations$_{c,t}$(%)		3.90***		
		(0.74)		
Analyst risk-free rate$_{c,t}$(%)			0.29***	
			(0.04)	
10-year treasury yield$_{c,t}$ (%)				0.20***
				(0.04)
Country FE	Yes	No	Yes	Yes
Observations	1,195	23	871	871
F Statistics	1.06	18.98	69.27	24.56
Within R^2	0.01	0.60	0.25	0.24
R^2 Shapley decomposition				
Inflation rate$_{c,t}$ (%)		25.86%		
10-Year inflation expectations$_{c,t}$(%)		74.14%		

Table 6: Discount rates and Terminal Growth Rates This table studies the relation between analysts' choice of discount rates and terminal values. In columns 1 and 2, the unit of observation is at the firm i, analyst j, and forecast year t levels. The sample period is 2000–2023. The dependent variable, *Discount* $rate_{i,j,t}$, is equal to the discount rate used by analysts in DCF models. *Terminal growth rate* refers to the terminal growth rate used by analysts in the DCF model. Variable definitions appear in Appendix C. The standard errors (in parentheses) are heteroskedastic-consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Dependent variable:	Discount $\text{rate}_{i,j,t}$ (%)	
	(1)	(2)
$\text{TGR}_{i,j,t}$ (%)	0.27***	0.03**
	(0.01)	(0.01)
Analyst*Firm FE	No	Yes
Year FE	No	Yes
Observations	48,927	37,662
F Statistics	487.53	6.21
R^2	0.03	0.76

Table 7: Analysts' Risk-Free Rate This table studies the properties of analysts' choice of risk-free rates. The unit of observation is at the firm i, analyst j, and forecast year t levels. The sample period is 2000–2023. Panels A and B examine a noisy information model *à la* Coibion and Gorodnichenko (2015), and regressions are estimated using ordinary least squares. The dependent variable, *Analysts' risk-free rate*$_{i,j,t}$, is equal to the risk-free rate used by analysts in DCF models. *10-year treasury yield* indicates the firm headquarters country's 10-year treasury yield. *Volatility*$^{RF}_{i,j,t}$ is the volatility of the 10-year treasury yield during the previous year at the monthly frequency, scaled by the sample average to facilitate readability of the coefficient. In Panel C, regressions are estimated using a probit model. The dependent variable *Analysts adjust risk-free rate*$_{i,j,t}$ is a binary variable equal to 1 if the analyst updates the measure from the previous year and zero otherwise. The variable of interest is *10-year treasury yield* $\Delta_{i,j,t}$, which is equal to the absolute difference between the current 10-year Treasury yield and the one observed in the previous year in percentage points. Variable definitions appear in Appendix C. Panels A, B, and C standard errors (in parentheses) are heteroskedastic-consistent and clustered at the firm level. In Panel D, the unit of observation is at the country "c" and year "t" level. standard errors (in parentheses) are heteroskedastic-consistent and clustered at the country level when regressions include all countries; otherwise, standard errors are estimated using heteroskedastic-consistent jackknife estimators. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Noisy Information	Analysts' risk-free rate$_{i,j,t}$ (%)		
	(1) Full Sample	(2) 10-Year Only	(3) US Only
Analysts' risk-free rate$_{i,j,t-1}$ (%)	0.67***	0.70***	0.66***
	(0.02)	(0.05)	(0.02)
10-year treasury yield$_{i,j,t}$ (%)	0.19***	0.21***	0.29***
	(0.01)	(0.05)	(0.03)
Observations	6,054	607	1,407
F Statistics	3270.71	228.62	705.44
R^2	0.71	0.71	0.63

Panel B: Risk-Free Rate Volatility	Analysts' risk-free rate$_{i,j,t}$ (%)		
	(1) Full Sample	(2) 10-Year Only	(3) US Only
Analysts' risk-free rate$_{i,j,t-1}$ (%)	0.66***	0.70***	0.69***
	(0.02)	(0.05)	(0.03)
10-year treasury yield$_{i,j,t}$ (%)	0.21***	0.29***	0.50***
	(0.02)	(0.06)	(0.06)
10-year treasury yield$_{i,j,t}$*Volatility$^{RF}_{i,j,t-1}$ (%)	-0.01***	-0.08**	-0.22***
	(0.00)	(0.03)	(0.04)
Volatility$^{RF}_{i,j,t-1}$	0.13***	0.56***	0.57***
	(0.02)	(0.18)	(0.12)
Observations	6,051	607	1,407
F Statistics	1782.00	186.29	480.98
R^2	0.71	0.72	0.64

Panel C: Extensive Margin Adjustments	Analysts' adjust risk-free rate$_{i,j,t}$		
	(1) Full Sample	(2) 10-Year Only	(3) US Only
10-year treasury yield $\Delta_{i,j,t}$ (pp)	0.15***	0.25***	0.25***
	(0.03)	(0.06)	(0.07)
Observations	6,045	606	1,407
Chi^2	25.54	16.70	13.40
Pseudo R^2	0.01	0.01	0.00

Panel D: Risk-free rate and Inflation	Analysts' risk-free rate$_{c,t}$ (%)			**US 10-year treasury yield$_{c,t}$** (%)
	(1)	(2)	(3)	(4)
Inflation$_{c,t}$ (%)	-0.00***			
	(0.00)			
10-year hist. avg. inflation$_{c,t}$ (%)		-0.00***		
		(0.00)		
SPF 10-year forecast inflation$_{c,t}$ (%)			5.19***	7.59***
			(1.69)	(1.65)
Country FE	Yes	Yes	No	No
Observations	1,053	1,013	24	24
F Statistics	463.49	136.14	9.42	21.11
R^2	0.00	0.00	0.42	0.52

Table 8: Analysts' Terminal Growth Rate This table studies the properties of analysts' choice of terminal growth rate. The sample period is 2000–2023. Regressions are estimated using ordinary least squares. The dependent variable, *Terminal growth rate*, is equal to the terminal growth rate used by analysts in DCF models. The unit of observation is at the country c and forecast year t level. There are three variables of interest: $Inflation_{c,t}$, $10\text{-}year\ treasury\ yield_{c,t}$, and $real\ GDP\ growth_{c,t}$, that are each measured in three ways using *current value*, *10-year historical average*, and the *Survey of Professional Forecasters 10-year forecast consensus*. Variable definitions appear in Appendix C. Standard errors (in parentheses) are heteroskedastic-consistent and clustered at the country level when regressions include all countries; otherwise, standard errors are estimated using heteroskedastic-consistent jackknife estimators. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Terminal growth rates and Macroeconomic Variables	Terminal growth rate$_{c,t}$ (%)				
	(1)	(2)	(3)	(4)	(5)
	Current	10-year hist. avg.	SPF 10-year forecast	Current	10-year hist. avg.
	US Only			**Full Sample**	
Inflation$_{c,t}$ (%)	0.00	-0.15	0.60	0.00	0.01
	(0.03)	(0.18)	(0.49)	(0.01)	(0.04)
Real GDP growth$_{c,t}$(%)	0.01	0.35***	0.63***	0.01***	0.09***
	(0.03)	(0.09)	(0.17)	(0.00)	(0.03)
10-year treasury yield$_{c,t}$ (%)	0.35***	0.25***	0.25***	0.03**	0.05*
	(0.06)	(0.08)	(0.07)	(0.01)	(0.02)
Country FE	No	No	No	Yes	Yes
Observations	23	23	23	605	605
F Statistics	9.88	68.12	47.26	5.45	4.34
R^2	0.74	0.92	0.83	0.64	0.66
Within R^2	0.74	0.92	0.83	0.03	0.07
R^2 Shapley Decomposition					
Inflation$_{c,t}$ (%)	0.29 %	17.05 %	23.99 %	4.67 %	13.76 %
Real GDP growth$_{c,t}$ (%)	1.49 %	40.92 %	39.73 %	45.09 %	41.72 %
10-year treasury yield$_{c,t}$ (%)	98.23 %	42.03 %	36.28 %	50.24 %	44.51 %

Appendix A: The terminal growth rate

Reference to inflation rate

Report 1: Credit Suisse, DTEGn.DE, 2023-01-22: We have assumed a 3.0% perpetual growth rate, somewhat above the current rate of inflation, reflecting longer-term growth prospects.

Report 2: Credit Suisse, ET.N^G13, 2013-01-22: Our long-term growth rate assumption is 3.0%, which we believe should be in-line with the long-term growth trend of inflation, given the relatively stable connection between gdp growth and advertising spending.

Report 3: Credit Suisse, 0066.HK, 2001-03-06: We believe that both of the current assumptions (a 5% terminal-growth and 2.5% inflation rate) are reasonable.

Report 4: UBS Equities, `030200.KS`, 2003-02-05: Our long-term growth forecast of 4.5%, which is applied to our 2003 forecasts, compares to a medium-term GDP and inflation rate of 3.5% and 3.0%, respectively.

Reference to GDP growth

Report 1: Deutsche Bank Equity, 1193.HK, 2017-03-28: Our target price is dcf-based with a wacc of 8.5% (3.9% risk-free rate, 1.0x beta, 5.6% equity risk premium, 6% pretax cost of debt, 25% effective tax rate, 20% debt/total asset ratio), and terminal growth rate of 1%, based on long-term forecasts for economic growth in china.

Report 2: Credit Suisse, ORI.AX, 2002-01-18: [...] terminal growth rate of 2.75% (21% discount to long-term forecast australian gdp 3.5%) [...].

Report 3: Deutsche Bank Equity, CEB.N^D17, 2011-02-10: [...] wacc is based on a beta of 1.0, risk free rate of 4.0%, 5.0% risk premium, a 3.0% long-term growth rate (slightly below the 3.5% long-term growth of the us economy), and zero debt in the capital structure.

Report 4: Deutsche Bank Equity, TLEVISACPO.M, 2010-03-17: Our perpetuity growth rate is 2.3%, and it is based on our assumption for mexican gdp growth in the long term (3.5%), the participation of the advertising market in the economy and potential growth of the new businesses.

Appendix B

Appendix B1: Risk-Free Rate Discussions

Report 1: National Bank, X.TO, 2010-03-25: Specifically, we use the yield on 10-year government of canada bonds (currently 3.5%) as a proxy for the risk-free rate [...].

Report 2: Nordea Markets, ORRON.ST, 2016-02-04: risk free rate (10-year us treasury bill) 2.20%.

Report 3: J.P. MORGAN, skyworth digital holdings, 2011-1: Our dec-11 price target is based on a dcf valuation that assumes a market risk premium of 6.0% and a risk-free rate of 4.2% (yield on 10-year government notes in china).

Report 4: Macquarie Research, 4568.T, 2023-01-08: For our dcf model, we calculate the cost of equity at 5.7%, applying risk-free rate of 0.3% (10- year japanese government bond yield), market risk premium of 6%.

Report 5: Santander, ENTEL.SN, 2004-01-04: The cost of equity was calculated assuming a risk-free rate of 5.0%, based on a yield to maturity of the chilean sovereign bond.

Appendix B2: Backward-looking Discussions of the Risk-Free Rate

Report 1: Warburg Research Gmb, CAGG.DE^A11, 2002-03-25: We equate the risk-free rate of return with the average annual yield on a ten-year german government bond.

Report 2: JPMorgan, 4527.T, 2014-03-06: [...] rebase our dcf timeframe for calculating fair value to fy2014-2018, revise our dcf risk-free rate from 2% to 1% (somewhat conservatively referencing the recent three-year average jgb 10-year yield of 85bp) in light of protracted low levels of interest rates [...].

Report 3: Deutsche Bank, MDNG.DE, 2011-01-06: We use a risk-free rate of 4.0% (in line with long-term government bond yields) [...].

Report 4: JPMorgan, CA.OQ^K18, 2012-03-05: E(rf) = expected risk-free rate based on the historical average of 5.3%.

Report 5: Credit Suisse, MEL.NZ, 2019-02-20: We use estimated mid-cycle (i.e. long-run) values for key WACC inputs, notably risk-free rate (4.6% assumed, vs current 3.0% 10-year NZ Government bond yields) and market risk premium (7.4% assumed, vs. 7% historical average).

Report 6: Deutsche Bank, PLZL.MM, 2018-03-22: Our wacc of 8.5% is based on DB standard equity risk premium for Russia of 6.0x, risk-free rate of 4.6% (historical average yield for Russia 30 eurobond) [...].

Appendix B3: Forward-looking Discussions of the Risk-Free Rate

Report 1: Macquarie Research, 0004.HK, 2005-02-01: [...] in fact, we expect wharf to achieve a positive return over and above its cost of capital on its core business, even adjusting for our house view that the risk-free rate will rise to 6% by year end (our 10-year yield forecast).

Report 2: Auerbach Grayson, C-GDRB.BU, 2012-02-03: Furthermore, although yields on Hungarian 10-year government bonds are set to decline in the medium to long run, with respect to the currently shaky situation (with uncertainties pushing up Hungarian government bond yields to nearly record highs once again), we increase our risk-free rate assumption from the earlier applied 7.7% to 8.8% for the detailed forecast period of 2012-16.

Report 3: Deutsche Bank, TMAR5.SA^D12, 2009-01-08: We use a risk-free rate of 300bps, which is where we expect the yield of 10-year us treasuries will end up by year-end this year.

Report 4: Macquarie Research, GPK.N, 2015-03-13: We note that our risk free rate of 3.5% is higher than current levels, but representative of a longer-term view as we do not expect current low interest rates to be sustained in perpetuity.

Report 5: Auerbach Grayson, GGRM.JK, 2017-02-24: This takes into account the forecast revisions, netted off by the change in our wacc assumption to 10.2% as we realigned our risk-free rate assumption to 7.3% based on our newly revised end-2017 10-year government bond yield forecast (from previously 6.5%).

Report 6: Credit Suisse, SPK.NZ, 2015-02-10: As Figure 29 highlights the spot risk free rate is currently below 4% in New Zealand and has been below 5% for several years. At the same time Figure 29 (and Figure 30) highlights reasons to believe that this level is low and not necessarily a rate to apply into perpetuity. In the context of historical levels of the risk free rate, and taking Credit Suisse forecasts and spreads to US bonds into account, we are not making adjustments to our long-term assumptions for risk free rate. We expect the NZ/US 10-year bond spread to stabilise around 150bp, to imply NZ 10-year bond yields around 4.6% by the end of 2016. We also expect monetary tightening to continue after that date.

Appendix C: Variable definition

Table C.1: Variable Definitions

Subscript t forecast year, i indicates a firm, j indicates an analyst, and c identifies a country.

Variable	**Definition**
10-year historical average GDP growth	The 10-year rolling average of the firm's headquarters' country GDP growth rate, obtained from the World Bank.
10-year historical averageinflation rate$_{c,t}$	The 10-year rolling average of the firm's headquarters' country inflation rate, obtained from the World Bank.
10-year historical average 10-Year Treasury Yield$_{c,t}$	The 10-year rolling average of the firm's headquarters' country 10-year treasury yield, obtained from Refinitiv Eikon.
10-year treasury yield $\Delta_{i,j,t}$	The absolute difference between the 10-year treasury yield at the time of the report and the yield one year prior. The 10-year Treasury yield is taken from Refinitiv Eikon.
Analyst adjusted the risk-free rate$_{i,j,t}$	A binary variable equal to 1 if the analyst adjusted the risk-free rate used in the model from the previous year, and zero otherwise.
Analysts' risk-free rate$_{i,j,t}$	The risk-free rate used by analysts when computing their discount rate in equity reports.
Analysts' equity beta$_{i,j,t}$	The equity beta used by analysts when computing their discount rate in equity reports.
Analysts' equity premium$_{i,j,t}$	The equity premium used by analysts when computing their discount rate in equity reports.
Discount rate$_{i,j,t}$	The discount rate used by analysts to evaluate firm cash flow in equity reports.

Explicit forecast horizon$_{i,j,t}$	Number of years over which analysts explicitly forecast cash flows, measured from equity reports.
Ln terminal growth rate$_{i,j,t}$	The natural logarithm of the terminal growth rate price plus 1, $\ln(1+\text{Terminal growth rate}_{i,j,t})$, measured from the equity reports.
Ln discount rate$_{i,j,t}$	The natural logarithm of the discount rate plus 1, $\ln(1+\text{Discount rate}_{i,j,t})$, measured from the equity reports.
Ln initial cash flow$_{i,j,t}$	The natural logarithm of the most recent cash flow generated by the firm, $\ln(\text{FCF}^0_{i,j,t})$, measured from the equity reports.
Ln FCF short-term growth rate$^{Year=1}_{i,j,t}$	The natural logarithm of the short-term growth rate on the first year of the explicit forecast horizon, $\ln(1+\text{FCF ST growth}^1_{i,j,t})$.
Ln FCF Medium-term growth rate$^{Year=2-3}_{i,j,t}$	The natural logarithm of the average short-term growth rate on the first, second, and third year of the explicit forecast horizon, $ln(1+\frac{\text{FCF ST growth}^2_{i,j,t}+\text{FCF ST growth}^{Y=3}_{i,j,t}}{2})$.
SPF 10-year forecast Inflation$_{c,t}$	The 10-year horizon forecast of inflation in the United States, obtained from the Philadelphia Federal Reserve Survey of Professional Forecasters.
SPF 10-year forecast 10-year treasury yield$_{c,t}$	The 10-year horizon forecast of the 10-year treasury yield in the United States, obtained from the Philadelphia Federal Reserve Survey of Professional Forecasters.
SPF 10-year forecast real GDP growth$_{c,t}$	The 10-year horizon forecast of real GDP growth rate in the United States from the Philadelphia Federal Reserve Survey of Professional Forecasters.
Real GDP growth$_{c,t}$	The firm's headquarters' country real GDP growth rate, obtained from the World Bank.

Inflation rate$_{c,t}$	The firm's headquarters' country inflation rate, obtained from the World Bank.
10-Year Treasury Yield$_{c,t}$	The firm's headquarters' country 10-year treasury yield, obtained from Refinitiv Eikon.
Terminal growth rate$_{i,j,t}$	The terminal growth rate$_{i,j,t}$ used by equity analysts in their DCF models, measured from the equity reports.
Uncertainty$_{i,j,t}$	Firm returns' monthly standard deviation measured over the previous year, using stock price data from Refinitiv Eikon.
US 10-Year Treasury Yield$_{c,t}$	The US 10-year treasury yield, obtained from Refinitiv Eikon.
Valuation$_{i,j,t}$	The natural logarithm of the target price, ln(Target Price$_{i,j,t}$), measured from the equity reports.
Volatility$^{RF}_{i,j,t}$	The standard deviation of the firm's headquarters' country monthly 10-year Treasury yield measured in the previous year. The 10-year Treasury yield is taken from Refinitiv Eikon.

Appendix Figures

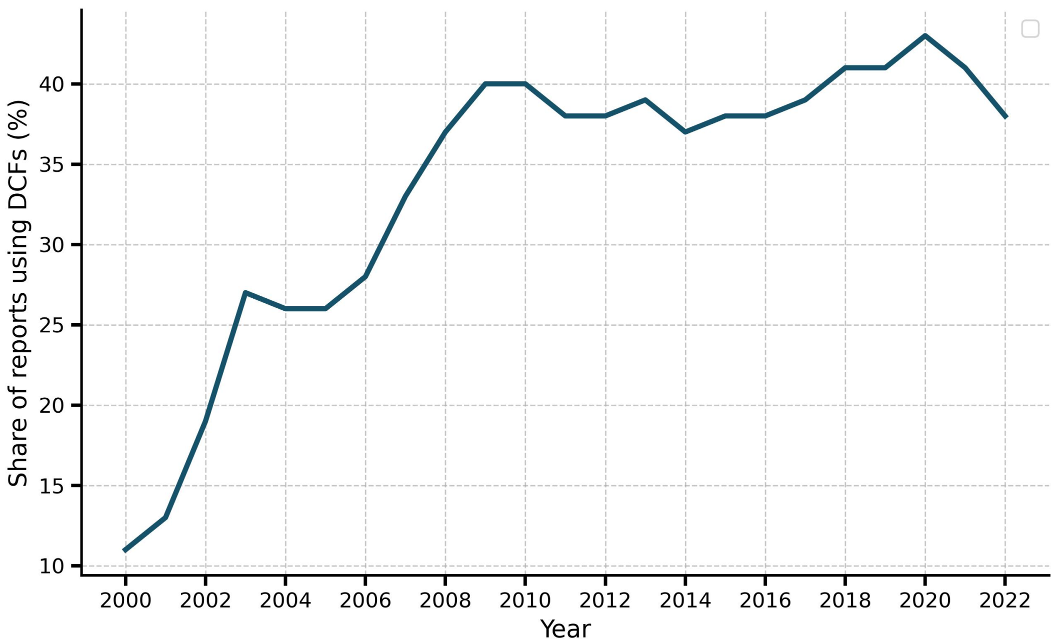


Figure A1: Share of equity reports using DCFs This figure plots the share of equity reports using DCF models to perform the analysis among the reports housed on Refinitiv. The x-axis represents years. The y-axis denotes the proportion of reports published in a given year in which the equity analyst specifically mentions using a discounted cash flow model to perform the valuation exercise. The sample includes all equity reports housed on the Refinitiv platform from 2000-2022.

DCF Model - Aixtron

Figures in EUR m	2011e	2012e	2013e	2014e	2015e	2016e	2017e	2018e	2019e	2020e	2021e	2022e	2023e	2024e
Sales														
Change														
EBIT														
EBIT-Margin														
Tax rate														
NOPAT														
Depreciation														
in % of Sales														
Change in Liquidity from														
- Working Capital														
- Capex														
Capex in % of Sales														
Other														
Free Cash Flow (WACC-Model)														

Model parameter			
Debt ratio		Beta	
Costs of Debt		WACC	
Market return			
Risk free rate		Terminal Growth	

Valuation (mln)			
Present values 2024e			
Terminal Value			
Liabilities			
Liquidity		No. of shares (mln)	
Equity Value		**Value per share (EUR)**	

Figure A2: Example of Complete Equity Report DCF This figure shows a representative example of discounted cash flow models when analysts supplement their recommendations with valuation models. This figure is taken from the Aixtron (Ticker = AIXGn) equity report, published by Warburg Research on October 27, 2011. *For copyright reasons, we redacted any information provided in the table.*

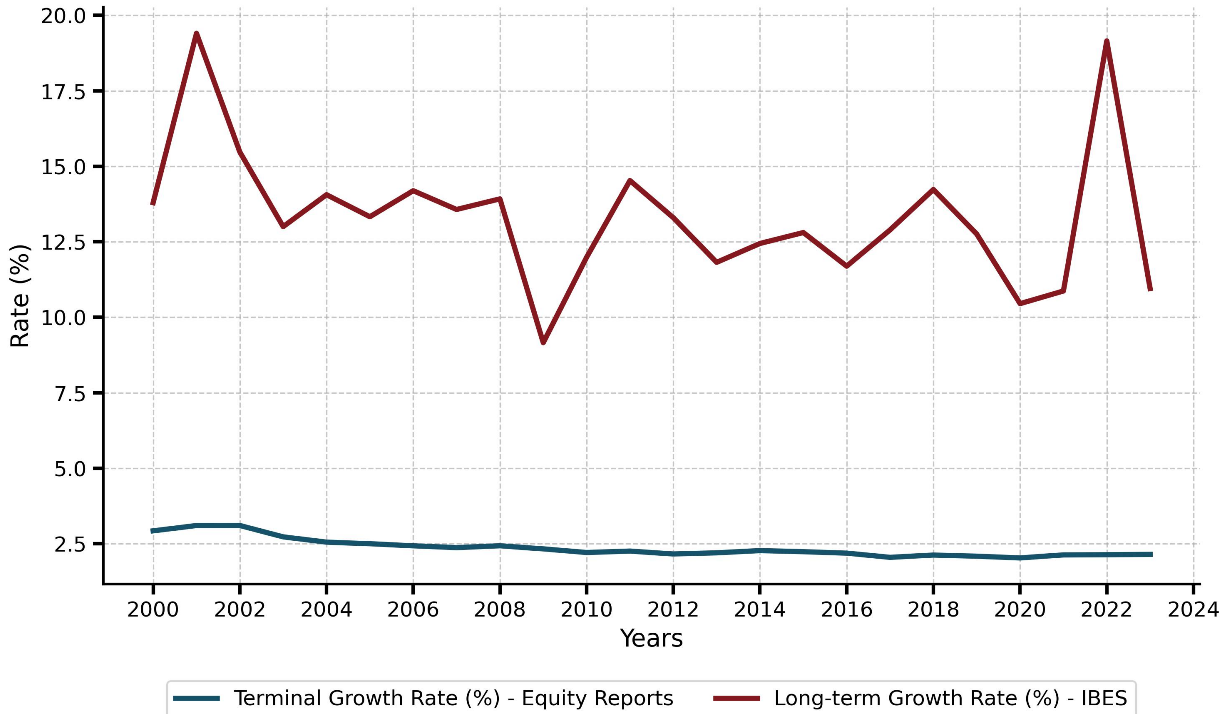


Figure A3: IBES Long-term Growth Rate Versus Equity Report Terminal Growth Rate This figure compares the trends for our sample's terminal growth rate and the IBES measure of *long-term growth rate* over the period 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. We restrict the sample to firms that are included in both samples. The solid blue line corresponds to the terminal growth rate, and the solid red line is the IBES long-term growth rate.

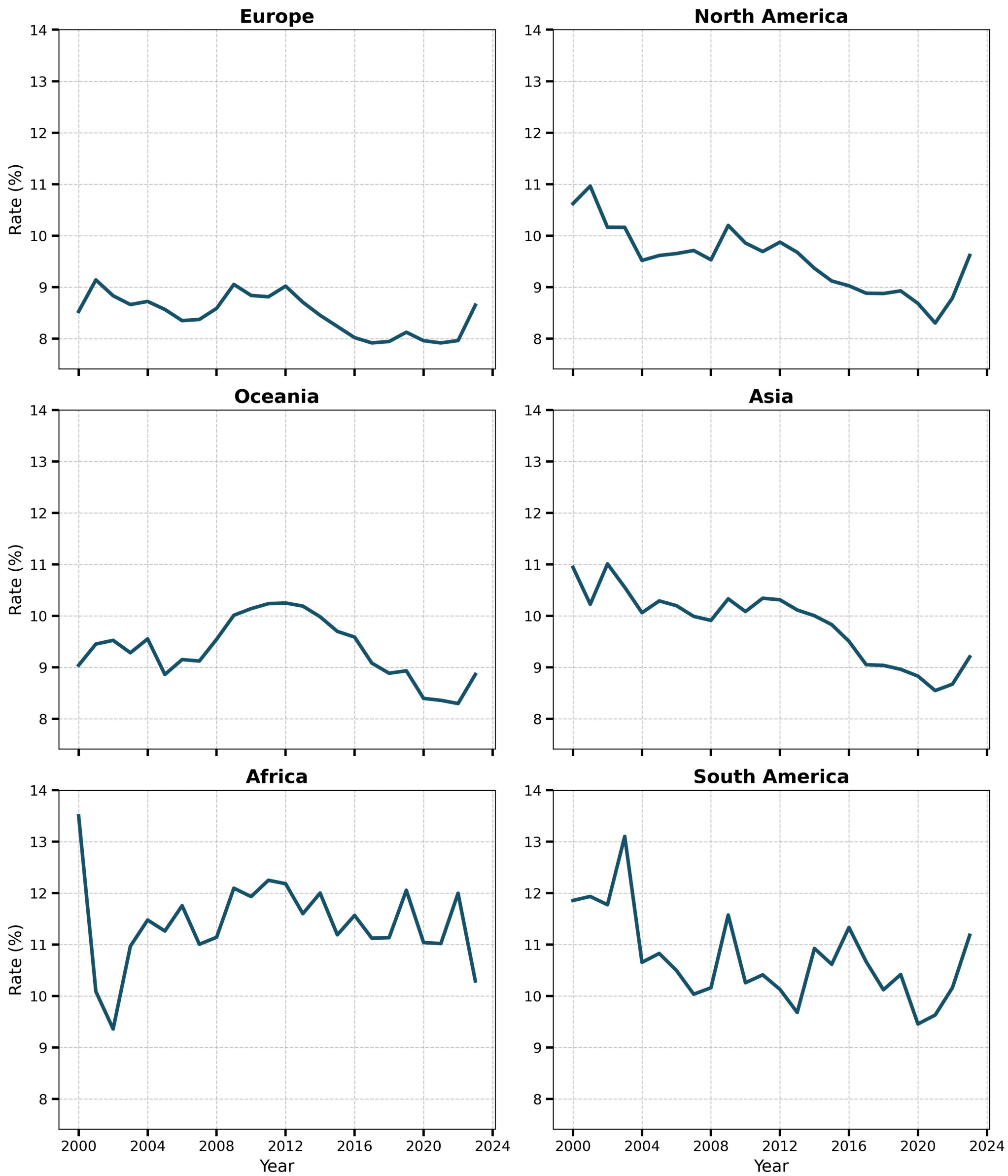


Figure A4: Discount Rate Trends by Continent This figure plots discount rate trends across all six continents over the sample period, 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which we have a measure of the discount rate. The solid blue line represents the average discount rate patterns for each region.

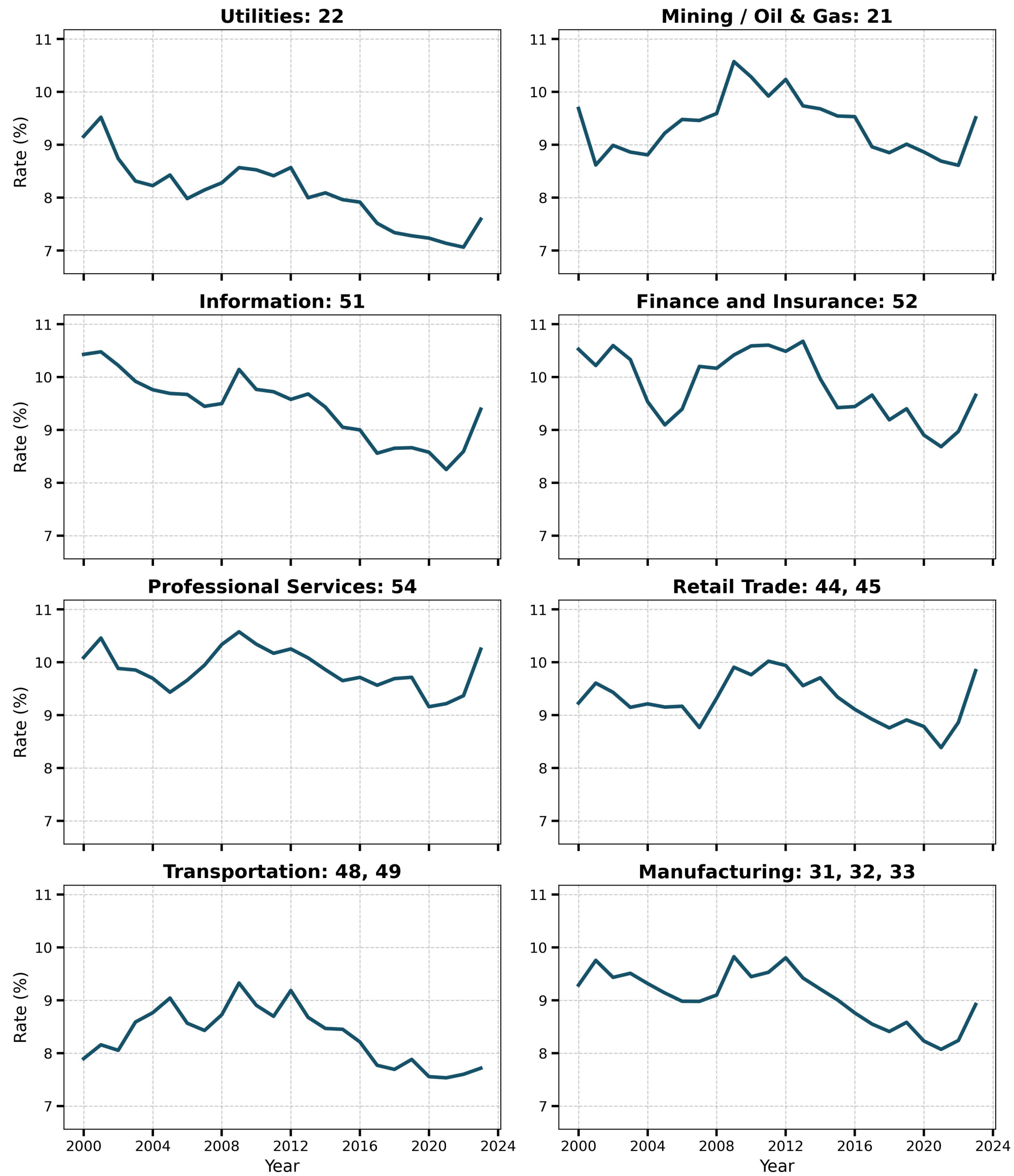


Figure A5: Discount Rate Trends by Major Industries This figure plots discount rate trends across the eight largest industries in our sample for the period 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which we have a measure of the discount rate and that are included in those industries. The solid blue line represents the average discount rate patterns for each industry.

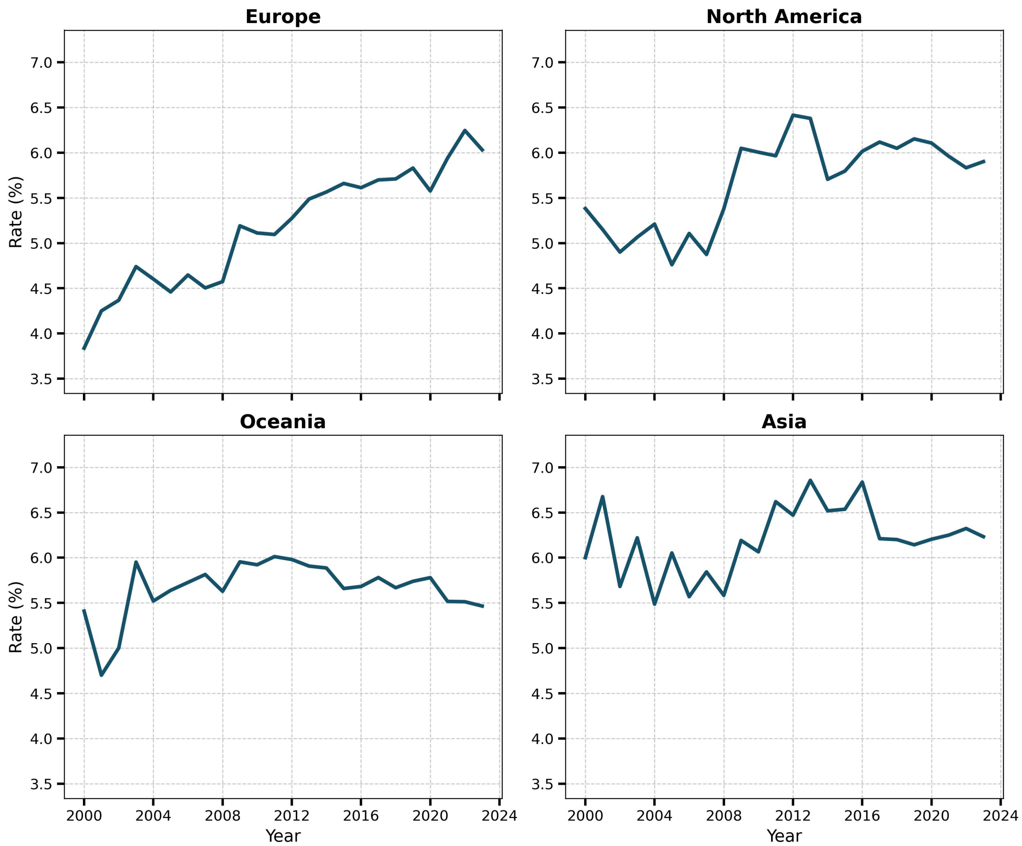


Figure A6: Equity Risk Premium By Continent This figure plots subjective equity risk premia trends for the four main continents in our sample for the period 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The solid blue line represents analysts' subjective equity risk premia trends.

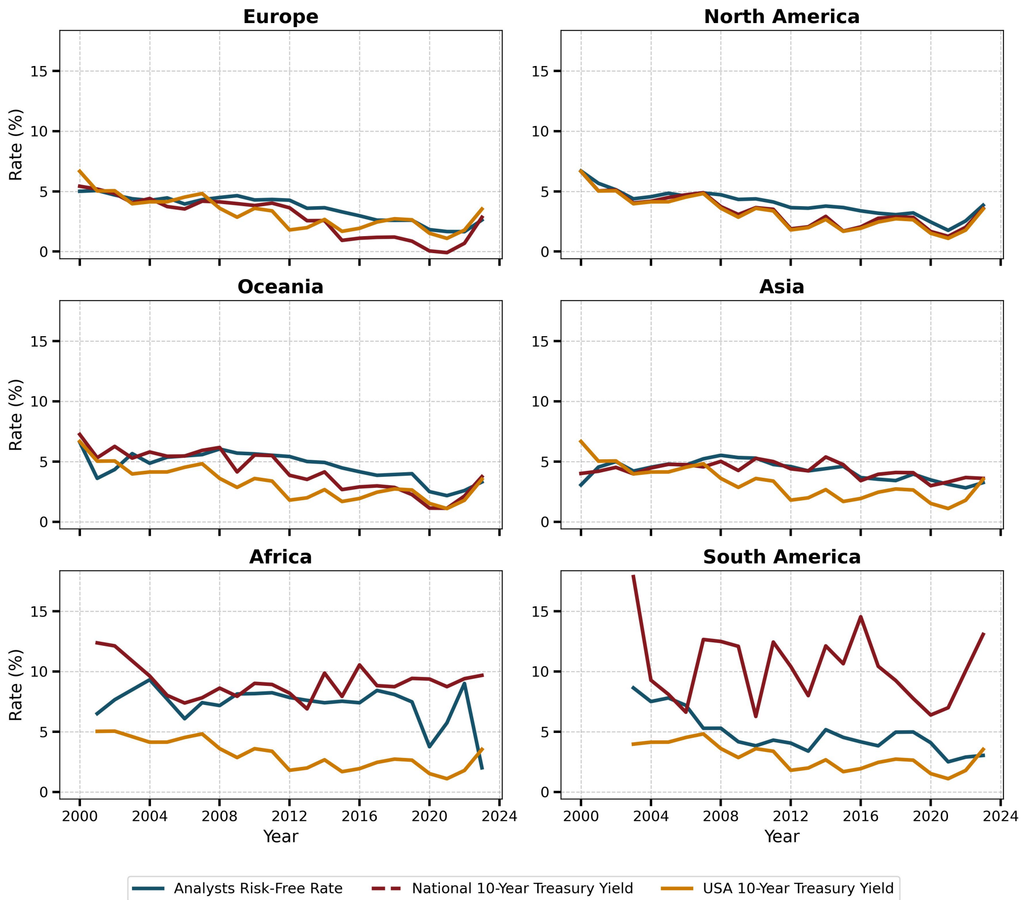


Figure A7: Risk-Free Rate Trends By Continents This figure plots analysts' risk-free rate trends across all six continents over the sample period, 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which we have a measure of analysts' risk-free rates. The solid blue line represents the average analysts' risk-free rate patterns for each region. The solid red line denotes the National 10-year treasury yield, and the solid yellow line indicates the US 10-year treasury yield.

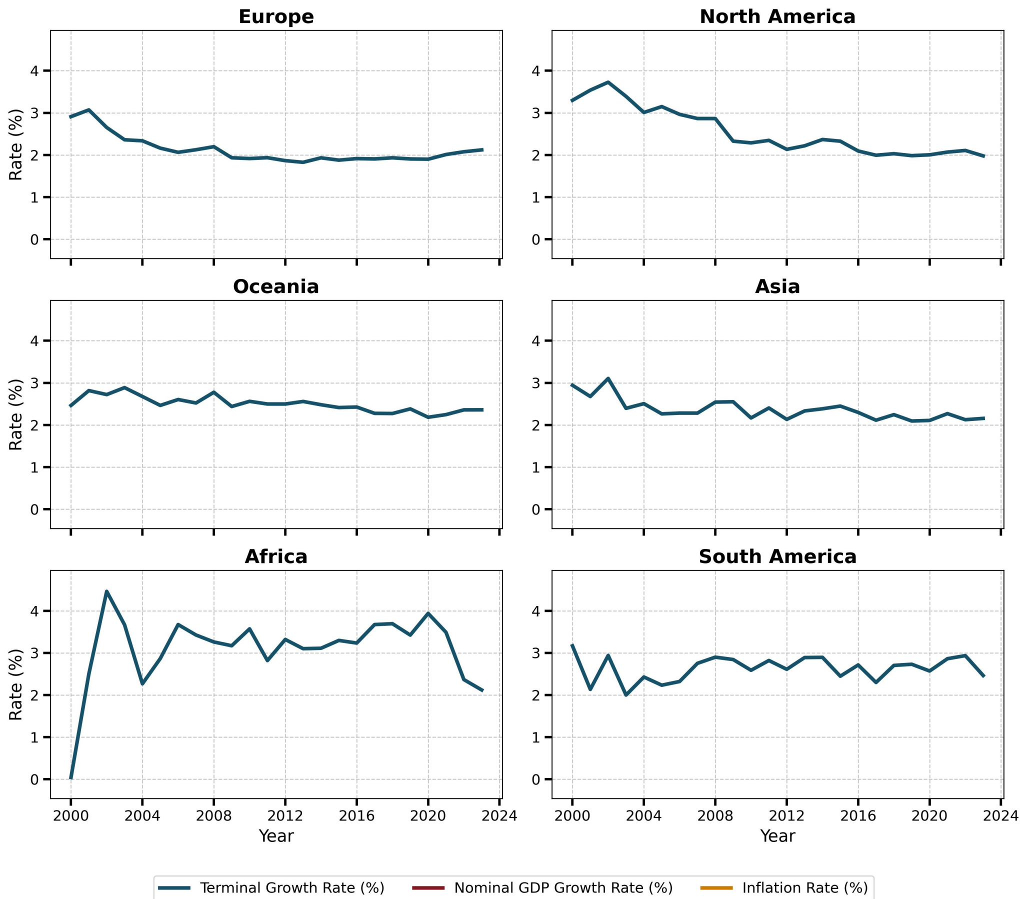


Figure A8: Risk-Free Rate Trends By Continents This figure plots analysts' terminal growth rates trends across all six continents over the sample period, 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which we have a measure of terminal growth rate.

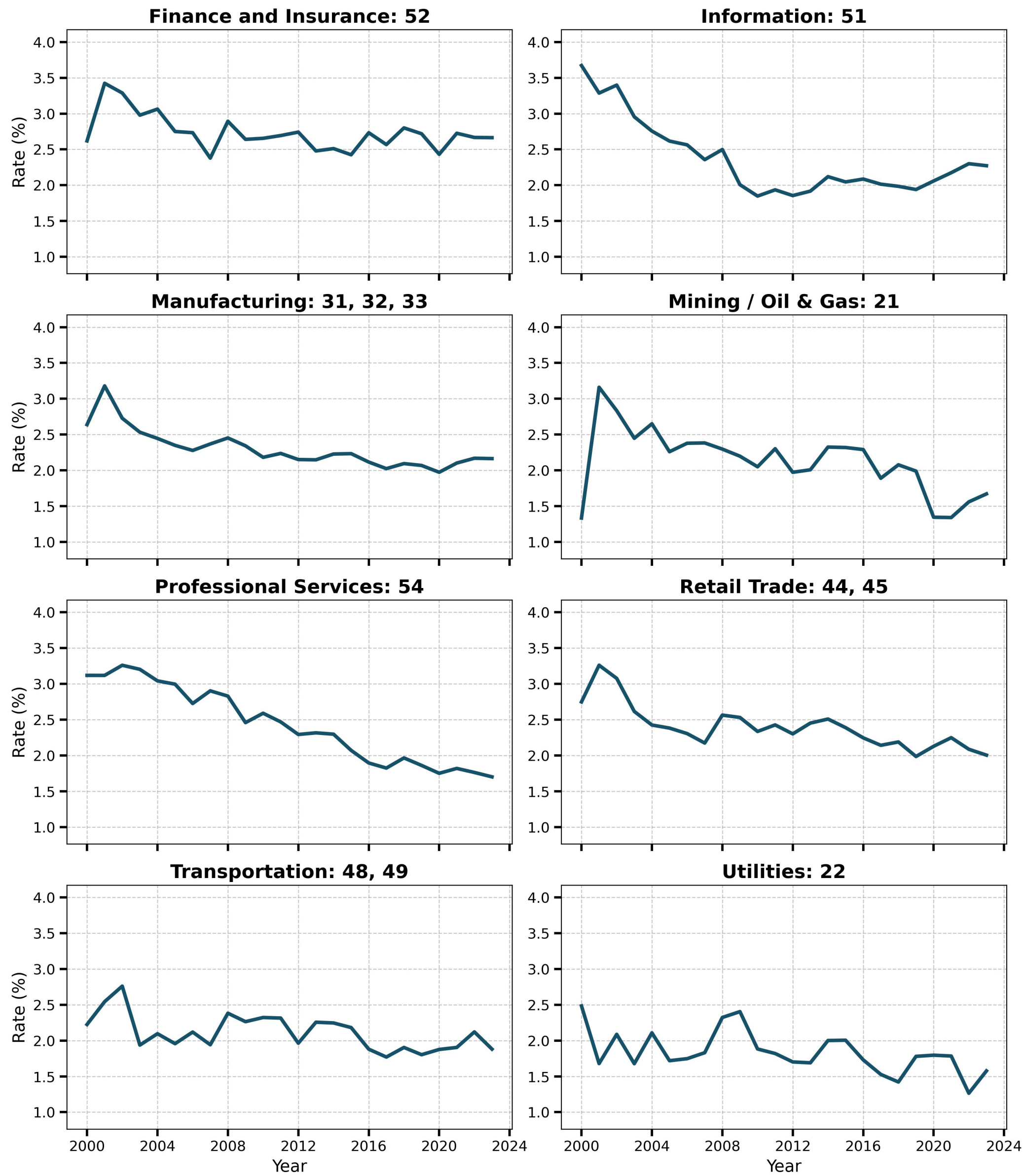


Figure A9: Terminal Growth Rate Trends By Industries This figure plots terminal growth rate trends for the eight largest industries in our sample for the period 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which we have a measure of the discount rate and which are included in those industries. The solid blue line represents analysts' terminal growth rate patterns.

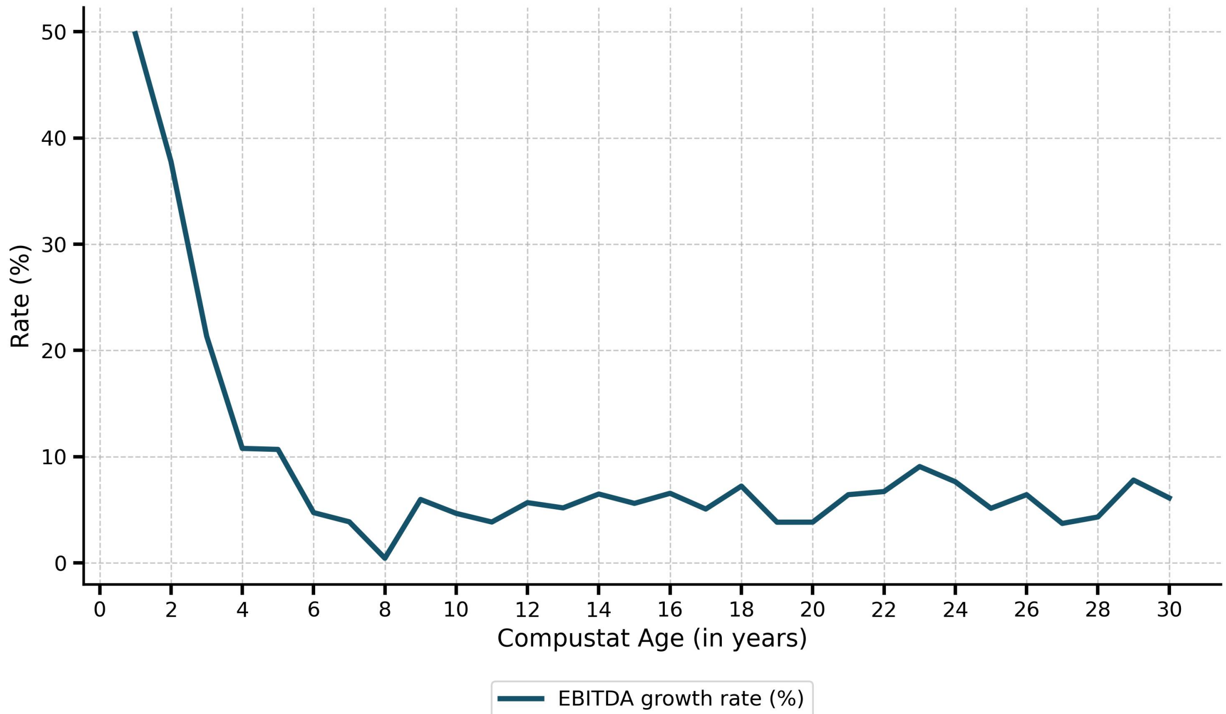


Figure A10: Earnings Growth and Firm Age This figure plots measures of firms' operating earnings (EBITDA) annual growth rates as a function of firm age. Firm age is measured from Compustat data as the difference between the current year and the first year a firm is recorded in the database plus 1. The x-axis represents firm age expressed in years. The y-axis denotes the growth rate of EBITDA measured in percentages. The sample includes all Compustat firms for which we have consecutive measures of EBITDA.

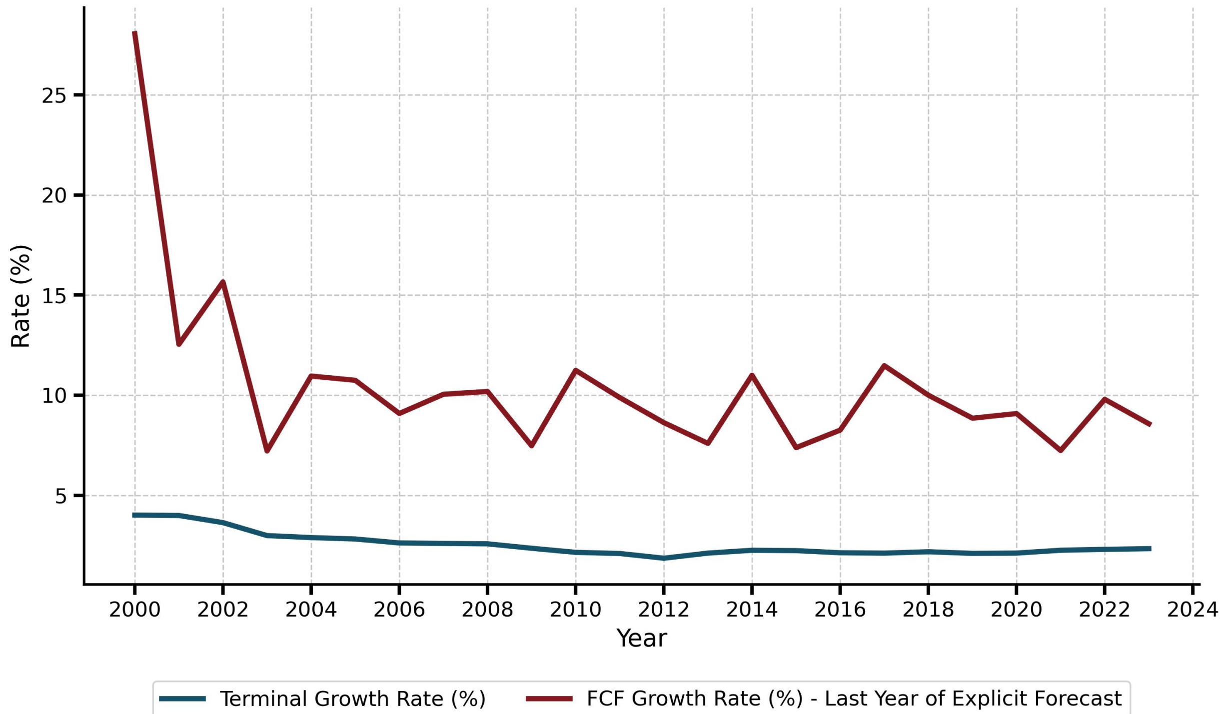


Figure A11: Last Year of Explicit Forecast Growth Rate Versus Terminal Growth Rate This figure compares the trends in the terminal growth rate and the growth rate measured for the last year of analysts' explicit forecast horizon trends for the period 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which we have both measures available. The solid blue line represents analysts' terminal growth rate patterns, and the solid red line corresponds to the growth rate measured for the last year of the explicit forecast horizon.

Appendix Table

Table A1: Statistics from textual analysis This table presents the results of the equity reports textual analysis on equity betas and choices of risk-free rate benchmarks when those items are directly discussed.

Panel A: CAPM benchmarks					
No. of years	**2 Years**	**3 Years**	**4 Years**	**5 Years**	**6 to 9 Years**
Frequency	314	158	20	469	83
Proportion (%)	30.1%	15.1%	1.9%	44.9%	8.0%
Asset pricing model	**CAPM**	**Fama-French**	**Barra-Beta**		
Frequency	908	0	30		
Proportion (%)	96.8%	0%	3.2%		
Data provider	**Bloomberg**	**Factset**	**Refinitiv**	**OneSource**	**NetAdvantage**
Frequency	571	35	39	0	0
Proportion (%)	85.9%	5.3%	5.9%	0%	0%
Market index (Intl. firms)	**S&P 500**	**Major national index**			
Frequency	38	161			
Proportion (%)	19.1%	80.9%			
Panel B: Risk-free rate benchmarks					
Treasury maturity	**T-bill**	**1- to 9-year**	**10-year**	**20-year**	**30-year**
Frequency	0	26	1,908	3	243
Proportion (%)	0%	1.2%	87.6%	0%	11.2%

Table A2: Risk-Free Rate Benchmarks Across Regions This table studies the properties of analysts' choice of risk-free rates benchmark across continents. The unit of observation is at the country c, and forecast year t levels. The sample period is 2000–2023. The dependent variable, *Analysts' risk-free rate*$_{i,j,t}$, is equal to the risk-free rate used by analysts in DCF models. *10-year treasury yield* indicates the firm headquarters country's 10-year treasury yield. *US 10-year treasury yield* refers to the 10-year treasury yield for the United States. Variable definitions appear in Appendix C. The standard errors (in parentheses) are heteroskedastic-consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Dependent variable:	Analysts' risk-free rate$_{c,t}$ (%)		
	(1)	(2)	(3)
National 10-year treasury yield$_{c,t}$ (%)	0.35***	0.87*	0.53***
	(0.08)	(0.07)	(0.05)
US 10-year treasury yield$_{c,t}$ (%)	0.28***	-0.46*	0.13
	(0.08)	(0.06)	(0.11)
Observations	423	47	268
F Statistics	32.74	85.27	89.42
R^2	0.59	0.65	0.70
R^2 Shapley Decomposition			
National 10-year treasury yield$_{c,t}$ (%)	75.11 %	70.92 %	97.44 %
US 10-year treasury yield$_{c,t}$ (%)	24.89%	29.08%	2.56%