Valuation Fundamentals*

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Abstract

We study subjective valuation using a comprehensive sample of 78,509 analyst reports that contain detailed information on short-term, medium-term, and terminal growth expectations, as well as subjective discount rates. Both growth expectations and subjective discount rates play a crucial role in explaining valuation fluctuations. Subjective discount rates are guided by theoretical recommendations (CAPM), track managers' estimates, reflect inflation, and vary over time with the risk-free rate and subjective betas being the main drivers of time-series fluctuations. Discount rates are unbiased predictors of future returns, return predictability is mainly associated with innovations in firm subjective betas, and the analyst's security market line is steeper than the econometrician's. To rationalize these patterns, we investigate how analysts update discount rate inputs. Drawing from textual descriptions and using a noisy information model, we find that analysts are forward-looking and attempt to filter estimation noise when adjusting inputs. These subjective adjustments appear to mitigate the effect of noise in model estimates, and lead to stickier processes than simply using benchmark model outputs. Finally, aggregate terminal growth rates track *real* GDP growth and *real* Treasury yields, but not inflation.

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

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1 Introduction

Asset valuation is determined by both future cash flows and discount rates. However, there is little consensus on whether subjective expectations of cash flows (De Bondt and Thaler, 1985; Hirshleifer et al., 2015; Bordalo et al., 2023b) or stochastic discount factors (Campbell and Cochrane, 1999; Bansal and Yaron, 2004; Cochrane, 2011) account for most of the fluctuations in asset prices. Moreover, there is a limited understanding of which models professionals use to determine these inputs and how they implement them in practice.

We explore these issues from a complementary but new angle by studying *subjective* valuation models. To conduct our analysis, we introduce one of the largest and most comprehensive datasets of equity analyst valuation models: 78,509 reports from 94 countries over 24 years. Collecting data from original documents offers several advantages over mainstream commercial databases. First, our dataset expands 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) by including the entire term structure of cash flow expectations. The long-term cash-flow expectations previously studied[1] correspond to a blend of analysts' 3- to 5-year forecasts, whereas we observe terminal growth rates that reflect the expected perpetual growth of the firm. Second, we have in-depth information about the components of analysts' subjective discount rates, separately observing equity betas, risk premia, and the risk-free rate. This allows us to work within the subjective expectation literature's main empirical framework, and to precisely account for the effect of subjective discount rates on valuations (Shiller, 1981; Cochrane, 2011). Third, while extant research has explored elements of what we study, we jointly observe all of the inputs used in valuations, enabling us to quantify the relative importance of each valuation input and investigate how these variables are jointly determined. Lastly, because our data are taken directly from equity reports, we can link *how* analysts motivate key inputs with their numerical values, directly relating professional valuation decisions to academic recommendations.

Our paper is organized around three main takeaways. First, we show that both discount

[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.

rates and growth rate expectations are important drivers of subjective valuation. Second, we find that analysts' subjective discount rates are unbiased predictors of future returns with this predictability being associated with adjustments to firm-level subjective betas over time. The slope of the resulting security market line (SML) for analyst betas is steeper (6.55%) than what is generated by an econometrician's CAPM estimation (about 0.77%). Lastly, we document that terminal growth rates track real macroeconomic variables, such as real GDP and real Treasury yield, but not inflation, resulting in estimates that are an order of magnitude (10 percentage points) smaller than the long-term growth expectations previously studied in the literature.

For the first takeaway, we perform two decomposition exercises to identify the key determinants of subjective valuation models. We first compare the relative contribution to valuation of the year-by-year cash flows in the *discrete period* to the contribution to value of the perpetual cash flows implicit in the *terminal value*. We find that, on average, the discrete-period discounted cash flows account for 29% of the total valuation, while the terminal value accounts for the remaining share, 71% (Panel A of Figure 1); and, as shown in Panels B and C, the relative contribution of the terminal value is negatively related to both the length of the discrete period and the discount rate. Analysts appear to choose the length of the discrete period heuristically (often, a 2-, 3-, or 10-year discrete period).

Separately, we use a variance decomposition approach to quantify how much of the time-series variation in subjective valuation is driven by each of the model components. We find that subjective discount rates explain 28% of the total variation in valuation, first-year cash flow growth expectations explain 38%, and long-term growth expectations explain 18%. This implies that when financial professionals adjust their beliefs about asset valuations, both discount rates and cash flow expectations matter. This implication contrasts with existing time-series arguments that either discount rates (Cochrane, 2011) or growth expectations at specific horizons (De La O and Myers, 2021; Bordalo et al., 2023b) are the dominant drivers of price fluctuations in the time series. In light of these findings, we focus much of our analysis on two valuation components that have received limited attention in the existing literature due to data challenges: (i) subjective discount rates, and (ii) terminal growth expectations.

With respect to the second takeaway, we study analysts' subjective discount rates in detail to gain a clearer understanding of their predictive properties and SML performance. We begin by documenting five stylized facts about discount rates, which allow us to validate the data, deepen our understanding of the *practice of finance*, and lay the groundwork for analyzing their asset pricing properties.

First, analysts' discount rate choices align with textbook recommendations (Berk and DeMarzo, 2019; Brealey et al., 2022). Nearly all specify that they use the weighted average cost of capital (WACC) to determine discount rates, and the discount rate used within a DCF model tends to be constant over the entire forecast horizon. Additionally, 96.8% of analysts rely on the capital asset pricing model, among the subsample of analyst reports that indicate a specific approach.

Second, in the aggregate, corporate managers and analysts broadly agree on discount rates. By comparing annual averages from a sample of manager discount rates (Gormsen and Huber, 2022) matched at the firm and year level, we document similar trends and levels in both groups. The discount rates in our full sample and the matched sample both decreased substantially from 2000 to 2021 across all regions and industries, consistent with the secular downward trend in the risk-free rate, followed by a sharp uptick in the discount rate starting in 2022.

Third, we find that analysts update their valuations over time, including discount rate inputs. To determine the drivers of discount rate variations in the time series, we decompose subjective discount rates into three components: risk-free rates, equity betas, and equity risk premia. Broadly, changes in the cost of equity account for 70% of discount rate fluctuations. Breaking this magnitude into individual components, the risk-free rate explains 35% of the discount rate variation, beta explains 19%, and equity risk premia explain 16%.

Fourth, we show that analysts do not appear to adjust their discount rates to offset changes in growth expectations (Cochrane, 2011; Adam et al., 2021). We find that a 1 percentage point (pp) increase in terminal growth expectations is associated with a 0.02 pp change in the discount rate. This mitigates concerns that analysts systematically adjust both variables in lockstep to mechanically reach a pre-specified price target in their valuation models.

Lastly, we find that inflation expectations impact valuation through the discount rate channel. We document a strong relation between subjective discount rates and long-term expectations of inflation, but no relation to contemporaneous measures of inflation. Decomposing discount rates into cost of equity components (the risk-free rate and the equity risk premium), we show that inflation expectations are channeled through the risk-free rate, with no pass-through arising from the equity premium.

These facts help guide an exploration of subjective discount rates' key asset pricing properties. We find that (i) analyst discount rates and cost of equity estimates are unbiased predictors of firm-specific one-year-ahead realized returns, (ii) within-firm time-series adjustment of subjective betas plays an important role in predicting future returns, and (iii) the security market line slope of analysts' subjective betas is substantially steeper than the one obtained when using the econometricians' CAPM estimates. This suggests that, relative to a standard implementation of the CAPM, analysts better capture market participants' required rates of return.

To better understand why analysts' CAPM-based discount rates perform better than implied by the existing literature (Black et al., 1972), we explore how analysts update their discount rates over time. We focus on the two most important drivers of discount rate fluctuations: (i) the risk-free rate and (ii) the CAPM beta. In addition to their importance in the discount rate variance decomposition, these two variables are often qualitatively discussed in the analyst reports and have well-known market-driven benchmarks against which to compare. This offers a unique opportunity to establish tight connections in the empirical analysis.

Starting with the risk-free rate, most analysts use headquarter-country long-term sovereign yields as their benchmark, with the 10- and 30-year maturities accounting for 87.6% and 11.2% of cases, respectively. While the numeric value of the analysts' subjective risk-free rate tracks the chosen sovereign yield, we find that adjustments do not follow in lockstep with changes in current market rates. Textual discussions in equity reports suggest that analysts view the market rate at the time of the report as a noisy proxy of the risk-free rate that will be realized over the horizon of their valuation forecast, which is typically 12 months.

In terms of equity betas, we show that analysts most often use 2 or 5 years of data to estimate beta. Similar to discussions about the risk-free rate, when analysts contrast their beta estimate with its comparable benchmark, they imply that differences in values relate to econometricians' betas being affected by estimation noise (see also Fama and French (1997)).

Broadly, we interpret these discussions as suggestive evidence that analysts attempt to account for both (i) expected changes in an input's value over the target price horizon (12 months) and, importantly, (ii) measurement noise. To explore these implications formally, we employ a model of Bayesian updating under noisy information (e.g., Coibion and Gorodnichenko (2015)). We show that the input-updating process is stickier than what would result from directly using current-period market benchmarks or values outputted by a reference model. Instead, analysts appear to put substantial weight on their previous estimate and only partially update toward the current-period benchmark value. This sticky updating can in part be attributed to analysts accounting for estimation noise. For both the risk-free rate and equity betas, our analysis indicates that the intensity and speed of the adjustment depend on the noise associated with the inputs' benchmark.

Paying attention to estimation noise when forming subjective estimates may help partially explain two of our key results: the steep SML slope and the predictive properties of analyst discount rates. By filtering noise that may be present in their benchmark estimates, analysts mitigate the effect of attenuation bias that can affect the econometrician's betas, with the end result of producing larger and more precise slope coefficients. This aligns with the notion that CAPM empirical failure might be driven by an informational gap between the econometrician and financial professionals (Andrei et al., 2023). Our results clarify the nature of this gap, by precisely identifying one of its sources—the updating process. Finally, our finding that these sticky discount rates better capture realized returns suggests that the *true* CAPM betas likely fluctuate less in the time-series than what is observed when estimating the CAPM with simple regressions.

For the third takeaway, we explore the factors influencing analysts' choices of terminal growth rates (TGRs). We find that TGRs typically vary between 1.5 and 3.0 percentage points (pp), which seems sensible given that our aggregate analysis identifies a statistical association between terminal growth expectations and both real GDP growth and real Treasury

Bond rates. The relation with GDP growth we measure in our regressions is bolstered by analysts' discussions in their equity reports. Standard macroeconomic models contextualize the importance of the long-term Treasury yield as a driver of long-term growth expectations: the risk-free rate is assumed to cap GDP growth in the long-run (Abel et al., 1989; Barro, 2023). However, we do not find a strong statistical relationship with inflation measures, suggesting that while valuation models are expressed in nominal terms, long-term expectations primarily track real variables. We also find that historical averages best explain the terminal growth rate choices made by analysts.

This evidence aligns with our observation that the updating of terminal growth rates exhibits persistence or stickiness, and recent evidence showing that long-term growth expectations are anchored in recent historical realizations (Nagel and Xu, 2022). Analysts slowly adjust their estimates to account for changes in reference macroeconomic variables but strongly anchor their estimates to their lagged estimates. We also note that the connection we find between long-term expectations and macro variables aligns with the findings of Bordalo et al.' (2023b).

Section 2 reviews related research, Section 3 discusses institutional details, Section 4 introduces the data collection methodology and summary statistics, Section 5 analyzes the discounted cash flow models, Sections 6 and 7 respectively explore the properties of subjective discount rates and terminal growth rates, and Section 8 concludes.

2 Literature Review

Our analysis complements the body of knowledge related to how financial professionals determine discount rates (Graham and Harvey, 2001; Brav et al., 2005; Kruger et al., 2015; Décaire and Bessembinder, 2021; Gormsen and Huber, 2022; Décaire et al., 2024; Hommel et al., 2023; Eaton et al., 2023; Jensen, 2024), that suggests normative recommendations for discount rate calculations (Levi and Welch, 2017; Welch, 2019), and the literature exploring the empirical failure of the CAPM. Various factors have been proposed as potential explanations for the CAPM's flat security market line, such as leverage constraints (Black et al., 1972; Frazzini and Pedersen, 2014), inflation (Cohen et al., 2005), risk preferences (Kumar, 2009; Bali et al., 2011), benchmarking of institutional investors (Baker et al., 2011; Buffa et al., 2014), stochastic volatility (Campbell et al., 2012), market sentiment (Antoniou et al., 2015), disagreement (Hong and Sraer, 2016), and private information (Andrei et al., 2023). Related to our work, Balakrishnan et al. (2021) also document a meaningful relation between subjective measures of the cost of equity and firm returns, though they leave unexplained the source and the mechanism underpinning this pattern. Our work complements this evidence and expands on both the predictive potential and the mechanism. We disaggregate analysts' discount rates into their subjective components and provide direct evidence that betas' time-series adjustments are the key element associated with the ability of subjective discount rates to predict future realized returns. Further, by identifying the nature of the mechanism that underpins analysts' updating processes—Bayesian updating under noisy information—our evidence helps explain why and how equity analysts' discount rates predict future realized returns. In relation to this broad set of papers, we highlight the importance of considering actions by financial professionals when testing the validity of asset pricing models.

We contribute to the literature studying the persistence of beliefs updating in financial economics (Coibion and Gorodnichenko, 2012; Malmendier and Nagel, 2015; Bouchaud et al., 2019; Nagel and Xu, 2022) by studying the updating process of another key variable in resource allocation—the discount rate. Where previous research points toward potential issues arising from the slow updating process, our results also highlight possible gains from such behavior by allowing professionals to filter out estimation noise and improving the accuracy of estimates from their reference models.

Our paper also adds to an expanding and dynamic stream of studies that use analysts' survey data to investigate asset price dynamics (Brav and Lehavy, 2003; Sadka and Scherbina, 2007; Derrien et al., 2022; Nagel and Xu, 2023a), and market participants' beliefs (La Porta, 1996; De La O and Myers, 2021; Nagel and Xu, 2022; Bordalo et al., 2023a,b; Décaire, 2023).

Additionally, our evidence introduces nuances to the money illusion discussion (Boudoukh and Richardson, 1993; Campbell and Vuolteenaho, 2004; Cohen et al., 2005) by documenting how and where professionals account for inflation in their valuation exercises. While analysts *explicitly* report their valuation models in nominal terms, our evidence suggests the existence of an *implicit* money illusion issue among financial professionals, where cash flows are expected to track the growth of *real* variables in the long run but are discounted with a *nominal* discount rate.

Also, by studying how financial professionals perform fundamental valuation, we contribute to the existing literature spurred by Shiller' (1981) valuation puzzle. De Bondt and Thaler (1985), Hirshleifer et al. (2015), and Bordalo et al. (2023b) argue that price fluctuations are primarily driven by cash flow growth expectations, whereas Campbell and Cochrane (1999) and Cochrane (2011) suggest that time-varying stochastic discount factors are the main source of price variation. Our results indicate that both components appear to be important in explaining variations in subjective valuations.

Finally, we provide new evidence about how valuation is performed in practice, shedding light on the inner mechanisms of resource allocation for firms and financial markets (Graham and Harvey, 2001; Duchin and Sosyura, 2013; Décaire and Sosyura, 2022b,a; Graham et al., 2015).

3 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. This preference is echoed by the common use of DCFs by professionals (Graham and Harvey, 2001; Mukhlynina and Nyborg, 2018). Our data document a time trend showing that the use of DCF models in equity reports has steadily increased over the past 20 years. Approximately 40%[2] of all reports included DCF analysis over the past 15 years[3] (Appendix Figure A1). Although there are similarities between DCFs and multiples, we highlight five advantages of studying DCFs.

First, valuation multiples disclose only a single metric—the multiple—whereas the DCFs we study report detailed modeling assumptions, thus making DCFs a richer setting for understanding the underpinnings of valuation and input determinants. Specifically, a multiples

[2]This statistic is obtained by dividing the number of equity reports using DCF models in their analysis over the total number of reports available on our data provider platform, Refinitiv Eikon, for every year in our sample as of September 2023.

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

approach implicitly assumes growth and discount rates, but these are obscured because the multiple is a single number. In contrast, the DCF data that we collect from each analyst report explicitly distinguishes between discount rates and growth expectations, as well as other DCF features, inputs, and modeling assumptions.

Appendix Figure A2 presents an example of a complete DCF model from an equity report[4]. 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 observed in analyst reports.

Second, many past studies using analyst data have relied on commercial databases, such as the Institutional Brokers' Estimate System (IBES) or Value Line, which mainly provide short- and medium-term expectations. The longest-term growth expectation (e.g., LTG) in these databases does not reflect the actual long-term expectations provided by analysts but instead generally reflects growth expectations over a three- to five-year horizon, whereas 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. Using a matched sample at the firm-year level, we find that the interquartile range of the consensus LTG from IBES is between 5.5% and 17.0%, in contrast to 1.5% to 3% for the terminal growth rates used by equity analysts.

Third, we examine the growth expectations of each company's free cash flows, a foundational source of value creation. Previous research instead examines dividends, which are lumpy and sticky, or earnings, which are more susceptible to accounting norms and manipulation than free cash flows. Also noteworthy, equity research firms mandate that analysts produce valuation targets over a 6- to 18-month horizon[5], standardizing the horizon in analysts' objective functions.

Fourth, DCF models implicitly nest a terminal multiple that explicitly reveals growth

[4] For copyright reasons, we redact the numbers used in the appendix figure.

[5] These same mandates explain why 99.5% of price targets are determined over a 6, 12, or 18-month horizon in IBES.

and discount rate assumptions:

$$V_0 = \underbrace{\sum_{i=1}^{H} \frac{FCF_{i-1}(1+g_{\mathrm{i}})}{(1+r)^i}}_{\text{Discrete Forecast}} + \underbrace{\frac{1}{(r-g_{\mathrm{T}})}}_{\substack{\text{Terminal}\\\text{Value}\\\text{Multiple}}} * \frac{FCF_H(1+g_{\mathrm{T}})}{(1+r)^H} \tag{1}$$

Moreover, the shorter the discrete period, the more significant the role of this implicit multiple within the DCF.

Lastly, we note that disclosure of DCF modeling details is provided on a voluntary basis. Studies have found that the intensity of information disclosure of DCF modeling assumptions is positively associated with report accuracy (Asquith et al., 2005; Hashim and Strong, 2018), and more detailed information disclosure leads to larger market reactions following changes in recommendations (Huang et al., 2023). By detailing their valuation thesis, informed analysts have the opportunity to differentiate their work from that of their uninformed rivals, thereby gaining credibility in the process. This suggests that our data are likely sampled from a relatively informed subset of analysts.

4 Methodology, Data, and Summary Statistics

We collect our data from equity reports (i.e., the original documents) published by analysts. We initially downloaded 157,549 equity reports mentioning DCF from 55 major equity research firms. We restrict the time window to reports published in the first three months of the calendar year (January 1$^{\text{st}}$ to April 1$^{\text{st}}$) from 2000 to 2023 to ensure that our data are measured at a similar time each year and due to download limitations. 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 results in 78,509 reports, each containing at least one variable used in our analysis.

For each variable in the analysis, we collect numerical values in four steps. First, documents are pre-processed using Python to identify sections of text, tables, and figures containing relevant information for the study. Second, we convert these different media into text snippets. Third, for each variable, we use artificial intelligence to extract the numerical value from these snippets. Fourth, we export to Excel the text snippets and the numerical values extracted by artificial intelligence – and our research team manually verifies each number. This last step of the collection effort is crucial for the integrity of the data. 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, the 10-year treasury yield from Refinitiv and the real gross domestic product (GDP) growth rate from the World Bank. For US firms, we add 10-year horizon forecasts of inflation, 10-year treasury yields, and the real GDP growth rate from the Philadelphia Federal Reserve Survey of Professional Forecasters (SPF). Finally, we gather measures of company accounting variables, realized stock prices, industry (NAICS), and country of headquarters using Refinitiv.

4.1 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 companies located in 94 countries during the 2000-2023 period. Panel A in Table 1 reports summary statistics for our sample. The average (median) firm owns assets with a book value of \$13.0 billion (\$2.2 billion) and has an investment rate of 5.7% (4.0%). These magnitudes are comparable to those of firms covered in IBES, where the average (median) IBES firm has assets with a book value of \$15.2 billion (\$0.8 billion) and 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 broadly distributed commercial analyst datasets.

The average firm is covered by 2.9 analysts and is included in the sample for an average of 4.4 years. In terms of geographic coverage, 38% of firms are headquartered in Europe, 29% in North America (25% in the US), 17% in Asia, 12% in Oceania, 3% in South America, and 1% in Africa. Twenty-four 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 21), 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 commercial datasets.

4.2 Discount Rate and Inputs

Panel B in Table 1 reports summary statistics for the 78,509 subjective discount rates collected for our analysis. The average (median) discount rate is 9.1% (8.9%). The average year in our sample contains 3,271 observations, with the minimum and maximum number of observations per year being 392 in 2000 and 5,290 in 2009, respectively. Panel A of Figure 2 presents the aggregate time trend for the discount rates used by analysts. Consistent with the secular decline in the risk-free rate in recent decades, we find that discount rates used by analysts steadily declined for most of the period, reaching a low of 8.2% during the nadir of the COVID-19 pandemic before rebounding in the most recent two years. The maximum annual average discount rate of 9.9% occurred following the 2008 Great Financial Crisis (Panel A of Figure 2).

The downward trend in discount rates is not specific to particular regions (Appendix Figure A4) or major industries (Appendix Figure A5). There is a steady, although shrinking, gap between the discount rates used to evaluate North American firms and their European counterparts, with that gap ranging from 0.4 to 2.2 percentage points 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.

Focusing on discount rate inputs, we first look at subjective betas. Analysts provide numerical estimates of their betas in 21,973 reports (28% of the sample). The average equity beta used by analysts is 1.10, and the 25th to 75th percentiles range between 0.9 and 1.25 (Table 1). Panel B of Figure 2 plots the average annual equity beta used by analysts, which indicates a reasonable range of exposure to systematic risk and peaks in years with economic turmoil.

Panels A to F of Appendix Figure A6 plot analyst equity betas across the eight main industries included in our sample. We find that across different industries, subjective betas exhibit various patterns and levels. The increase we document during times of economic turmoil for the unconditional betas, such as during the Great Financial Crisis, is visible in all of these industries.

In terms of the risk-free rate used by analysts, 19,448 reports (25% of the sample) disclose the specific numerical value employed in the discount rate calculation. When discussed in reports, the 10- and 30-year maturities are used in 87.6% and 11.2% of cases, respectively (Panel A of Appendix Table A1). Looking at firms located in Asia, Europe, and Oceania respectively, Appendix Table A2 shows numerically that the region-specific 10-year treasury yield better tracks analysts' choices of the risk-free rate than does the US Treasury yield. 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 company headquarters countries is 4.5% (4.0%); in comparison, the 10-year US Treasury yield is 3.2% (3.1%).

Panel C of Figure 2 plots the risk-free rate used by analysts alongside 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 the process for analysts' risk-free rates is more persistent (smoother) and tends to be higher than the actual 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.

Finally, the numerical value of the equity risk premium is disclosed in 19,812 reports (25% of the sample). Panel B of Table 1 shows that the average (median) equity risk premium used by analysts is 5.5% (5.7%). Panel D of Figure 2 plots 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. To benchmark these magnitudes with publicly available sources of equity risk premium estimates, Appendix Figure A8 compares time trends for the analyst measure with the annual equity risk premium data sourced from Aswath Damodaran's website Damodaran (2023), for the US firms in our sample. While the analyst equity risk premium is more persistent, both series have similar trends and levels, showing a sharp increase in average levels following the Great Financial Crisis.

Panels A to D of Appendix Figure A9 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 differ across regions, the measure is volatile in most regions, consistent with evidence suggesting that subjective risk premia vary over time (Nagel and Xu, 2023b); however, the subjective equity premia in our sample exhibit substantially less volatility than the objective measures produced in the literature (e.g., Martin (2017)).

4.3 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%). Panel A of Figure 3 displays the trend of the annual average terminal growth rate; from a peak of 3.11 percentage points in 2001, the measure has steadily declined to a low of 2.02 percentage points in 2020. Appendix Figure A10 presents regional trends for terminal growth rates across continents. We find that all regions experienced a sustained decline in the long-term growth rate over the sample period.

Additionally, Appendix Figure A11 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, stabilizing at an average of approximately 2% in the second half of the 2010s. The information and oil & gas industries averaged the sharpest declines, while the transportation and finance industries experienced the smallest reductions.

Finally, Panel B of Figure 3 presents the average term structure of growth expectations. On average, growth expectations decline rapidly over the first five years of the forecast horizon, to then slowly approach the terminal growth rate. We find that the growth expectations at the three- and five-year horizon averages 25% and 10%, respectively, with a mean value of 16% at the four-year horizon. This magnitude is consistent with IBES LTG average value of 15% that we obtain for the firms of our sample (Figure A3).

4.4 DCF Design

Discounted cash flow (DCF) models are, in their simplest form, the combination of two parts: (i) explicit year-by-year forecasts over a discrete period that lasts several years and (ii) a terminal value that captures all remaining periods. Combined, these two parts allow financial professionals to value every cash flow that a firm is expected to generate through infinity. We find that the average explicit forecast is modeled over a 6.24-year horizon (Panel B of Table 1), and the choice of horizon over which to forecast discrete cash flows varies over time (Panel A of Figure 4). The most common horizons are 3 and 10 years, which together account for 39.9% of the discrete period horizon, with 3 years being the sample mode (Panel B of Figure 4). This is in line with the heuristics discussed in financial textbooks and previous surveys (Mukhlynina and Nyborg, 2018).

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 discrete (year-by-year) 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 A12 shows a significant gap (average = 7.11 percentage points, p-value < 0.01) 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 flow growth expectations reach a steady state.

5 Explaining Subjective Valuation

In this section, we explore the drivers of subjective valuation by analyzing the contribution to value and performing a variance decomposition. Then, in the following sections, we detail the properties of two key inputs: subjective discount rates and terminal growth rates.

5.1 Subjective Valuation Decomposition

In this section, we explore how various DCF inputs affect changes in valuation over time. We start by expressing Discounted Cash Flows (DCFs) in a way that highlights its key inputs and aligns with how analysts perform valuation in practice. Our DCF analysis reflects several key features of the practice of valuation discussed in previous sections: (i) the required rate of return—the discount rate—is constant over the forecast horizon of a given valuation, (ii) the DCF terminal value directly satisfies the no-bubble condition (i.e., $g_T < r$), and (iii) cash flows are the basis of the valuation, instead of earnings or dividends:

$$\mathrm{E}_0^*[V_0] = \sum_{i=1}^{H} \frac{E_0^*[FCF_i]}{(1+E_0^*[r])^i} + \underbrace{\sum_{i=H+1}^{\infty} \frac{E_0^*[FCF_H] * (1+E_0^*[g_T])^{i-H}}{(1+E_0^*[r])^i}}_{\text{Terminal value}} \tag{2}$$

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

$\mathrm{E}_0^*[\mathrm{V}_0]$ represents the analyst's equity valuation for the 12-month forecast horizon at the time of the forecast, $E_0^*[FCF_i]$ is the analyst's expectation of the firm's cash flows in year i at the time of the forecast, H is the discrete period forecast horizon, $E_0^*[r]$ is the analyst's subjective discount rate, and $E_0^*[g_T]$ denotes the terminal growth rate. The discrete forecast horizon, H, corresponds to the number of years over which analysts explicitly model cash flows year by year. For the period following H, analysts use a terminal value to capture the value of all future cash flows. In Discounted Cash Flow (DCF) models, the terminal value directly accounts for the no-bubble condition, such that $(E_0^*[r] - E_0^*[g_T]) > 0$. Using the DCF structure, we perform two complementary exercises: (i) a decomposition of the level of the value, (ii) a variance decomposition.

For the level decomposition, we find that 71% of the average DCF valuation comes from the terminal value (Panel B of Table 1). Panel A of Figure 1 illustrates the time-series properties of this statistic. It exhibits persistence throughout the sample period, on average. Panel B of Figure 1 shows that the terminal value share of the DCF value is negatively related to the number of years included in the discrete period. For a 3-year discrete period, the terminal value accounts for approximately 78% of total firm value, compared to 70% (62%) for a 6-year (9-year) discrete period. Panel C of Figure 1 documents that the contribution of the terminal value (which is based on far-in-future cash flows) is negatively related to the chosen discount rate. For a 7% discount rate, the terminal period accounts for approximately 78% of value, in comparison to 65% for a 12% discount rate.

For the variance decomposition, we apply the Campbell-Shiller decomposition and linearize the DCF using a strategy introduced in De La O and Myers (2021):

$$1 + E_0^*[r] = \frac{E_0^*[FCF_1] + E_0^*[V_1]}{\mathrm{E}_0^*[V_0]} \tag{4}$$

$$\ln(1 + E_0^*[r]) = k - \ln(E_0^*[V_0]) + \ln(FCF_0) + \ln\left(\frac{E_0^*[FCF_1]}{FCF_0}\right) + \rho \ln\left(\frac{E_0^*[V_1]}{E_0^*[FCF_1]}\right) \tag{5}$$

Reorganizing the equation as a function of $\ln(\frac{E_0^*[V_0]}{FCF_0})$, the decomposition becomes:

$$ln(\frac{E_0^*[V_0]}{FCF_0}) = k - \ln(1 + E_0^*[r]) + \ln\left(\frac{E_0^*[FCF_1]}{FCF_0}\right) + \rho \ln\left(\frac{E_0^*[V_1]}{E_0^*[FCF_1]}\right) \tag{6}$$

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

$$ln(\frac{E_0^*[V_0]}{FCF_0}) = k + \sum_{i=1}^{H} \rho^{i-1} \ln(1 + E_0^*[g_i]) + \frac{\rho^H}{1-\rho} \ln(1 + E_0^*[g_T]) - \frac{1}{1-\rho} \ln(1 + E_0^*[r]) \tag{7}$$

This allows us to express valuation as a function of variables that are observed in DCF models or that can be measured: (i) the growth expectations, (ii) the subjective discount rate, and (iii) ρ, a normalizing constant around which the Taylor expansion is done based on the average natural logarithm of the price-to-dividend ratio used in previous studies (Cochrane, 2011; De La O and Myers, 2021). To match the expected growth horizon that has been explored in existing work, we define the short-term horizon using the 1-year growth forecast (De La O and Myers, 2021), the medium-term horizon as the expected growth at the 2- and 3-year horizon, and the long-term growth horizon as the terminal growth rate used in the DCF model, $E_0^*[g_T]$, to capture the effect of longer-term expectations explored in (Bordalo et al., 2023a) and (Bordalo et al., 2023b).

In the last step, to identify the share of variation in valuation ratio attributable to each DCF component, we take the covariance with respect to $ln(\frac{E_0^*[V_0]}{FCF_0})$ on both sides of the equation, and we divide through by the left side term of the equation. The variance decomposition can then be expressed as:

$$\begin{aligned}1 \approx \sum_{i=1}^{H} \frac{cov(\rho^{i-1}\ln(1+E_0^*[g_i]), ln(\frac{E_0^*[V_0]}{FCF_0}))}{var(ln(\frac{E_0^*[V_0]}{FCF_0}))} + \frac{cov(\frac{\rho^H}{1-\rho}\ln(1+E_0^*[g_T]), ln(\frac{E_0^*[V_0]}{FCF_0}))}{var(ln(\frac{E_0^*[V_0]}{FCF_0}))} \\ - \frac{cov(\frac{1}{1-\rho}\ln(1+E_0^*[r]), ln(\frac{E_0^*[V_0]}{FCF_0}))}{var(ln(\frac{E_0^*[V_0]}{FCF_0}))}\end{aligned} \tag{8}$$

Each right-hand side term of Equation 8 can be interpreted as the share of variance of the valuation ratio, $var(ln(\frac{E_0^*[V_0]}{FCF_0}))$, associated with the first term in the covariances. Importantly, these magnitudes can be estimated using a series of univariate ordinary least squares regressions. That is, we separately regress each of the right-hand side variables from Equation 7 on the equation's left-hand side variable.

While the spirit of our strategy follows De La O and Myers (2021), our analysis differs in that it is conducted at the firm level. Specifically, we perform these regressions for each firm in our sample individually. This strategy allows us to conduct our analysis at the firm level, which mutes the effect of cross-sectional variation across firms in our calculations. We adopt this approach because we are interested in decomposing the time-series variation of individual company valuation. Specifically, the coefficients reported in Panel A of Table 2 are averages over individual regressions estimated for each company for which we perform the variance decomposition[6]. Importantly, we note that the combined value of the coefficients presented in Panel A of Table 2 equals 1.005. This is reassuring considering that the combined effect of the DCF inputs should account for all of the variation in the valuations.

Our analysis reveals that 72% of valuation fluctuations are associated with cash flow expectations, whereas changes to subjective discount rates explain the remaining 28% (see Table 2 Panel A). Breaking down the respective contributions of expectations at different horizons, we note that the 1-year growth forecast is associated with the greatest share of the

[6] If we were to alternatively perform these regressions on the entire set of firms at once with firm fixed effects, the conclusions derived in this section do not materially change.

variation in valuation, accounting for 38% of the valuation fluctuations, while the terminal growth rate is the second most significant driver among the growth expectation variables, accounting for 18% of the fluctuations in valuations.

Panel B of Table 2 explores the importance of the initial cash flow growth expectation in the variance decomposition, conditional on three value-relevant dimensions. Columns 1 and 2 compare the coefficient between firms that have the volatility of their first-year cash flows in the time series above and below the sample median. These columns clarify the importance of first-year cash flow variance on its weight in the variance decomposition (note from Panel A that the standard deviation of this variable is greater than that of any other variable in the analysis).[7] Secondly, we split the sample between firms with above- and below-median discount rates. Intuitively, fluctuations in short-term growth expectations should have larger impact when discount rates are high, since a greater share of a firm's discounted cash flows would then be coming from short-term cash flows. Columns 3 and 4 of Panel B confirm that intuition. Lastly, in Columns 5 and 6, we compare the share of the variance attributable to short-term growth expectations between young and old firms. Young firms are more likely to experience higher volatility in short-term growth expectations and have higher discount rates, effectively combining the dynamics explored in Columns 1-4; thus, short-term growth expectations explain a larger share of valuation fluctuation for younger firms.

Recapping the two decomposition exercises in Tables 1 and 2, we find that explicit cash flow forecasts account for a relatively small share of the DCF total value (29% versus 71% for the terminal value, Panel B of Table 1) — but growth expectations for discrete forecasts explain the largest portion of the variance decomposition (55% versus 18% and 28% for terminal growth rates and discount rates, respectively, in Panel A of Table 2). Beyond the fact that the variance decomposition is conducted on the DCF valuation ratio, and not the DCF itself, these differences in magnitude are not in direct contradiction. We clarify the

[7] Part of this large magnitude is mechanically driven by outliers; cash flows can take negative and positive values, which can make the computation of growth rates problematic in some instances, such as during periods following large negative cash flow shocks.

intuition using a simplified three-component DCF model such that:

$$\mathrm{E}_0^*[V_0] = \frac{E_0^*[FCF_1]}{(1+E_0^*[r])^1} + \frac{E_0^*[FCF_2]}{(1+E_0^*[r])^2} + \frac{E_0^*[FCF_T]}{(1+E_0^*[r])^2(E_0^*[r]-E_0^*[g_T])} \tag{9}$$

Expressing the DCF as a function of expected growth rates and initial cash flow to make the connections between the level and variance decompositions more salient:

$$\begin{aligned}\mathrm{E}_0^*[V_0] =& \frac{(1+E_0^*[g_1]) \times FCF_0}{(1+E_0^*[r])^1} + \frac{(1+E_0^*[g_1]) \times (1+E_0^*[g_2]) \times FCF_0}{(1+E_0^*[r])^2} \\ &+ \frac{(1+E_0^*[g_1]) \times (1+E_0^*[g_2]) \times (1+E_0^*[g_T]) \times FCF_0}{(1+E_0^*[r])^2(E_0^*[r]-E_0^*[g_T])}\end{aligned} \tag{10}$$

Equation 10 shows that, through compounding, the first-year expected growth rate affects each of the expected cash flows in the DCF. Thus, while the first-year cash flows' dollar amount is small in comparison to the cumulative sum of a firm's expected cash flows, changes in the first-year expected growth rate affect the entire series of cash flows. This helps explain the larger role of the first-year growth expectations in the variance decomposition.

In summary, the results in this section highlight three key facts: (i) the bulk of a DCF valuation is captured by its terminal value, (ii) subjective discount rates are important in explaining how professionals adjust their beliefs about asset value over time, and (iii) both short-term and terminal growth expectations are important in explaining time-series variation in subjective valuation. Our takeaways thus differ from the emphasis in the existing literature that market price fluctuations in the time-series are primarily driven by changes in discount rates (Cochrane, 2011), by first-year growth expectations (De La O and Myers, 2021), or by long-term growth expectations (Bordalo et al., 2023a,b).

Based on these insights, and the fact that subjective discount rates and terminal growth rates have received limited attention in the empirical literature due to data challenges, the rest of our analysis primarily focuses on these two variables. The following two sections exploit the granularity of our data and explore the properties of these two inputs in detail.

6 Subjective Discount Rates

This section has three parts in which we (i) document key facts about the practice of finance regarding discount rates, (ii) present new asset pricing results related to subjective discount rates, and (iii) study how analysts determine discount rate inputs.

6.1 Subjective Discount Rates — Stylized Facts

We document a set of stylized facts about the practice of finance associated with the underlying economics, variation, and specification of subjective discount rates.

6.1.1 Discount Rate Calculation Methods

First, we show that analysts' discount rate calculations reflect textbook recommendations. A textual analysis of the equity reports indicates that the weighted average cost of capital (WACC) is the systematic choice for analysts' discount rates. In terms of the cost of equity, the textual analysis reported in Panel B of Appendix Table A1 shows how analysts select 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%). Additionally, another 645 reports specify the data provider from which their reference betas are sourced; these 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: (i) return horizon and (ii) market benchmark. Analysts commonly use a 5-year horizon (44.9%) or 2 years (30.1%) to estimate their betas. When cross-referencing return horizons with return frequencies, two strategies dominate: (i) using two years of returns at a weekly frequency, and (ii) using five years of returns at a monthly frequency. Second, given the lack of consensus in the academic literature on the market benchmark to use when estimating betas, we provide evidence on analysts' benchmarks. 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%).

6.1.2 Managers versus Analysts

Second, we show that corporate managers and equity analysts produce broadly similar estimates of the discount rate. We benchmark our estimates against those used internally by companies by matching our analyst measures with the raw data used in Gormsen and Huber (2022). In total, we match 751 firm-year pairs, for which we have both manager and analyst estimates in a given year.[8] As shown in Panel E of Figure 2, for the average firm in this subsample, the discount rates used by analysts and those used by managers exhibit similar magnitudes and time trends. The two aggregate time series exhibit a correlation of 0.89. We interpret these similarities as suggestive evidence that firm managers and equity analysts measure discount rates with broadly comparable methods. To address potential concerns that observed differences might be driven by managers mimicking analysts, or vice versa, we note that Décaire et al. (2024) report cross-sectional variation in the discount rates used by different analysts studying the same firm at the same time.

6.1.3 Time-Series Variation in Discount Rates

Third, we explore the time-series properties of subjective discount rates. On average, analysts update firm-level discount rates by 0.81 percentage points in absolute terms from their previous year's estimates, resulting in a 9% year-over-year change when using the sample average as a baseline. This indicates that discount rates used by equity analysts vary over time.

To identify the key drivers of these time-series fluctuations, we perform a variance decomposition. The starting point of our decomposition is the weighted average cost of capital equation:

$$WACC = W_E \cdot C_E + W_D \cdot (1 - \tau) \cdot C_D, \tag{11}$$

where W_E and W_D are the weights of equity and debt in the capital structure, C_E and C_D are the cost of equity and debt for the firm, and τ is the firm's corporate income tax rate.

[8] We thank Kilian Huber and Niels Gormsen for providing summary information on manager annual averages, derived from their original data, for firm-years matched to those in our sample.

Using an approach similar to the decomposition in Section 4.1, we express the variance of WACC as:

$$\operatorname{var}(WACC) = \operatorname{cov}(W_E \cdot C_E, WACC) + \operatorname{cov}((1-\tau)\cdot W_D \cdot C_D, WACC) \tag{12}$$

$$1 = \frac{\operatorname{cov}(W_E \cdot C_E, WACC)}{\operatorname{var}(WACC)} + \frac{\operatorname{cov}((1-\tau)\cdot W_D \cdot C_D, WACC)}{\operatorname{var}(WACC)} \tag{13}$$

$$\begin{aligned} 1 = {} & \frac{\operatorname{cov}(W_E \cdot rf, WACC)}{\operatorname{var}(WACC)} + \frac{\operatorname{cov}(W_E \cdot \beta \cdot ERP, WACC)}{\operatorname{var}(WACC)} \\ & + \frac{\operatorname{cov}((1-\tau)\cdot W_D \cdot C_D, WACC)}{\operatorname{var}(WACC)} \end{aligned} \tag{14}$$

Equation 14 allows us to separate the share of the variance in WACC that can be attributed to the cost of equity components, the risk-free rate and $\beta * ERP$ versus the cost of debt. To estimate the share of the time-series variance associated with cost of equity inputs, we regress each cost of equity input on subjective discount rates. We perform this analysis for each firm individually, as detailed in Section 5.1. This approach allows us to conduct our analysis at the firm level and ensures that we mute the effect of cross-firm variation on our estimates, as our main goal is to understand what drives professionals' company-level discount rate adjustments over time. In Panel A of Table 3, we report the average coefficient obtained from these individual regressions[9]. We find that the cost of equity explains 70% of the variation in the discount rate used by analysts. While our dataset does not include the cost of debt, this suggests that the remaining share of the variation is likely attributable to either the cost of debt or ad hoc adjustments made by analysts that are beyond the classical weighted average cost of capital definition.

We can break down the variance decomposition of the cost of equity into component pieces: the risk-free rate and the cost of risk (i.e., equity beta × equity risk premium). Our analysis indicates that the risk-free rate explains 36% of discount rate fluctuations, while the cost of risk accounts for 35%.

In a second step, Panel B of Table 3 presents the results of an analysis that decomposes the cost of risk components into equity betas and the equity risk premium. To isolate the

[9] Performing these regressions on the entire set of firms at once with firm fixed effects does not materially alter the conclusions derived in this section.

effect of equity betas and the equity risk premium, we use the following strategy:

$$\ln(\beta \cdot \text{ERP}) = \ln(\beta) + \ln(\text{ERP}) \tag{15}$$

$$\text{var}(\ln(\beta \cdot \text{ERP})) = \text{cov}(\ln(\beta), \ln(\beta \cdot \text{ERP})) + \text{cov}(\ln(\text{ERP}), \ln(\beta \cdot \text{ERP})) \tag{16}$$

$$1 = \frac{\text{cov}(\ln(\beta), \ln(\beta \cdot \text{ERP}))}{\text{var}(\ln(\beta \cdot \text{ERP}))} + \frac{\text{cov}(\ln(\text{ERP}), \ln(\beta \cdot \text{ERP}))}{\text{var}(\ln(\beta \cdot \text{ERP}))} \tag{17}$$

This final step of the decomposition shows that the quantity of systematic risk (beta) explains 30% more of the discount rate process than the price of risk (risk premium) at the firm level in the time series.

Combined, the evidence in this section highlights that subjective discount rates vary over time, both in the aggregate and at the firm level. Moreover, our time-series variance decomposition highlights the importance of the risk-free rate and equity betas in explaining discount rate fluctuations, motivating our deeper analysis of these inputs in sections 6.2 and 7.

6.1.4 Relation to Growth Expectations

Fourth, we show that equity analysts do not adjust discount rates and growth expectations in tandem, both at the valuation model level and in the aggregate. This mitigates concerns that our analysis of discount rates captures variations in growth expectations due to mechanical adjustments performed by analysts. At the DCF model level, Column 1 of Table 4 shows that the relation between discount rates and growth expectations is positive and statistically significant at the 1% level without including any controls, such that a 1 pp increase in growth expectations is associated with a 0.12 pp increase in the discount rate. While small, this magnitude is expected, given that a wide set of factors, such as macroeconomic variables, are likely to affect both inputs in a similar fashion. However, when accounting for such factors using country*year fixed effects in Column 2, as well as firm fixed effects to focus on how an analyst jointly updates both inputs over time for a given firm, we obtain a regression coefficient of 0.02. This small magnitude suggests that analysts do not simply adjust their discount rates to offset changes in growth expectations or vice versa. To extend this conclusion to aggregate outcomes, we plot the difference between discount rates and terminal growth rates—r minus g—over time (Figure 5). If this relation is flat through time, it would suggest that discount rates are chosen to offset growth expectations. We find that the difference ranges from 6.05 to 7.69 percentage points throughout the sample period, around an average of 6.85 percentage points. Moving from the highest to the lowest value of this range implies a change in the DCF terminal multiplier from 16.5x to 13.0x, a 27% drop in the value of the terminal multiple.

6.1.5 The Effect of Inflation

Finally, we show that subjective discount rates are positively related to inflation expectations, but not to contemporaneous inflation. Table 5 reports the results of linear regressions of discount rates on market measures of inflation. Column 1 examines whether analysts account for current inflation, while Column 2 examines the relation with long-term expected inflation obtained from the Philadelphia Federal Reserve's Survey of Professional Forecasters. In Column 1, the estimated effect of current inflation on the discount rate is economically small and negative. In contrast, in Column 2 the 10-year inflation forecast from the Survey of Professional Forecasters is significant at the 1% level, and the regression coefficient is positive and large. To better understand how inflation expectations are channeled through to the discount rate, in Columns 3-6 we repeat the exercise on two components of the cost of equity–the risk-free rate, and the equity risk premium. Our results indicate that inflation expectations are channeled through the risk-free rate component exclusively, with an almost perfect pass-through: the regression coefficient is equal to 0.96 and statistically significant at the 1 percent level. Overall, this suggests that expected future inflation affects valuation through the discount rate, and that this effect is primarily channeled through the risk-free rate.

Overall, these facts about the practice of finance serve in two ways as the backbone for the rest of this section's analysis. First, they guide our empirical design choices, helping us choose the proxies and components of the discount rate on which to focus. Second, they provide evidence mitigating concerns about the validity of the data.

6.2 Subjective Discount Rates — Asset Pricing Properties

We now study (i) the return predictability properties of subjective discount rates, and (ii) how subjective betas relate to future realized returns in security market line tests. These analyses provide novel evidence about the performance of the *subjective* implementation of the CAPM and also help evaluate the credibility of analysts' estimates.

6.2.1 Return Predictability

In our first set of tests, we focus on the predictive properties of subjective discount rates. We calculate realized total stock returns at the one-year horizon using data from Thomson Reuters (Refinitiv). The one-year horizon aligns with the 12-month forecast horizon analysts use in their target price predictions. For this set of tests, we benchmark our main specification to the design in Gormsen and Huber' (2023), to which we add increasingly granular sets of fixed effects.

Table 6 presents the results of this test. In Column 1, we regress one-year future total returns on subjective discount rates. The point estimate of the slope coefficient is equal to 1.49, and the constant term is -0.71. This analysis shows that subjective discount rates are unbiased predictors of firm future returns in the Mincer-Zarnowitz sense, in that we fail to reject the joint null hypothesis that the slope coefficient is equal to 1 and the constant term is equal to 0, as shown by the coefficients associated with rows H_0^A and H_0^D in Table 6.[10] However, the regression R-square is small, with a value of 0.004. While this small R-square does not invalidate the fact that subjective discount rates likely capture inherent features associated with the marginal financial market participants' required returns on average, a substantial share of the one-year realized returns variation remains unexplained after controlling for discount rates.

The specification in Column 1 includes no fixed effects, meaning that the relation we capture may be affected by both time-series and cross-sectional properties of discount rates. To isolate the role of cross-sectional versus time-series differences in discount rates, we gradually introduce fixed effects. Column 2 adds month-year fixed effects. This allows us to

[10] Testing for both hypotheses individually leads to the same conclusion.

account for market conditions during the forecasting period, effectively comparing how differences in betas in a given year help predict the cross-section of future returns. Finally, in Column 3, we augment the model with more granular fixed effects, country*month-year and firm fixed effects, to respectively account for specific market conditions in a firm's country during the forecasting period, and also to evaluate how changes to the discount rate of a particular firm over time are associated with changes in realized future returns for the same firm. This combination of fixed effects controls time-invariant firm effects and country-time effects, the latter holding constant potential macroeconomic factors (e.g., Treasury yield); this combination of fixed effects means that the regression coefficients capture within firm innovations in subjective discount rates after controlling for time-varying macro factors. For all these alternative specifications, we fail to reject the null hypothesis that the slope coefficient is different from one.[11] These tests indicate that subjective discount rates appear to be unbiased predictors of future returns. For all three coefficients obtained in Columns 1-3, we note that the magnitudes obtained are likely to be distorted by the fact that the cost of equity accounts for less than 100% of the discount rate. Rescaling the regression in Column 1, by the average value for the market weight of equity among Compustat firms over our sample period–75%[12]–we obtain an adjusted coefficient equal 1.12, supporting the implication of unbiasedness.

To confirm that our documented effect is driven by the cost of equity component of WACC, and not the cost of debt, we redo the analysis using a subsample of 9,117 observations for which we simultaneously observe analysts' choice of risk-free rate, equity betas, and equity risk premium, giving us the subjective cost of equity. Columns 4-6 replicate the fixed effects strategy from Columns 1-3 using the subjective cost of equity as the dependent variable. While our cost of equity sample is smaller, we find qualitatively and quantitatively similar results. The estimated coefficients in Column 4 indicate that analysts' cost of equity is an unbiased predictor of future realized total returns at the one-year horizon, and Columns 5 and 6 show that our results are robust to including a granular set of fixed effects. Our favored specification, which includes country*month-year and firm fixed effects, yields a slope

[11] For the regressions that include fixed effects, it is not possible to test for the hypothesis that the constant term is equal to zero as it is multicollinear with the fixed effects.

[12] 1-market leverage = 1-$\frac{dlc+dltt}{dlc+dltt+csho*prcc_f}$

coefficient of 0.99. This suggests that, after accounting for the average annual market return realized in the firms' country, a 1 pp change in a firm's average subjective cost of equity is associated with a 0.99 pp increase in the firm's future realized return.

Last, we break down the cost of equity variable into its risk-free rate component and the cost of risk ($\beta \times ERP$), and repeat the exercise in Columns 7-9 of Table 6. Our evidence suggests that the return predictability of the cost of equity, both in the time-series and in the cross-section, is more reliably captured by the $\beta \times ERP$ component, rather than the risk-free rate. While the sign on the risk-free rate coefficient in Columns 7 and 8 is consistent with economic intuition, the significance is mixed. Further, the estimated coefficient becomes small and not statistically significant in Column 9, reflecting that this column controls for time-varying macroeconomic factors at the country level (i.e., country*month-year fixed effects).

6.2.2 Security Market Line Analysis

In our second set of tests evaluating the asset pricing properties of analysts' subjective discount rates, we perform a security market line (SML) analysis in which we compare the slope of the CAPM-based subjective betas with econometrician-estimated CAPM betas. Having established in the previous section that returns predictability is likely to be associated with betas and the ERP, in this section we explore in greater detail each of these input variables and their relation with excess returns. A long-standing literature has raised concerns about the CAPM being a valid empirical model, partly because it empirically generates a flat SML (e.g., Black et al. (1972)). Panel A (and B) of Figure 6 plots the security market line for analyst betas (and separately, for 60-month CAPM betas). Both estimates share similar patterns for small values of beta, but the pattern becomes increasingly noisier for larger values of 60-month econometrician betas, and the range (x-axis) of 60-month econometrician betas is twice as large as the range for subjective betas. Visually, noise is less prevalent in the analyst beta sample, resulting in a steeper relation between analysts' estimates and future realized returns.

Panel A of Table 7 formalizes this relation using an OLS regression. Column 1 presents the results from regressing 1-year realized total excess returns on analysts' betas. As a comparison benchmark, we replicate the exercise for CAPM betas measured using 2 and 5 years of monthly returns in Columns 3 to 5, the two most common horizons used to measure betas according to our textual analysis (Section 6.1.1). The coefficient obtained for analyst betas reflects a markedly steeper slope (6.69 percentage points) than those obtained with econometrician's beta estimates (2.52, 2.73). Further, we fail to reject the null hypothesis that the intercept is different from 0 for the subjective betas' SML regression (p-value = 0.49), but we do reject the null hypothesis in the specification using the econometrician CAPM betas. The analyst regression coefficients are more consistent with the theory of CAPM than those obtained by using econometrician CAPM betas, for which we obtain statistically significant intercept values of 6.89 and 6.96 (p-value = 0.00 and 0.00), respectively, in Columns 3 and 5. Columns 2, 4, and 6 expand the analyses by including country*year-month and firm fixed effects. The introduction of the fixed effects slightly reduces the subjective betas' SML slope (6.55), but dramatically reduces the slope coefficients for the econometrician betas (0.77, 1.62), and increases their p-values (0.24, 0.46 not shown in the table). Further, we note that the average value of the equity risk premium in our sample is equal to 5.70%, an average value broadly similar to other sources of the equity risk premium (Figure A8). Row H_0^A shows that we fail to reject the null hypothesis that $CAPMbeta$ regression coefficients for analysts are different from 5.70% when using analyst betas (Columns 1 and 2), but we strongly reject the hypothesis when using econometrician betas (Columns 3 to 6).

In a final exercise, we decompose the excess return into its components, equity betas and the equity risk premium, for the subset of data for which we jointly observe subjective betas and equity risk premia. To isolate the effect of each variable, we start by breaking down the relation between CAPM betas and the equity risk premium:

$$\mathrm{ret}_{i,t+1} - \mathrm{rf}_{t+1} = \beta_{i,j,t} \cdot \mathrm{ERP}_{i,j,t} \tag{18}$$

$$\mathrm{ret}_{i,t+1} - \mathrm{rf}_{t+1} = e^{\ln(\beta_{i,j,t} \cdot \mathrm{ERP}_{i,j,t})} = e^{ln(\theta_{i,j,t})} \tag{19}$$

This strategy leverages the fact that both betas and ERP are generally considered to be positive definite variables, a feature validated in our sample. Thus, the natural logarithm of these variables is defined for each observation. We then take a first-order Taylor approximation around $ln(\theta_0)$ and set θ_0 equal to the long-term average for the cost of risk in the sample ($\overline{\beta \cdot \text{ERP}} = 0.062$).

$$\text{ret}_{i,t+1} - \text{rf}_{t+1} \approx e^{ln(0.062)} \cdot (1 + ln(\beta * \text{ERP}) - ln(0.062)) \tag{20}$$

$$\text{ret}_{i,t+1} - \text{rf}_{t+1} \approx k + 0.062 \cdot ln(\beta) + 0.062 \cdot ln(\text{ERP}) \tag{21}$$

Equation 21 suggests that if each component equally explains excess total returns, we should obtain regression coefficients of magnitudes close to 0.062 for both variables in the regression including no fixed effects (Column 1 of Table 7, Panel B). We obtain positive and statistically significant coefficients of reasonable magnitude for both inputs, but importantly we fail to reject the null hypothesis only for equity betas (see H_0^A and H_0^B). Column 2 adds Country*Month-Year fixed effects as well as firm fixed effects and confirms the important relation between innovations in analyst betas and returns predictability hinted at in Section 6.2.1. Columns 3-6 replicate the specifications using econometrician betas estimated using 2 and 5 years of returns. Our results show that econometrician betas are significantly smaller than the value predicted by Equation 21 (see row H_0^B), and become insignificant when including the fixed effects. Broadly, the econometrician beta slope coefficients do not appear to be meaningfully associated with future realized excess returns.

Overall, the predictive regressions and SML analyses indicate that CAPM-based subjective discount rates produced by analysts perform well relative to a standard econometric implementation of the CAPM. The source of this predictability appears to stem mainly from analyst estimates of CAPM betas, and a share of this predictability is associated with how analysts adjust their betas over time, as shown by regressions that include firm and year-month-country fixed effects. In the next section, we explore the nature of analyst subjective adjustments as a potential explanation for the superior performance of analyst discount rates.

6.2.3 Noisy Updating

To shed light on the nature of the subjective adjustments that might be associated with the performance of analyst discount rates, we investigate analysts' updating processes for two key inputs: (i) the risk-free rate and (ii) CAPM betas. In addition to being the key drivers of discount rate fluctuations, as discussed in Section 6.1.3, our decision to focus on these inputs is a practical one. These two variables are often qualitatively discussed in analyst reports, which allows us to gather qualitative evidence about how analysts motivate their subjective adjustments. These inputs also have clear market-driven benchmarks against which to compare.[13]

We start by presenting qualitative evidence from written discussions in equity reports. Broadly, when analysts discuss updating the risk-free rate and beta, two patterns stand out. First, analysts openly discuss their choice to not systematically and completely update the numeric values for these key inputs to reflect changes in the spot market or current benchmark estimates (Appendix A). In other words, generally, analysts only partially update their subjective risk-free rate and beta inputs to reflect current market conditions. Second, analysts express concern about the degree to which current measures of these inputs properly capture the true state of these inputs, or reflect the value these inputs will take over the 12-month price target horizon. For instance, when discussing how they update their risk-free rate, analysts indicate that they rely on a combination of (i) backward- and (ii) forward-looking information. Specifically, analysts compare the current market yield with historical averages and what they expect the rate to be over the forecast horizon, often expressing a view that current market conditions might not be sustainable over the forecast horizon (Appendix A1). Similarly, for equity betas, analysts point out that CAPM estimates might fail to adequately capture all sources of risk deemed important, or that current measures deviate too much from their historical levels (Appendix A2). We interpret these discussions as suggestive evidence that analysts perceive the current values of the risk-free rates and estimated betas as noisy proxies of what they believe will actually be realized over the forecast horizon or what truly represents the state of these inputs. In other words, analysts appear to account for noise when using current values of these key inputs to update their subjective inputs.

To formalize the insights from these qualitative discussions, we borrow from the noisy

[13] Furthermore, the risk-free rate is continuously discussed in the 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 or salience as the updating dynamic.

information empirical literature (e.g., Coibion and Gorodnichenko (2015)) and model the decision to update the risk-free rate (and CAPM beta) as follows:

$$X_{i,j,t}^{Benchmark} = X_{j,t}^{Sustainable} + \omega_{j,i,t}, \tag{22}$$

where i is a particular analyst, j denotes a firm, t represents a year, $X_{i,t}^{Benchmark}$ is the current signal that analysts receive from the market to inform them about the national 10-year treasury yield (or, the CAPM beta), $X_{j,t}^{Sustainable}$ is the sustainable risk-free rate (or, *true* beta) 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' updating process as follows:

$$F_{i,j,t}X_{j,t}^{Sustainable} = GX_{i,j,t}^{Benchmark} + (1-G)F_{j,i,t-1}X_{j,t}^{Sustainable}. \tag{23}$$

$F_{j,t}X_{j,t}^{Sustainable}$ represents the analyst's subjective expectation of the sustainable risk-free rate (*true* beta) over the forecast horizon, and $F_{j,i,t-1}rf_{j,t}^{Sustainable}$ is the analyst's subjective expectation of the sustainable risk-free rate (*true* beta) from the previous forecast. In these models, $1-G$ can be interpreted as the degree of information rigidity. If the current period $X_{i,j,t}^{Benchmark}$ were to be perfectly informative about the sustainable risk-free rate (or, *true* beta), then G would equal one. If G is less than one, the updating process exhibits some level of stickiness or persistence, such that analysts only partially update toward the benchmark value.

We first perform the noisy updating analysis for analysts' choice of risk-free rate. Panel A in Table 8 presents the results. The regression is estimated as a linear model, where the dependent variable is *Analysts' Risk-free Rate*, the risk-free rate taken from equity reports. We use the 10-year national Treasury yield as our proxy for $rf_{j,i,t}^{Benchmark}$, the risk-free rate market benchmark that analysts commonly reference in reports. Column 1 presents the results based on Equation 23. We obtain an OLS "G" coefficient for the variable $rf_{j,i,t}^{Benchmark}$ equal to 0.20. This indicates that changes in spot 10-year Treasury yields are not fully incorporated into analysts' subjective risk-free rate inputs. Instead, we find that analysts heavily weigh their previous measure of risk-free rates, as reflected in the 0.67 coefficient for

$F_{j,i,t-1} rf^{Sustainable}_{j,t}$.

To directly tie the updating dynamic to the effect of noise in the treasury yield updating process, we interact $X^{Benchmark}_{i,j,t}$ with a measure of volatility for the national treasury yield. Specifically, $Volatility^{Rf}_{j,t}$ is equal to the monthly standard deviation of the 10-year Treasury yield during the previous year. Intuitively, higher volatility is associated with greater uncertainty about the exact level that reflects the 10-year Treasury yield over the valuation horizon. Consistent with the role of signal noise in Bayesian updating, Panel B in Table 8 finds that an increase in $Volatility^{Rf}_{j,t}$ is associated with a reduction in the weight analysts put on the current market signal for the 10-year Treasury yield. These results are consistent with analysts forming their subjective beliefs in a manner that accounts for noise, resulting in a sticky updating process.

For completeness, and to mitigate measurement concerns regarding analysts' choice of the risk-free rate benchmark, Columns 3 to 6 of each panel replicate the regression from columns 1 and 2 using subsets of the data where analysts explicitly mention in their reports using the 10-year Treasury yield or using only firms headquartered in the United States, respectively. Décaire et al. (2024) shows that while there is disagreement on the choice of risk-free rate benchmarks for firms located outside of the US, there appears to be a near-unanimous consensus about the use of US Treasuries for US firms. We note that for all three panels, our results remain qualitatively unchanged using those alternative subsamples.

We apply the same empirical framework to analysts' choice of betas. Panel B of Table 8 presents results from regressions that use the two most common benchmarks to estimate the CAPM: 24 and 60 months of returns. Columns 1 and 2 present the results using 24 month betas, and Columns 3 and 4 replicate the analysis with the 60-month betas. In both cases, we find that analysts tend to put significant weight on their previous-period estimates, leading to stickiness in the subjective betas they use. Importantly, 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. We measure CAPM beta estimation noise with the standard errors obtained from the respective econometric CAPM benchmark (24 or 60 months).

Finally, we explore (and rule out) the possibility that the persistence of subjective betas is primarily driven by other types of adjustments, such as Blume1973 adjusted betas. Blume's strategy shrinks CAPM betas toward the market beta, 1.0. Formally, the approach can be expressed as:

$$\text{Adjusted beta} = \frac{2}{3}\text{CAPM beta} + \frac{1}{3} \times 1 \tag{24}$$

Such a decision rule yields a simple empirical prediction. If sufficient professionals apply Blume's adjustment, we should expect to observe that when CAPM betas are smaller than 1, the subjective betas should be larger than the adjusted betas, and when CAPM betas are larger than 1, we should expect the opposite. Panel C of Figure 6 plots the subjective betas against their econometrician CAPM counterpart. While we cannot rule out the fact that some analysts might use a shrinkage adjustment, the graphical evidence indicates that it this does not appear to be the dominant adjustment.

The results of this section yield two key insights. First, our quantitative and qualitative analyses suggest that when determining key discount rate inputs, analysts view the spot values for the market benchmark as an imperfect proxy of what they believe for both (i) the risk-free rate should be over their forecast horizon, and (ii) the proper measure of exposure to risk (beta). Second, our evidence suggests that analysts' updating intensity is inversely related to the noise associated with the benchmark input, making analysts' choice of discount rate inputs (i) persistent over time and (ii) increasingly sticky in periods of high noise.

Lastly, relating this updating dynamic to the asset pricing properties of subjective discount rates and betas can help us undertand the relatively good performance of analysts' discount rates. Analysts appear to filter out estimation noise, updating their estimates less when changes are "uncertain," in contrast to econometricians who systematically update a given measure. The analyst approach has the potential to reduce the effect of measurement noise in the analysts' estimate, effectively mitigating attenuation bias. This, in turn, has the potential to generate larger regression coefficients than otherwise obtained when performing an SML evaluation of the CAPM.

7 The Terminal Growth Rate

In this last section, we investigate the economic factors shaping how analysts determine long-term growth rates, one of the key determinants of valuation models.

Qualitatively, the text in equity reports ties long-term growth rates to long-term inflation expectations and the expected long-term GDP growth rate. Analysts often refer to inflation 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."[14] The GDP growth rate is often referred to as a potential upper bound: "[We use a] terminal growth rate of 2.75% (21% discount to long-term forecast Australian GDP 3.5%) [...]."[15] Mathematically, this upper bound makes sense because in the long run a given firm cannot outgrow the overall economy, else the firm's size would eventually rival or surpass the economy itself. Academic research suggests a third variable that affects long-term growth: 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-oriented guides.[16] Conceptually, the dynamic efficiency condition of macroeconomic theory formalizes this relation because, in the long run, the risk-free rate caps the growth rate of the economy (Cass, 1965; Phelps, 1961), making it an intuitive reference variable.

We perform regression analyses to determine which of these economic factors appears to quantitatively drive terminal growth rates. Panel A of Table 9 presents results from linear regressions with a dependent variable of *Analysts' terminal growth rate* 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 versions of each regressor to get a sense of how the use of these variables is implemented: (i) the current estimate, (ii) the 10-year historical average, and (iii) 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

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

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

[16] See for example Aswath Damodaran's discussion on the terminal growth rate: https://pages.stern.nyu.edu/~adamodar/pdfiles/valonlineslides/session9.pdf

the United States. Considering historical averages and long-term forecasts for these variables aligns with the descriptions made by analysts in equity reports (Appendix B).

Columns 1-3 of Table 8 Panel A examine which economy-wide variables best explain the terminal growth rate process in the US data. 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 ($R^2 = 0.88$) of the terminal growth rate process than do current measures ($R^2 = 0.64$) or the SPF 10-year forecasts ($R^2 = 0.76$). In the regression based on 10-year historical averages (Column 2), both real GDP growth and the 10-year Treasury yield each explain more than 40% of the variation in terminal growth rates. Similar relative patterns are documented in the full set of countries in Columns 4 and 5, 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 historical macroeconomic realizations.

We note that the estimated inflation coefficient is not statistically significant in any of the specifications, and that the variable explains the smallest share of the regression R^2. 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).

Lastly, finding that historical averages best explain aggregate terminal growth expectations suggests that there is a persistent updating process for terminal growth rates. To quantify this notion, and to connect to the sticky updating documented above for the risk-free rate and beta, we apply a version of Equation 23 to the firm-level terminal growth rates. We explore three possible market benchmarks—GDP growth, Treasury yield, and inflation—to build upon the results of Table 9, Panel A. Panel B of Table 9 reports the results of this test. The large and significant coefficient on lagged terminal growth indicates that firm-level terminal growth rates are persistent, and that updating is sticky with respect to innovations in real GDP growth and Treasury yields.

Overall, the results of this section help refine our understanding of how financial professionals conceptualize long-term growth expectations. 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 in the data.

8 Conclusion

In this paper, we introduce one of the largest and most comprehensive datasets collected from equity analyst reports, which allows us to directly observe most of the DCF inputs used in target valuations. In contrast to the existing literature, we show that subjective expectations and discount rates both play an important role in explaining expected valuation fluctuations.

We find that analyst discount rates are unbiased predictors of future returns and the relation between subjective CAPM-based betas and future realized returns better align with the theory of CAPM than simple econometric estimates of the CAPM. By directly showing that firm-level innovations in subjective betas are associated with return predictability, and by characterizing the nature of analysts' updating process, our results deepen the current state of understanding about how professionals implement common academic models.

We also document the economic underpinnings driving analyst valuation: forecasted (but not current) inflation affects discount rates, and real GDP growth and Treasury yields (but not inflation) drive terminal growth rates.

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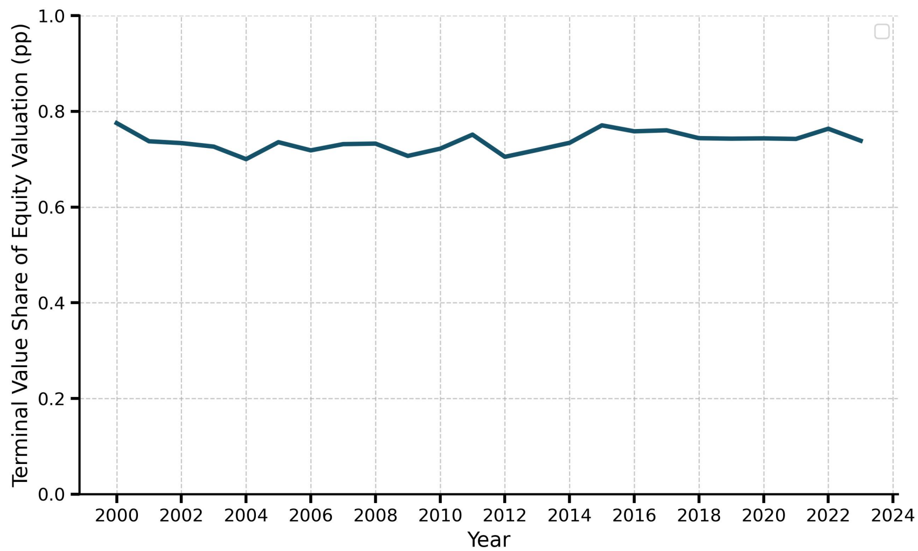
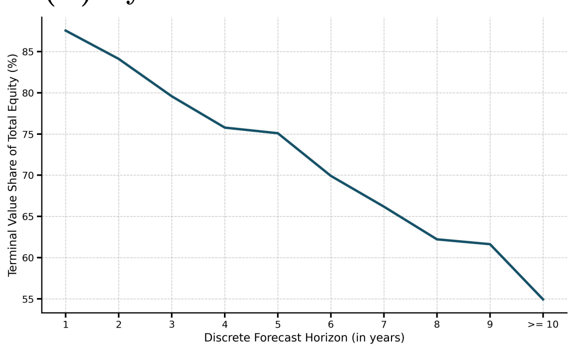
(A) Terminal Value Share of Total Equity by Year.



(B) By Horizons of Discrete Period.



(C) By Discount Rates.

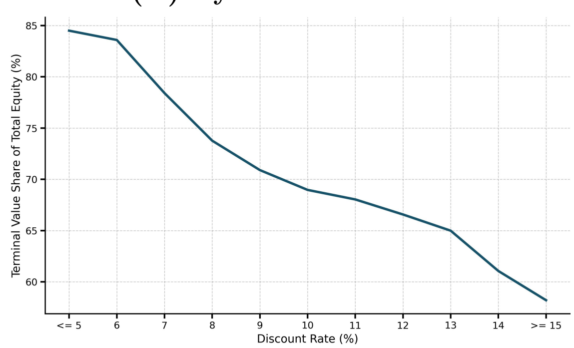


Figure 1: **Terminal Value Share of Total Equity** This figure plots the share of equity valuation that is associated with DCF (Discounted Cash Flow) terminal values for the period 2000–2023. For Panel A, the x-axis is expressed in years, and For panel B, the x-axis denotes the number of years used to forecast the discrete cash flows. For Panel C, the x-axis represents the discount rate used in the DCF model. 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.

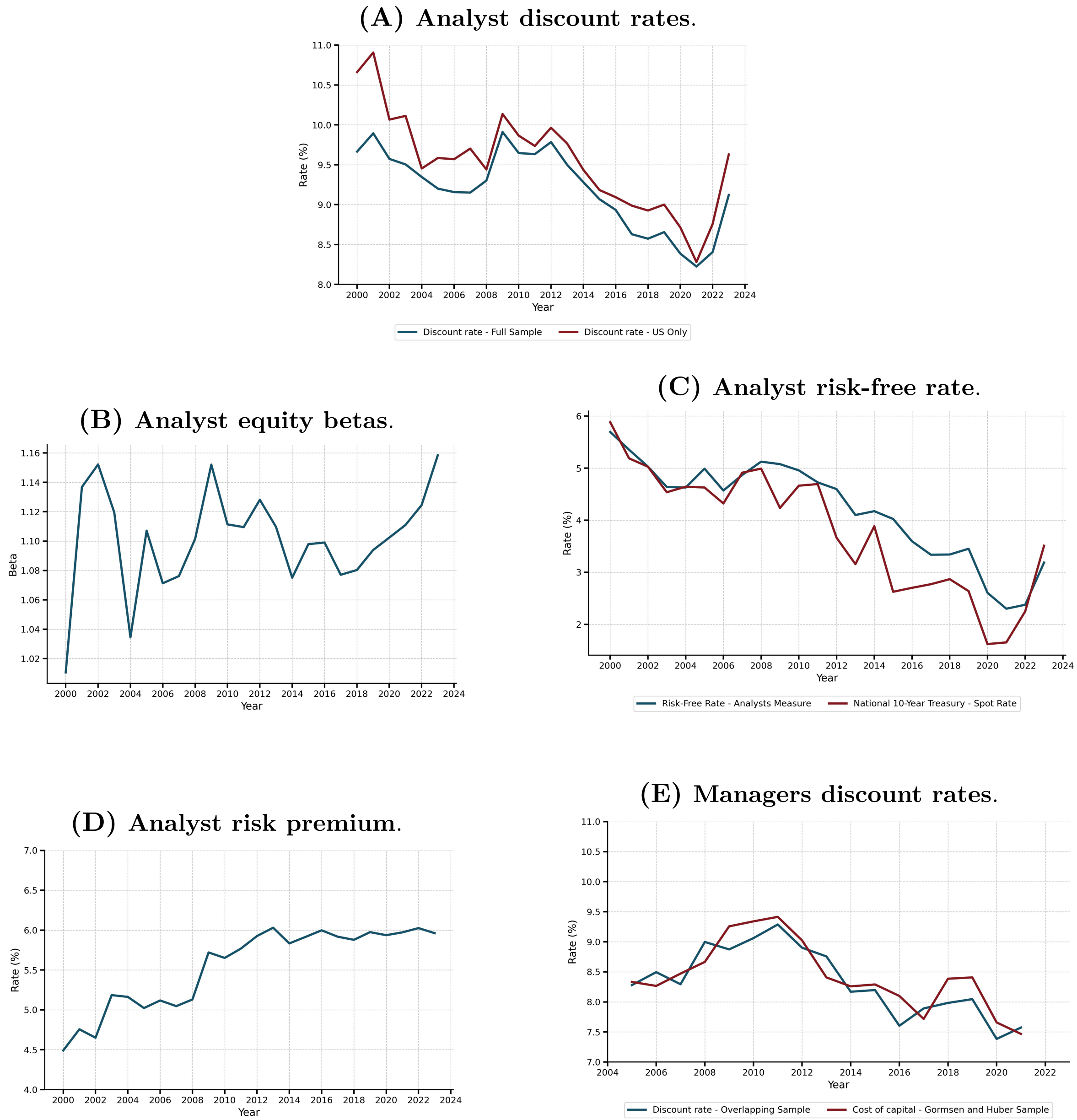


Figure 2: **Subjective Discount Rates and Inputs** This figure plots the time trends for discount rates, its key components, and a comparison with managers' discount rates over the sample period, 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages, with the exception of Panel B 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. Panel B plots trends in equity betas used by equity analysts. Panel C 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' countries. In Panel E, we match our sample with Gormsen and Huber' (2023) 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.

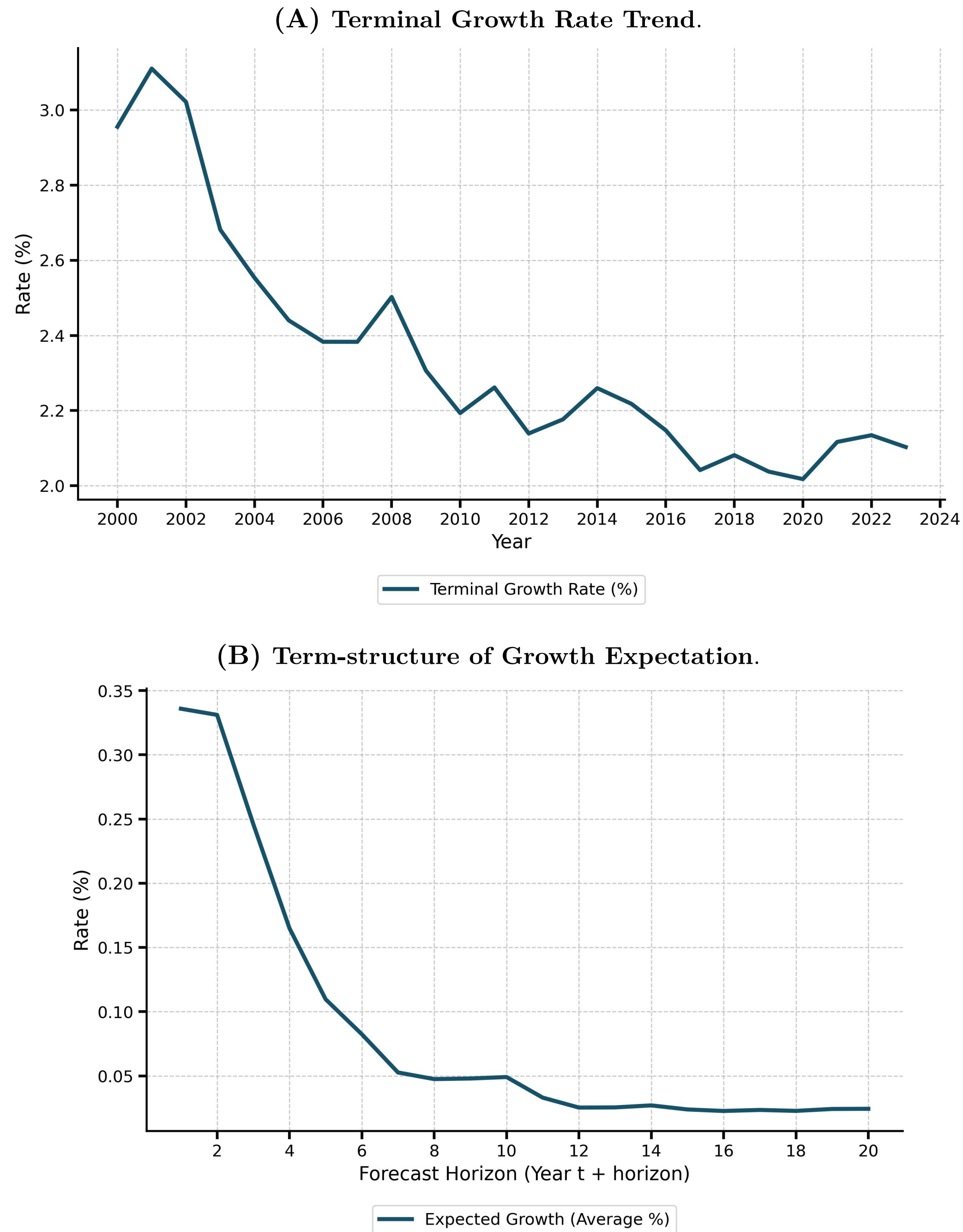
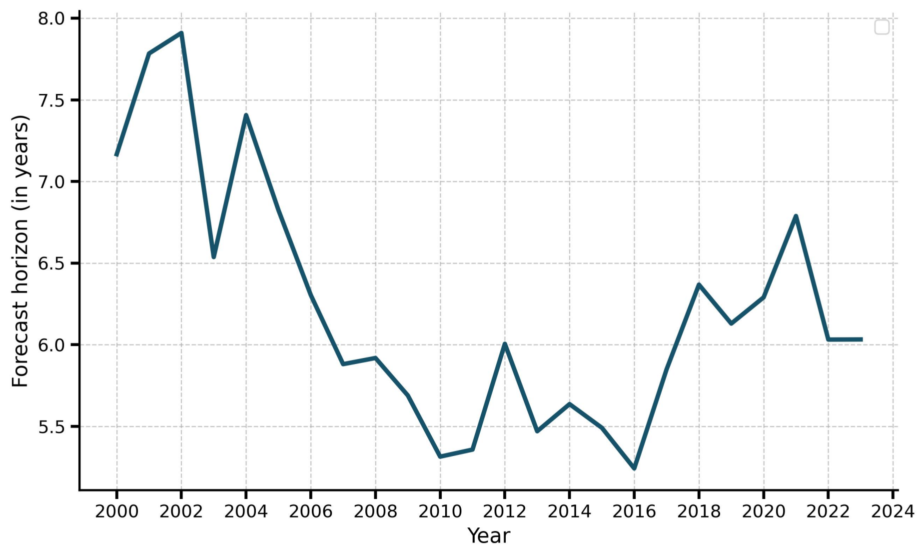


Figure 3: **Analysts' Terminal Growth Rate** This figure plots analysts' terminal growth rates over the sample period, 2000–2023. In Panel A, the x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which we have a measure of analysts' terminal growth rates. The solid blue line represents analysts' terminal growth rate patterns (51,016 observations). In Panel B, the x-axis represents the forecast horizon. For example, a value of 1 indicates the growth rate that an analyst expects the firm to achieve by the end of the current year.

(A) Explicit Forecast Horizon Trend.



(B) Explicit Forecast Horizon Histogram.

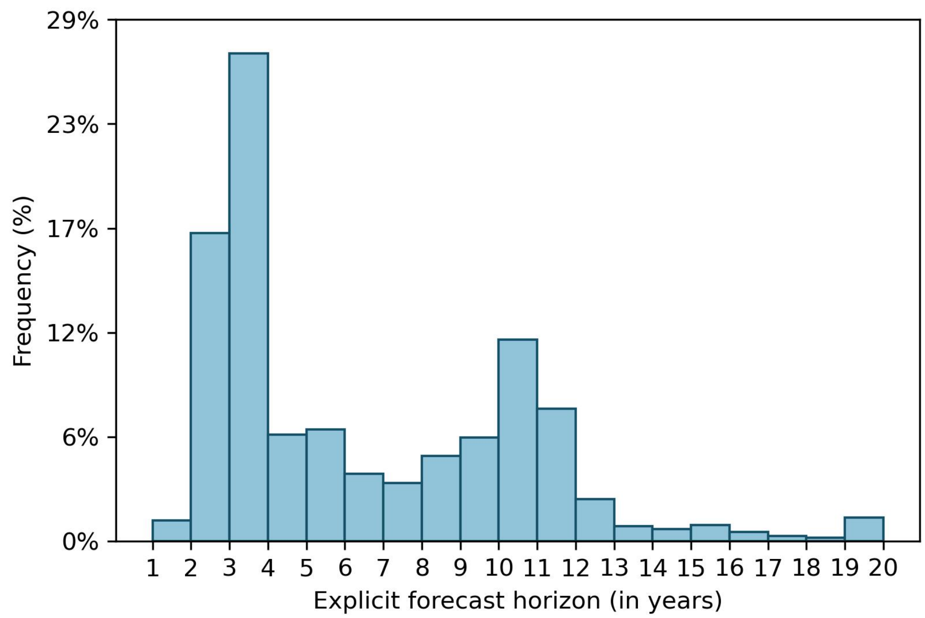


Figure 4: **Forecast Horizon** This figure plots the explicit forecast horizon patterns for the period 2000–2023. Panel A shows the time trend. The x-axis is expressed in years, and the y-axis denotes the average number of years used in analysts' explicit forecasts. The sample includes all firms for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

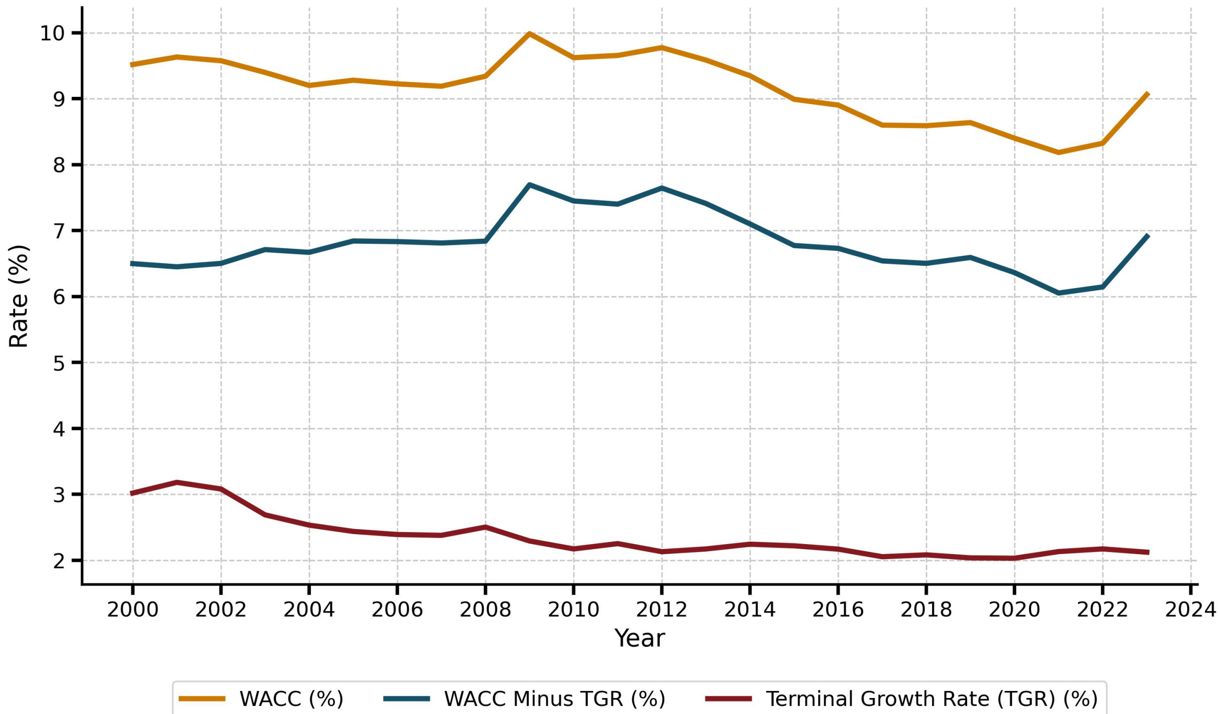


Figure 5: Discount Rate Minus Terminal Growth Rate Trend This figure plots the difference between the discount rate and the terminal growth rate for the period 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which 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.

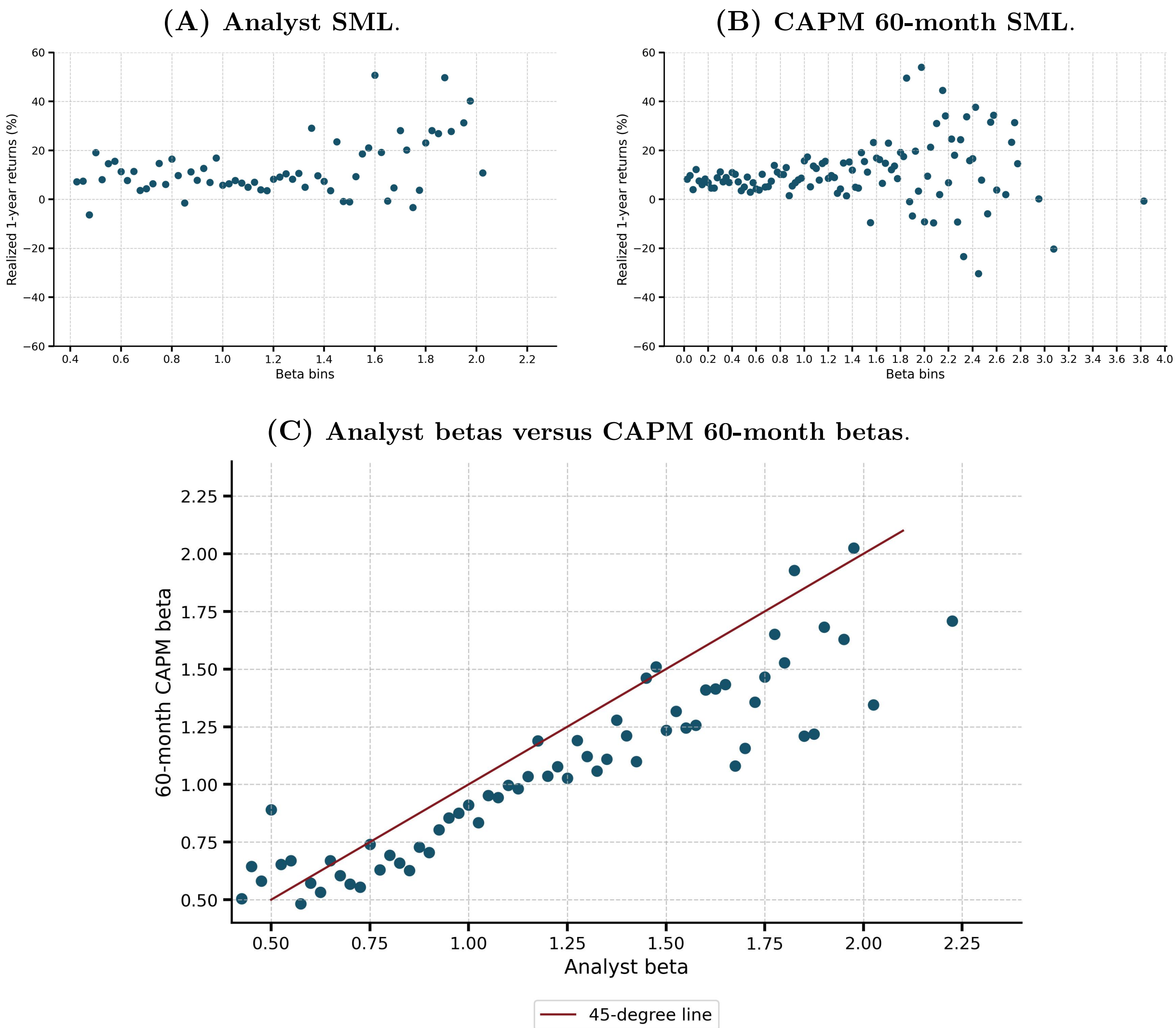


Figure 6: **Analyst betas and adjustments** This figure plots analyst betas patterns in the cross-section and time-series for the period 2000-2023. The x-axis in Panels A, B, and c denotes beta bins in 0.05 increments. A minimum of 5 observations per bin is required for those graphs. In Panels A and B, the y-axis corresponds to the 1-year realized total returns from Refinitiv. In Panel C, we plot average 60-month beta estimates on the y-axis against analyst subjective betas on the x-axis.

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

Panel C: Economic Data Series	Mean	25^{th} Pct.	Median	75^{th} Pct.	Std. Dev.	No. Obs.
Future Variables (Refinitiv)						
1-Year Total Realized Return (%)	12.87	-14.80	8.06	31.80	51.79	49,847
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: Valuation Decomposition This table performs the variance decomposition of analysts' DCF valuations. The coefficients correspond to the Campbell-Shiller coefficients averaged across all firms for which the variance decomposition is performed individually. The sample period is 2000–2023. Panel A presents the full decomposition for the three types of variables presented in Equation 7: (i) *FCF growth*$^1_{i,j,t}$ is the natural logarithm of the explicit forecast for the first year, $\ln(1+\text{FCF growth}^1_{i,j,t})$. (ii)*FCF growth*$^2_{i,j,t}$ is the natural logarithm of the explicit forecast for the second year multiplied by its Campbell-Shiller coefficient, $\rho\ln(1+\text{FCF growth}^2_{i,j,t})$. (iii)*FCF growth*$^3_{i,j,t}$ is the natural logarithm of the explicit forecast for the third year multiplied by its Campbell-Shiller coefficient, $\rho^2\ln(1+\text{FCF growth}^3_{i,j,t})$. (iv) *Terminal growth rate*$_{i,j,t}$ is equal to the natural logarithm of the terminal growth used by the analyst multiplied by its Campbell-Shiller coefficient, $\frac{\rho^3}{1-\rho}\ln(1+\text{TGR}_{i,j,t})$. (v) *Discount rate* corresponds to the natural logarithm of the discount rate used to evaluate firm cash flows multiplied by its Campbell-Shiller coefficient, $\frac{1}{1-\rho}*\ln(1+\text{Discount rate}_{i,j,t})$. The variable of interest, *Equity valuation*$_{i,j,t}$, is equal to the natural logarithm of the analyst's equity valuation in the DCF model minus the natural logarithm of the initial cash flow, $\ln(\text{Valuation}_{i,j,t})-\ln(\text{FCF}_0)$. Panel A performs the variance decomposition using a pooled regression on each firm individually and reports the averaged Campbell-Shiller coefficients. Panel B explores how the average coefficient obtained for the first-year cash flows varies across different subsamples split at the median on three firm characteristics: (i) firm-level variance of the first-year cash flows, (ii) discount rates, (iii) firm birth cohort. The regressions are estimated using ordinary least squares, and the standard errors (in parentheses) are estimated using heteroskedastic-consistent jackknife estimators. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Valuation decomposition	FCF growth^1_i	FCF growth^2_i	FCF growth^3_i	Terminal growth$_i$	Discount rate$_i$
	(1)	(2)	(3)	(4)	(5)
Valuation$_i$	0.38***	0.13***	0.04***	0.18***	-0.28***
	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)
Dependent Variable Mean	0.56	0.21	0.15	0.02	0.09
Dependent Variable Standard Deviation	8.60	0.90	0.86	0.01	0.02
Total observations	5,539	5,539	5,539	5,539	5,539
Number of firms	701	701	701	701	701

Panel B: Cross-Sectional Cut	FCF growth^1_i					
Cross-sectional cut variable:	Var(FCF growth^1_i)		Discount rate		Young Firm	
	$\geq$ Median	$<$ Median	$\geq$ Median	$<$ Median	Young	Old
	(1)	(2)	(3)	(4)	(5)	(6)
Valuation$_i$	0.60***	0.16***	0.46***	0.31***	0.47***	0.31***
	(0.07)	(0.02)	(0.06)	(0.03)	(0.09)	(0.04)
Number of firms	352	352	352	352	218	207

Table 3: 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. Variable definitions appear in Appendix C. The regressions are estimated using ordinary least squares. Standard errors (in parentheses) are estimated using heteroskedastic-consistent jackknife estimators. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: WACC Decomposition	Cost of equity$_i$	Risk-free rate$_i$	Beta$_i$*Risk premium$_i$
	(1)	(2)	(3)
Discount rate$_i$	0.70***	0.36***	0.35***
	(0.03)	(0.03)	(0.02)
Total Observations	9,622	9,622	9,622
Number of firms	1,573	1,573	1,573
Panel B: Cost of Risk Decomposition	ln(Beta$_i$)	ln(Risk premium$_i$)	
	(1)	(2)	
ln(Equity risk premium$_i$*beta$_i$)	0.54***	0.42***	
	(0.03)	(0.03)	
Total Observations	9,622	9,622	
Number of firms	1,573	1,573	

Table 4: Discount rates and Terminal Growth Rates This table studies the relation between analysts' choice of discount rates and terminal values. 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. TGR, the *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 rate$_{i,j,t}$ (%)	
	(1)	(2)
TGR$_{i,j,t}$ (%)	0.12***	0.02**
	(0.03)	(0.01)
Firm FE	No	Yes
Year*Country FE	No	Yes
Observations	48,927	45,417
F Statistics	14.77	4.09
R^2	0.01	0.63

Table 5: Discount Rate and Inflation Expectations This table presents the results of an analysis relating discount rates and their inputs to inflation expectations. The sample period is 2000–2023 and covers US firms only, given the use of data from the Philadelphia Survey of Professional Forecasters (SPF) for the 10-year inflation expectations. There are three dependent variables, Analyst risk-free rate, subjective ERPs, and subjective discount rates. The variables of interest are the real treasury yield, 10-year Treasury yield (Real), obtained by applying the Fisher equation to the 10-year treasury yield and the 10-year inflation expectations from the SPF. 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 rate$_{i,j,t}$ (%)		Analysts' risk-free rate$_{i,j,t}$ (%)		ERP$_{i,j,t}$ (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
10-year Treasury yield (Real)$_{c,t}$ (%)	0.42***	0.40***	0.60***	0.54***	-0.30***	-0.31***
	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
10-year Inflation expectation (SPF)$_{c,t}$ (%)		0.74***		0.96***		0.13
		(0.13)		(0.21)		(0.20)
Current Inflation$_{c,t}$ (%)	-0.12***		-0.00		0.00	
	(0.01)		(0.02)		(0.02)	
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,460	18,913	3,187	3,187	3,125	3,125
F Statistics	369.87	314.66	129.02	121.15	34.01	34.54
R^2	0.53	0.52	0.59	0.60	0.51	0.51

Table 6: Ex-post realized returns and analyst discount rates This table studies the relation between analyst subjective discount rates and one-year ex-post realized returns. The dependent variable, *Realized returns*, is a firm total realized return from year t to t+1. There are two variables of interest. In Columns 1-3, *Required return* corresponds to the subjective discount rate used by analysts. In Columns 4-6, *Required return* denotes the subjective cost of equity. The sample period is 2000–2022. The unit of observation is at the firm i, analyst j, and forecast year t level. The regressions are estimated using ordinary least squares. Standard errors (in parentheses) are heteroskedastic-consistent and clustered at the firm and at the month-year level to follow the empirical design used in Gormsen and Huber (2023). Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Dependent variable	Realized return$_{i,j,t+1}$								
	Subjective Discount Rate			Subjective Cost of Equity			Subjective rf and $\beta * ERP$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(β_1) Required Return$_{i,j,t}$	1.49*	0.84*	0.72***	1.70**	1.02**	0.99**			
	(0.78)	(0.45)	(0.19)	(0.80)	(0.44)	(0.46)			
(β_2) Risk-Free Rate$_{i,j,t}$							1.56	1.14**	-0.54
							(1.22)	(0.46)	(0.68)
(β_3) $\beta^{CAPM}_{i,j,t} * ERP_{i,j,t}$							1.79**	0.96*	1.46***
							(0.78)	(0.56)	(0.49)
Constant	-0.71			-5.52			-5.52		
	(4.90)			(6.62)			(6.64)		
Month-year FE	No	Yes	No	No	Yes	No	No	Yes	No
Country*Month-year FE	No	No	Yes	No	No	Yes	No	No	Yes
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes
H_0^A: $\beta_1 = 1$ (P-value)	0.53	0.15	0.15	0.38	0.99	0.99			
H_0^B: $\beta_2 = 1$ (P-value)							0.65	0.77	0.03
H_0^C: $\beta_3 = 1$ (P-value)							0.31	0.94	0.88
H_0^D: Constant = 0 (P-value)	0.89			0.41			0.41		
H_0^A & H_0^D (P-value)	0.49			0.68					
H_0^B & H_0^C & H_0^D (P-value)							0.78		
Observations	49,847	49,844	45,720	9,117	9,115	6,685	9,117	9,115	6,685
F Statistics	3.70	3.42	14.81	4.50	5.28	4.67	2.72	3.49	7.32
R^2	0.00	0.23	0.47	0.01	0.25	0.57	0.01	0.25	0.57

Table 7: Analyst Equity Betas This table presents the properties of analysts' equity betas. The sample period is 2000–2023. In Panel A, the variable of interest (*CAPM beta*), corresponds to *Analyst beta* in Columns 1-2, econometrician 24-month CAPM beta in Columns 3-4, and econometrician 60-month CAPM beta in Columns 5-6. The unit of observations is measured at the firm *i*, analyst *j*, and year *t* levels. The dependent variable, *Realized returns*, is a firm total realized return from year t to t+1. Standard errors (in parentheses) are heteroskedastic-consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: SML regression	Excess total return$_{i,j,t+1}$					
	Analyst beta		24-month		60-month	
	(1)	(2)	(3)	(4)	(5)	(6)
CAPM beta$_{i,j,t}$	6.69***	6.55***	2.73***	0.77	2.52**	1.62
	(1.84)	(2.22)	(0.78)	(1.04)	(0.98)	(1.39)
Constant	1.33		6.89***		6.96***	
	(1.93)		(0.70)		(0.86)	
Country*Month-year FE	No	Yes	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes	No	Yes
H_0^A: $\beta_1 = 5.70\%$ (P-value)	0.59	0.70	0.00	0.00	0.00	0.00
H_0^B: $Constant = 0$ (P-value)	0.49		0.00		0.00	
Observations	13,416	11,291	12,124	10,181	10,595	8,857
F Statistics	13.24	8.71	12.14	0.55	6.64	1.36
R^2	0.00	0.58	0.00	0.58	0.00	0.58

Panel B: Beta prediction	Excess total return$_{i,j,t+1}$					
	Analyst beta		24-month		60-month	
	(1)	(2)	(3)	(4)	(5)	(6)
(β_1) ln(ERP$_{i,j,t}$)	0.12***	0.05	0.13***	0.04	0.10***	0.05
	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.04)
(β_2) ln(CAPM beta$_{i,j,t}$)	0.11***	0.13***	0.03***	0.01	0.03***	0.03
	(0.03)	(0.04)	(0.01)	(0.01)	(0.01)	(0.02)
Constant	0.43***		0.47***		0.40***	
	(0.07)		(0.07)		(0.07)	
Country*Month-year FE	No	Yes	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes	No	Yes
H_0^A: $\beta_1 = 0.062$ (P-value)	0.01	0.81	0.01	0.66	0.10	0.69
H_0^B: $\beta_2 = 0.062$ (P-value)	0.10	0.12	0.00	0.00	0.00	0.17
Observations	9,117	7,247	7,537	5,884	6,943	5,497
F Statistics	12.15	10.56	11.56	0.15	9.10	1.53
R^2	0.00	0.52	0.00	0.53	0.00	0.51

Table 8: Discount Rate Updating Process This table studies the properties of analysts' discount rate updating process. The sample period is 2000–2022. Regressions are estimated using ordinary least squares. In Panel A, the dependent variable, *analyst risk-free rate*, is equal to the risk-free rate used by analysts in the calculation of their discount rate at time t. In Panel B, the dependent variable, *analyst betas*, is equal to the equity beta used by analysts in the calculation of their discount rate at time t. The unit of observation is at the firm i, analyst j, and forecast year t level. The variables of interest are *analyst risk-free rate*$_{i,j,t-1}$, *10-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*. In Panel B, the unit of observation is at the firm i, analyst j, and year t level. The current real 10-year treasury yield is obtained by applying the Fisher equation to the current 10-year treasury yield and using the 10-year inflation expectations from the survey of professional forecasters. 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%.

Panel A: Risk-free rate adjustment:	Analysts' risk-free rate$_{i,j,t}$ (%)					
	Full Sample		10-Year Only		US Only	
	(1)	(2)	(3)	(4)	(5)	(6)
Analysts' risk-free rate$_{i,j,t-1}$ (%)	0.67***	0.66***	0.70***	0.68***	0.66***	0.69***
	(0.02)	(0.02)	(0.05)	(0.05)	(0.03)	(0.03)
10-year treasury yield$_{i,j,t}$ (%)	0.20***	0.21***	0.16***	0.23***	0.30***	0.51***
	(0.02)	(0.02)	(0.05)	(0.06)	(0.03)	(0.06)
10-year treasury yield*Volatility$^{RF}_{i,j,t}$ (%)		-0.01***		-0.06***		-0.22***
		(0.00)		(0.02)		(0.05)
Volatility$^{RF}_{i,j,t}$		0.13***		0.47***		0.53***
		(0.03)		(0.13)		(0.14)
Observations	6,154	6,151	602	602	1,428	1,428
F Statistics	3121.49	1726.63	159.17	136.29	737.01	661.85
R^2	0.70	0.71	0.68	0.69	0.63	0.63
Panel B: Beta adjustments	Analyst beta$_{i,j,t}$					
	24-month CAPM		60-month CAPM			
	(1)	(2)	(3)	(4)		
Analyst beta$_{i,j,t-1}$	0.79***	0.77***	0.76***	0.74***		
	(0.01)	(0.01)	(0.01)	(0.01)		
CAPM beta$_{i,j,t}$	0.04***	0.05***	0.06***	0.08***		
	(0.00)	(0.01)	(0.01)	(0.01)		
CAPM beta$_{i,j,t}$ * Std. Error beta$_{i,j,t}$		-0.03***		-0.06***		
		(0.01)		(0.02)		
Std. Error beta$_{i,j,t}$		0.07***		0.14***		
		(0.01)		(0.04)		
Observations	6,751	6,751	6,015	6,015		
F Statistics	2889.50	1536.66	2576.10	1381.82		
R^2	0.65	0.65	0.65	0.65		

Table 9: 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. In Panel A, 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.* In Panel B, the unit of observation is at the firm i, analyst j, and year t level. The current real 10-year treasury yield is obtained by applying the Fisher equation to the current 10-year treasury yield and using the 10-year inflation expectations from the survey of professional forecasters. 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	Aggregate 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$_{c,t}$ (%)	-0.02	-0.55	0.78	-0.00	-0.03
	(0.04)	(0.37)	(0.71)	(0.01)	(0.05)
Real GDP growth$_{c,t}$(%)	0.03	0.59***	0.80	0.02***	0.10**
	(0.05)	(0.18)	(0.52)	(0.01)	(0.04)
10-year treasury yield$_{c,t}$ (%)	0.51***	0.42**	0.41*	0.04**	0.06*
	(0.12)	(0.17)	(0.22)	(0.02)	(0.03)
Country FE	No	No	No	Yes	Yes
Observations	23	23	23	605	605
F Statistics	6.30	35.87	20.07	4.20	2.83
R^2	0.64	0.88	0.76	0.59	0.60
Within R^2	0.64	0.88	0.76	0.03	0.07
R^2 Shapley Decomposition					
Inflation$_{c,t}$ (%)	0.16	14.61	22.69	4.88	17.21
Real GDP growth$_{c,t}$ (%)	2.06	43.04	38.18	32.36	34.30
10-year treasury yield$_{c,t}$ (%)	97.78	42.35	39.13	62.75	48.49

Panel B: Firm-level TGR Updating	Terminal growth rate$_{i,j,t}$ (%)	
	(1)	(2)
Terminal growth rate$_{i,j,t-1}$ (%)	0.67***	0.64***
	(0.02)	(0.04)
Current Inflation$_{c,t}$ (%)	-0.00	-0.01
	(0.00)	(0.01)
Current 10-year treasury yield$_{c,t}$ (%)	0.03***	
	(0.00)	
Current Real 10-year treasury yield$_{c,t}$ (%)		0.50***
		(0.08)
Current Real GDP growth$_{c,t}$(%)	0.01**	0.04***
	(0.00)	(0.01)
Observations	17,339	4,946
F Statistics	549.81	181.93
R^2	0.48	0.46

Appendix A

Appendix A1: Risk-Free Rate

Report 1: 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 2: 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 3: 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) [...].

Report 4: 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 5: 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 6: 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 7: 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%).

Appendix A2: Equity Betas

Report 1: HSBC, 0968.HK, 2023-02-28: [...] using a dcf model assuming a risk-free rate of 2.0%, equity risk premium of 5%, equity beta of 1.0, and a cost of equity of 7%, resulting in a wacc of 5.4% (all unchanged).

Report 2: Deutsche Bank, IRE.AX, 2015-02-25: [...] key dcf inputs remain unchanged: beta 1.05; wacc 9.5% & tgr 3.5% (based on gdp).

Report 3: BNP Paribas, BNG.MI^E12, 2001-03-19: [We use] a wacc of 7.11% based on a beta of 0.82 versus the Bloomberg adjusted beta of 0.54, which we consider unrealistically low.

Report 4: JPMorgan, 1888.HK, 2011-03-07: We have assumed a beta of 1.2, higher than the beta of 0.9 on Bloomberg, given that the company's risks are higher in 2010 compared to 2009 with rising commodity costs and the possibility of volatility from any Renminbi appreciation.

Report 5: Macquarie Research, 3383.HK, 2016-03-30: a subjective forward beta of 2.00 is used for our target price instead of historical beta of 1.41 for nav to account for lower management execution risks and future market volatilities affecting the valuation of assets.%).

Report 6: Macquarie Research, MAHB.KL, 2013-01-28: We have also used a beta of 0.76x which is higher than its historical 2-year average beta of 0.67x.

Appendix B: 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 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
1-year realized total return	The 52-week realized total return (capital gain and income), obtained from Refinitiv.
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 average inflation 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 "N" year 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, $ln(1 + \text{FCF ST growth}^N_{i,j,t})$.
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.
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 DCF valuation, 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

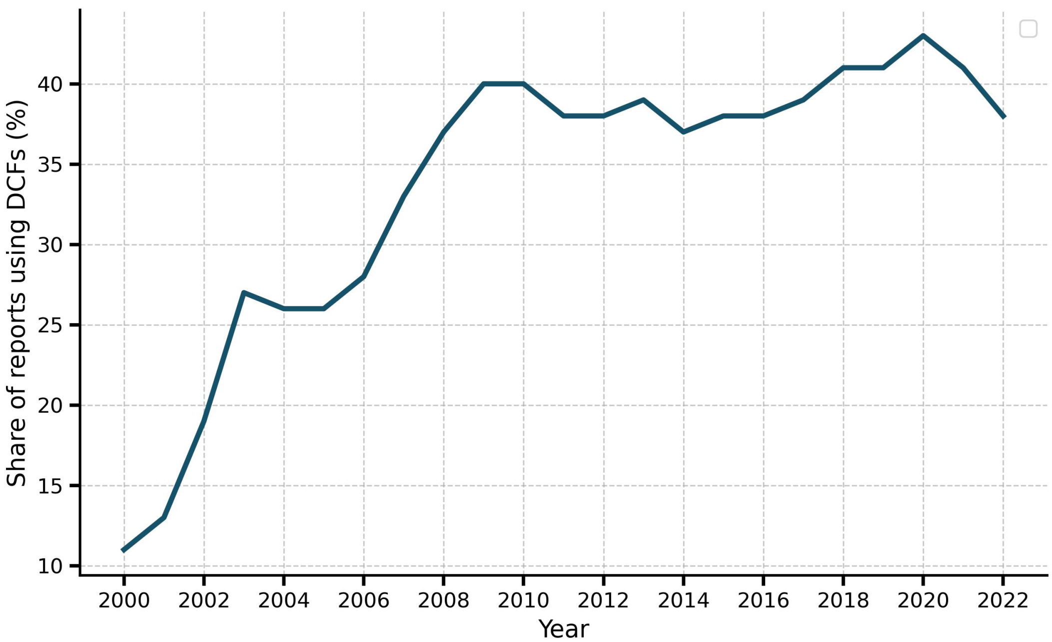


Figure A1: Share of equity reports using DCFs This figure plots the share of equity reports using DCF models to perform the analysis among the reports housed on Refinitiv. The x-axis represents years. The y-axis denotes the proportion of reports published in a given year in which the equity analyst specifically 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.*

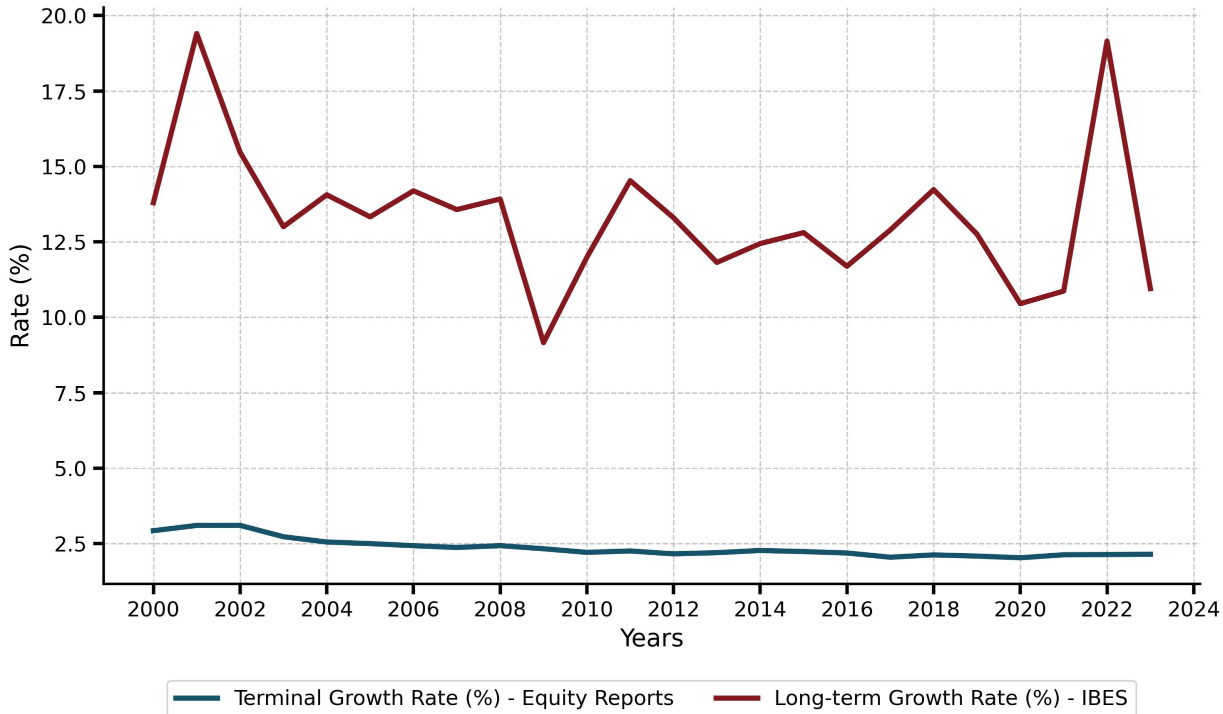


Figure A3: IBES Long-term Growth Rate Versus Equity Report Terminal Growth Rate This figure compares the trends for our sample's terminal growth rate and the IBES measure of *long-term growth rate* over the period 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured 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.

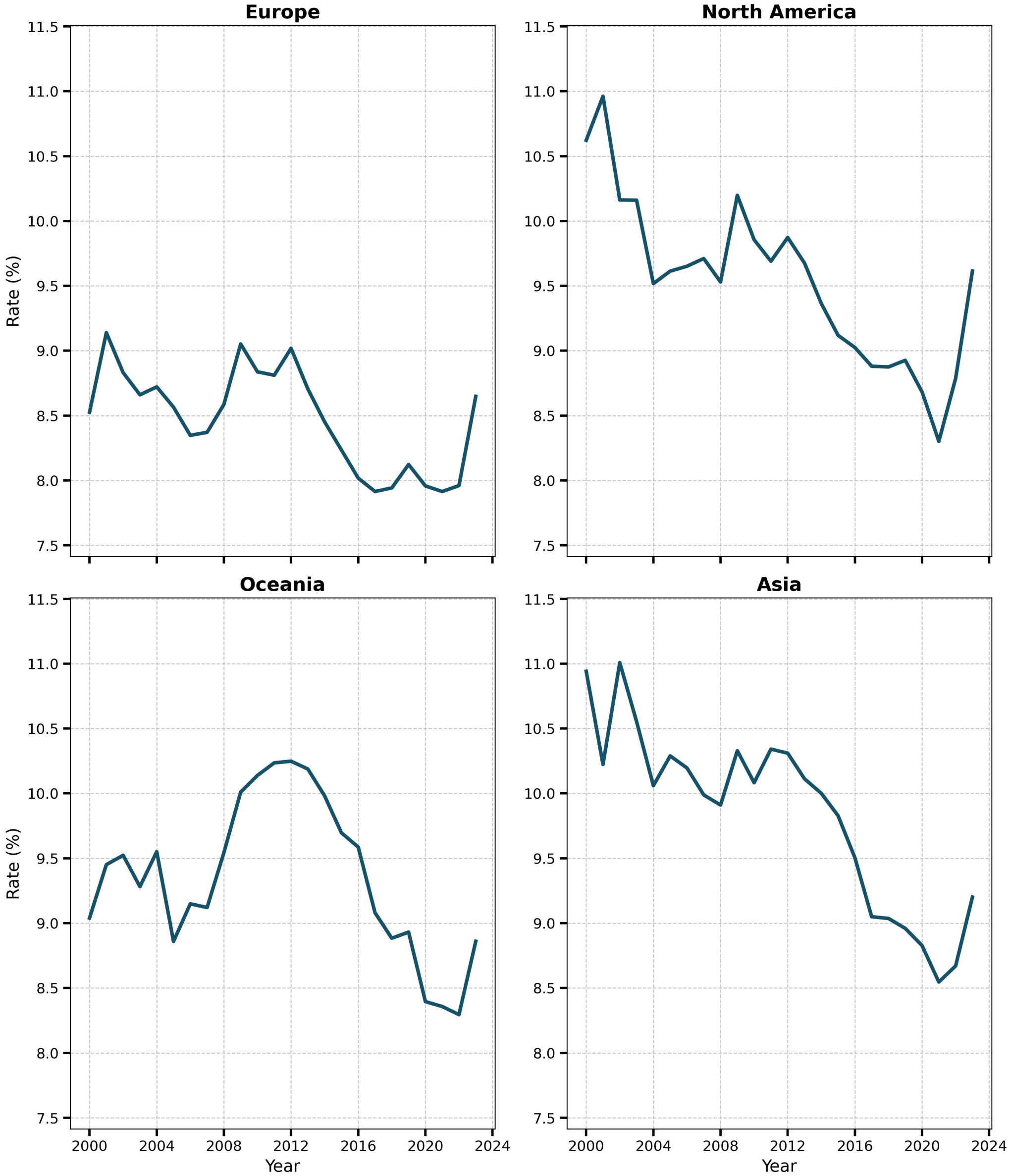


Figure A4: Discount Rate Trends by Continent This figure plots discount rate trends across all six continents over the sample period, 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which we have a measure of the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

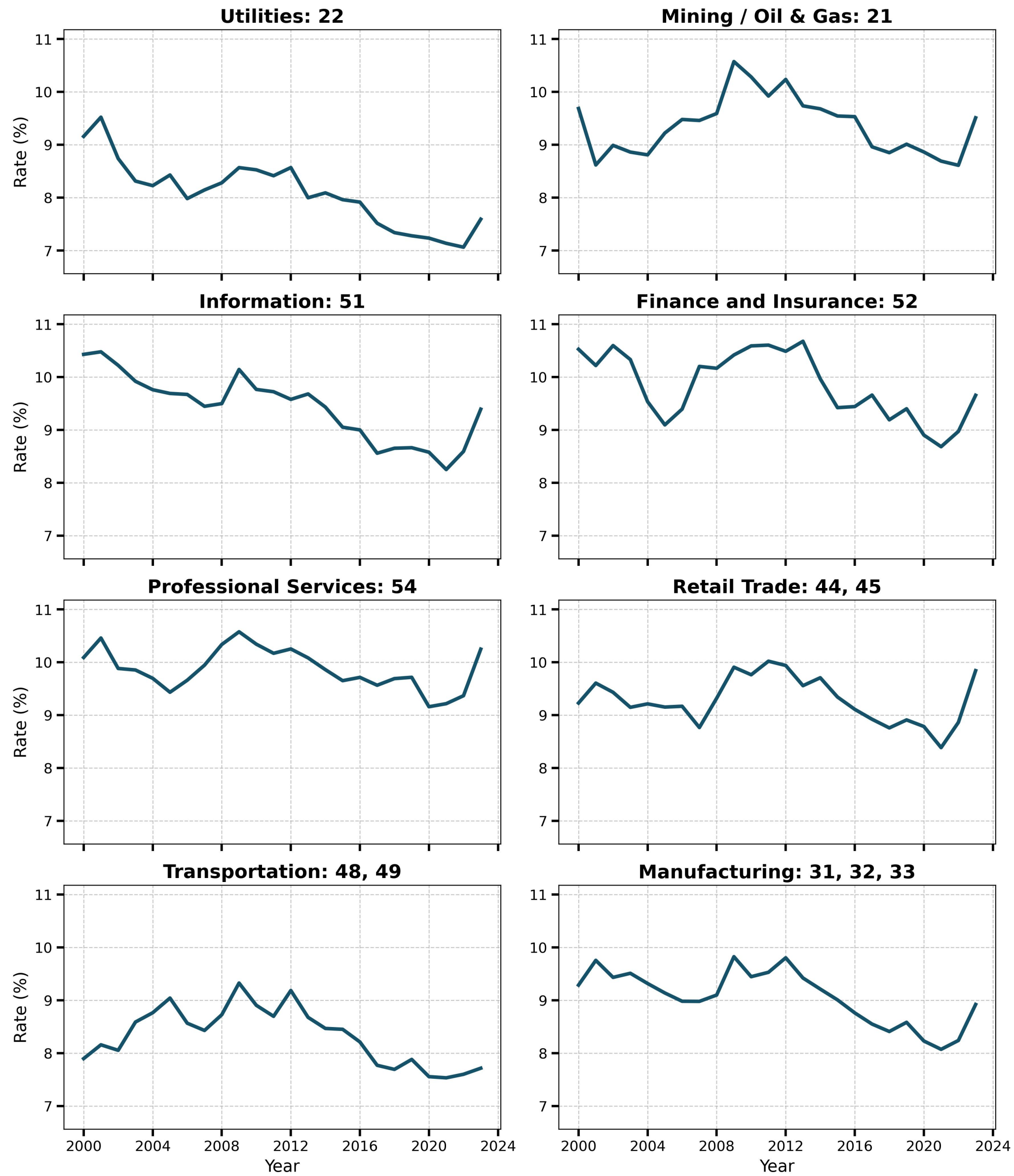


Figure A5: Discount Rate Trends by Major Industries This figure plots discount rate trends across the eight largest industries in our sample for the period 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which we 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.

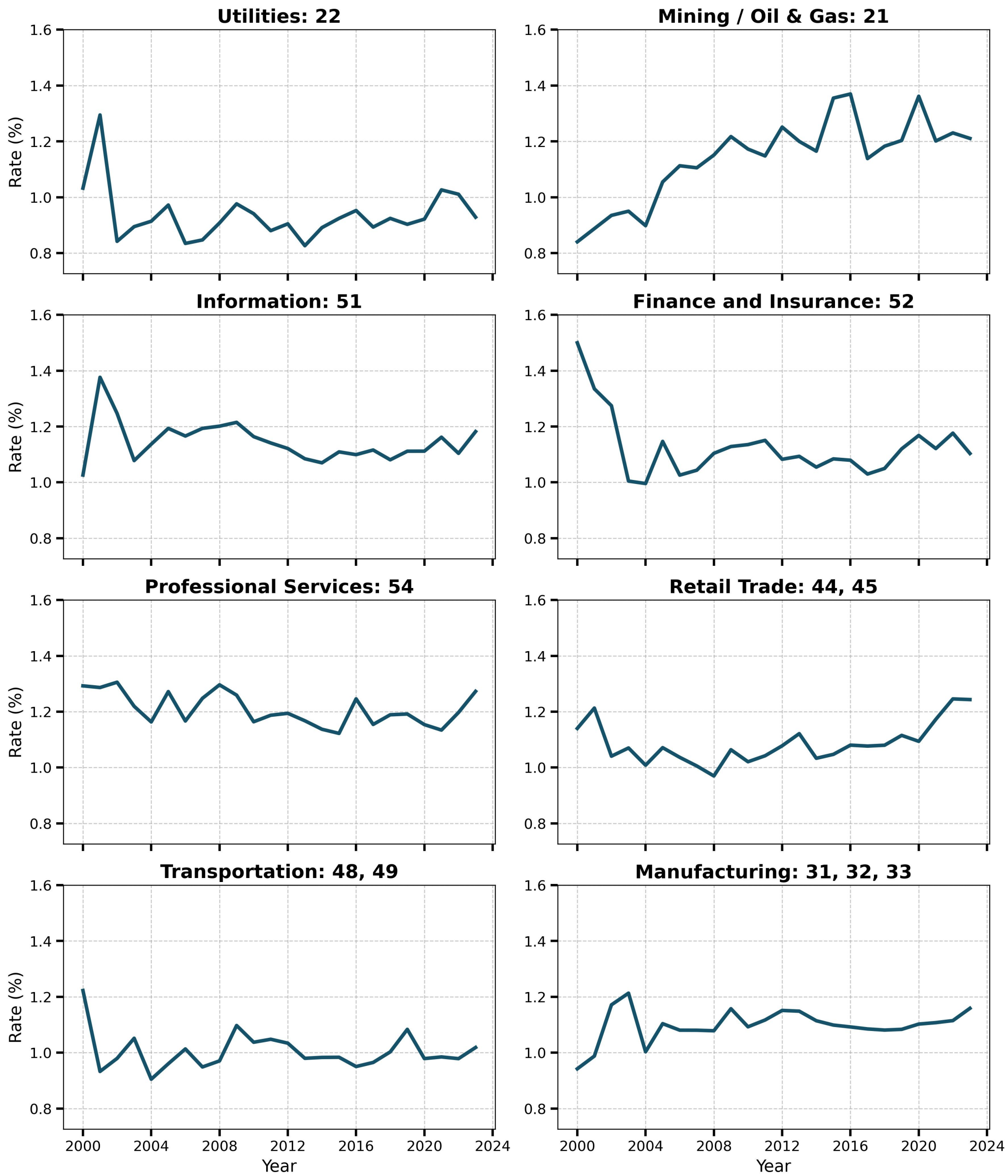


Figure A6: Betas Trends by Major Industries This figure plots subjective beta trends across the eight largest industries in our sample for the period 2000–2023. The x-axis is expressed in years, and the y-axis denotes the beta values. The sample includes all firms for which we have a measure of the subjective betas and that are included in those industries. The solid blue line represents the average subjective beta patterns for each industry.

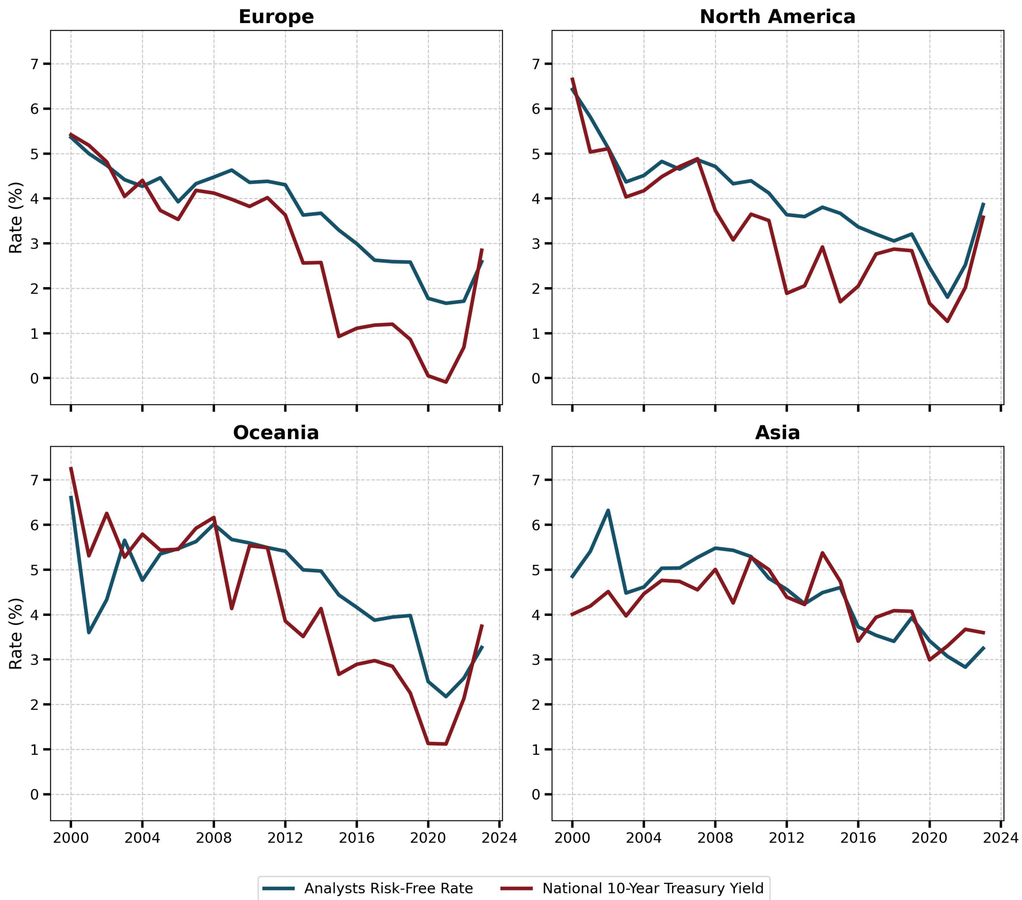


Figure A7: Risk-Free Rate Trends By Continents This figure plots analysts' risk-free rate trends across all six continents over the sample period, 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which we have a measure 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.

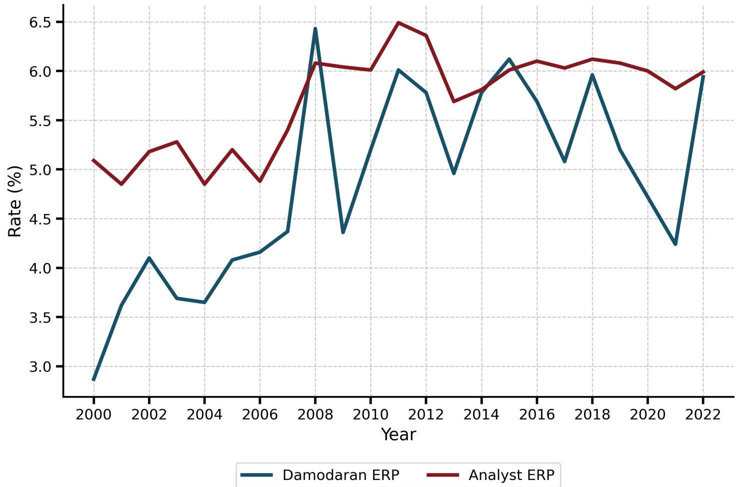


Figure A8: Analyst Equity Risk Premium Versus Benchmarks (US only) This figure compares the subjective equity risk premia trends with Aswath Damodaran public version for the US over the period 2000–2023 (Damodaran, 2023). The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The solid blue line represents analysts' Damodaran equity risk premia for the US, and the solid red line denotes the subjective equity risk premia.

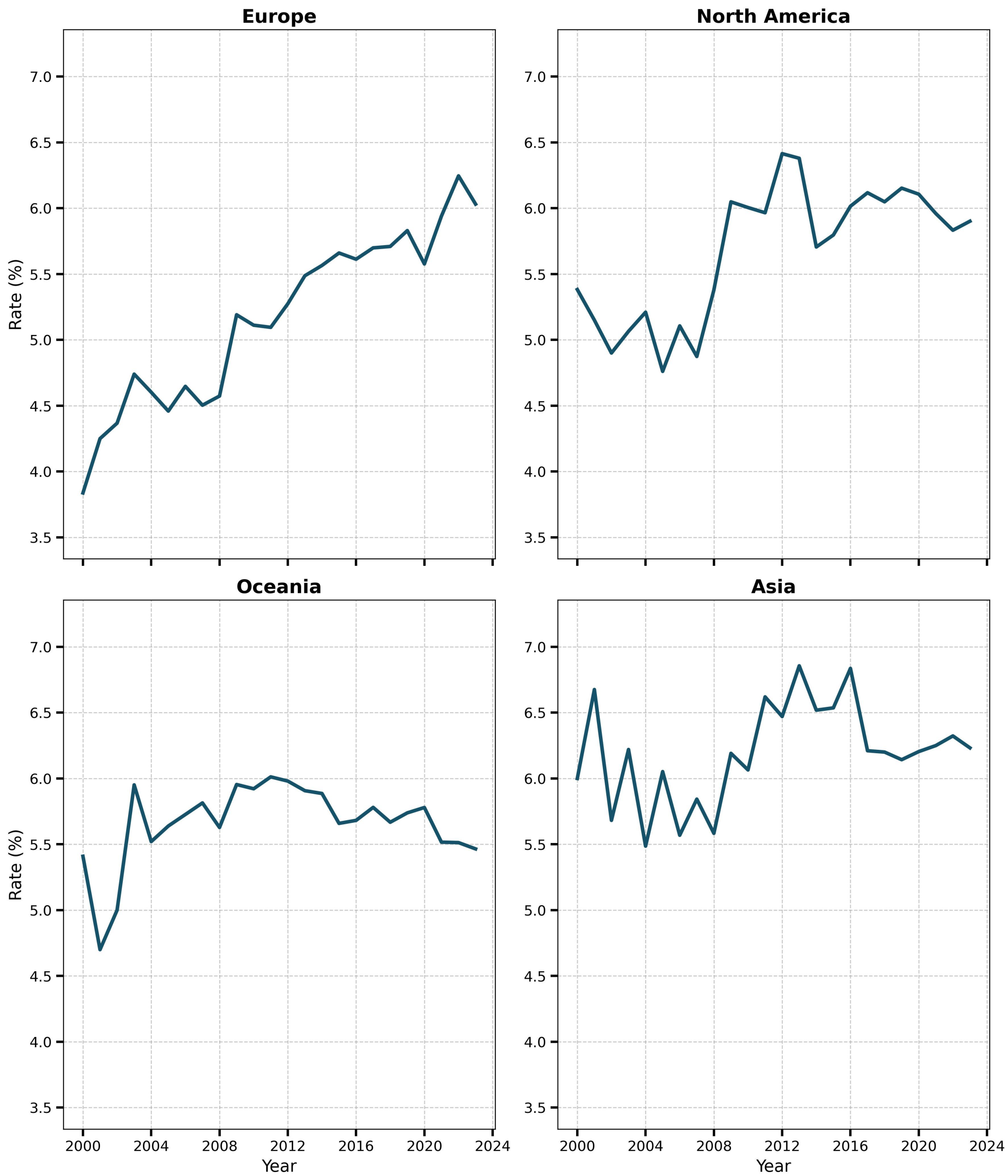


Figure A9: Equity Risk Premium By Continent This figure plots subjective equity risk premia trends for the four main continents in our sample for the period 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The solid blue line represents analysts' subjective equity risk premia trends.

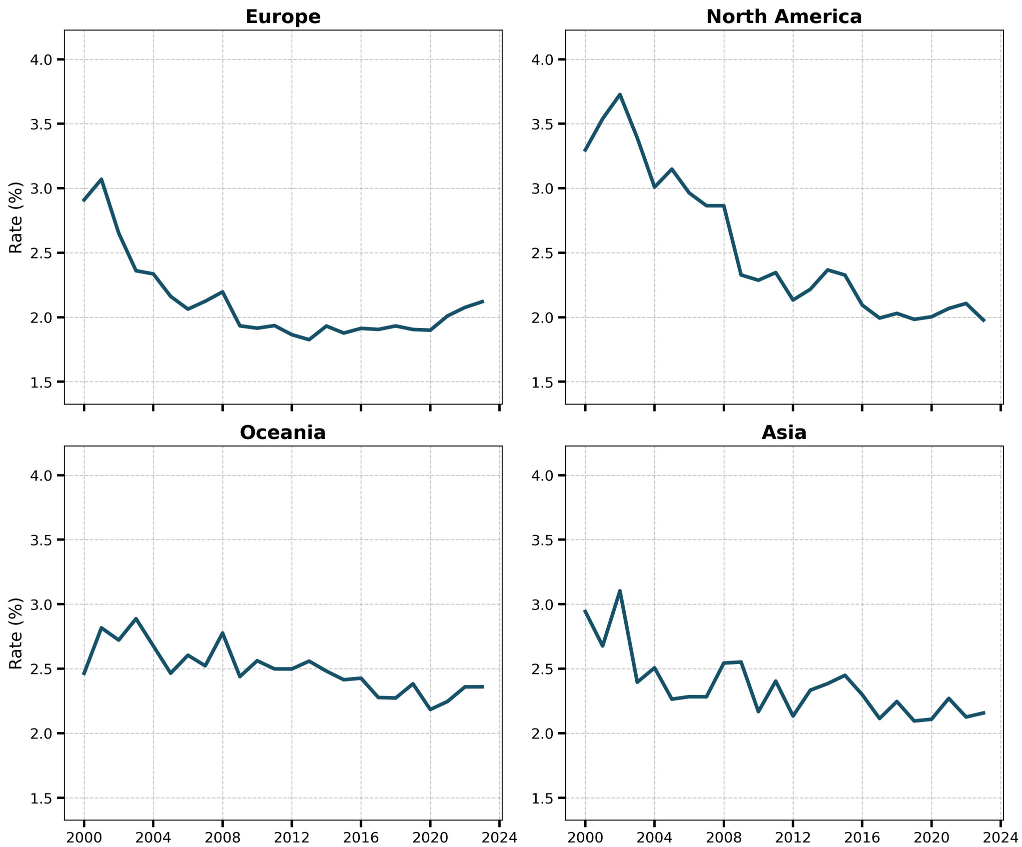


Figure A10: Terminal Growth Rate Trends By Continent This figure plots analysts' terminal growth rates trends across all six continents over the sample period, 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which we have a measure of terminal growth rate.

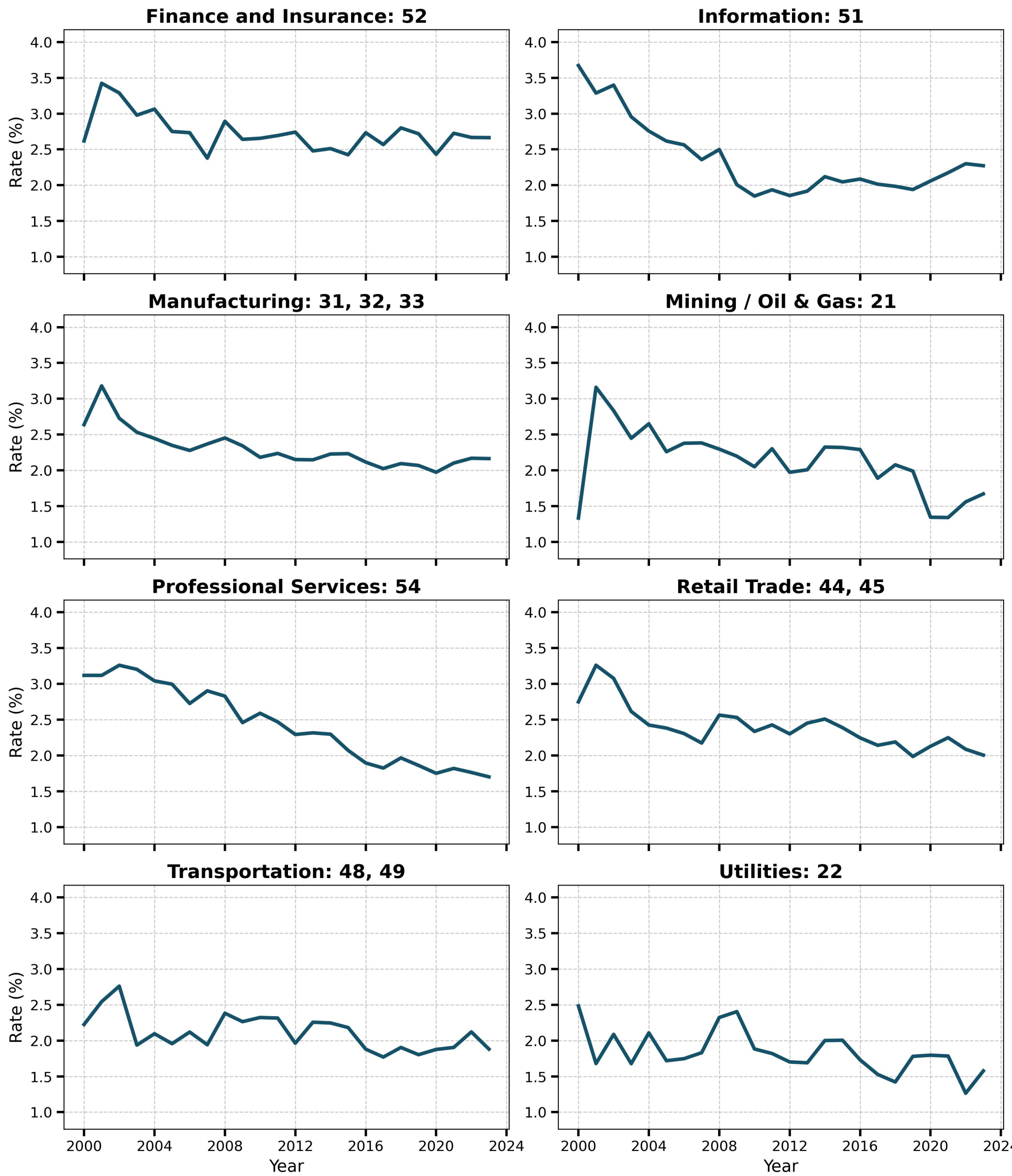


Figure A11: Terminal Growth Rate Trends By Industries This figure plots terminal growth rate trends for the eight largest industries in our sample for the period 2000–2023. The x-axis is expressed in years, and the y-axis denotes the rates measured in percentages. The sample includes all firms for which 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.

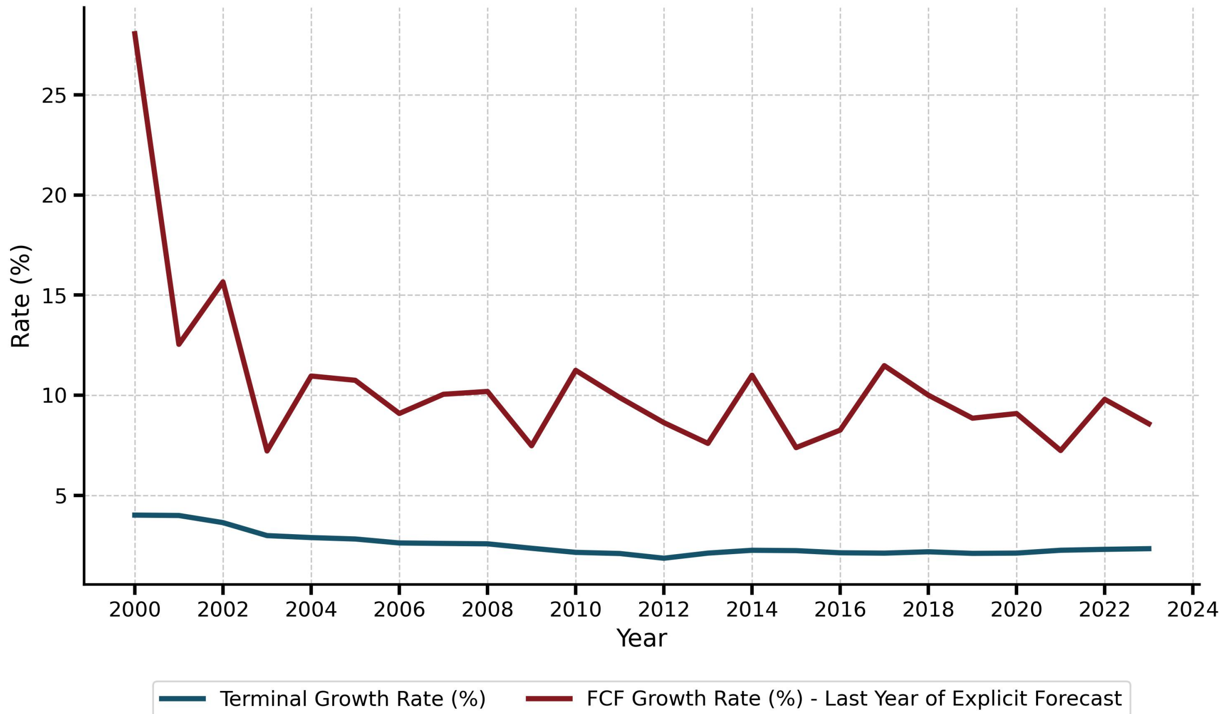


Figure A12: Last Year of Explicit Forecast Growth Rate Versus Terminal Growth Rate This figure compares the trends in the terminal growth rate and the growth rate measured for the last year of analysts' explicit forecast horizon trends for the period 2000–2023. The x-axis is expressed in years, and the 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: 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%
Panel B: 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%			

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$_{c,t}$ (%)		
	Europe	Oceania	Asia
	(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%