What Drives Very Long-Run Cash Flow Expectations?*

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February 28, 2024

Abstract

Expectations of firms' cash flows far into the future are central to corporate finance and asset pricing. Using a large, novel dataset on professional forecasters' *terminal growth rates (TGR)* of firms that includes information about forecaster identities, allowing us to gather detailed personal backgrounds of forecasters, we establish key facts and identify drivers of their (very) long-run cash flow expectations. First, TGR expectations contain distinct economic information relative to other forecasting series, such as IBES long-term growth (LTG) forecasts which capture shorter, 3-5-year forecast horizons. Second, TGR expectations strongly and robustly predict realized long-run firm growth. Third, consistent with firm life cycle models, TGR expectations decline with firm age. Fourth, with the exception of very mature firms where a firm's country and industry primarily account for the variation in TGRs, there exists large, persistent heterogeneity in TGR expectations across forecasters. Finally, compared to other settings, forecaster demographics and backgrounds explain a larger part of the persistent heterogeneity in TGR expectations.

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

Keywords: Long-term expectations, behavioral finance, valuation, professional forecasters, analyst identities and backgrounds, firm life cycle

*For their excellent research assistantship, we thank our research team: Eisa Alloughani, Sebastian Gortarez Ortiz, Tej Kulkarni, Aditeya Pattiwar, Andre Radic, Reed Simons, Cole Streitmatter, and Mingyang Zhang. Paul Décaire gratefully acknowledges financial support from the Center for Responsible Investing at Arizona State University.

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1 Introduction

Long-run expectations are central to investment decisions. They are associated with the largest share of expected revenues for research and development projects, and explain most of the variation in prices (Brunnermeier et al., 2021; Bordalo et al., 2023). Further, long-term variables account for more than 70% of valuation targets produced by financial professionals (Mukhlynina and Nyborg, 2018; Decaire and Graham, 2023).

Confirming the importance of longer-term expectations, a burgeoning and dynamic literature has made significant progress in documenting and explaining how investors and analysts determine their beliefs at horizons beyond 2 years—in particular, using analyst earnings growth forecasts formed over a horizon of 3-5 years[1]—, as well as in explaining discount rates.[2] At the same time, little to nothing is known about how investors form *very long-term expectations* beyond a few years and into the distant future. This paper makes a step towards closing this gap. Precisely, we use novel data on analysts' *terminal growth rate expectations* to investigate (i) the relation between these long-term expectations and realized firm growth rates, (ii) the evolution of firm characteristics in shaping these expectations throughout a firm's life cycle, and (iii) the role of individual characteristics, backgrounds, and experiences in explaining heterogeneity in long-term belief formation dynamics across analysts.

The existing gap in the literature stems from three main empirical challenges. First, no comprehensive datasets exist to date that contain measures of long-term growth rate expectations for individual firms. We use a new dataset on more than 40,000 terminal growth rates (TGR), i.e., data that uncovers the beliefs of professional forecasters about a firm's growth potential until *infinity*. The data, collected from analyst equity reports using a series of artificial intelligence document processing programs, pdf extraction functions, and optical character recognition (OCR), covers TGRs for approximately 8,000 firms located in

[1] Notable work includes Nagel and Xu (2022), De la O and Myers (2023), and Bordalo et al. (2023), who study equity analysts' 3-5-year earnings growth expectations using the Institutional Brokers' Estimate System (IBES) LTG data.

[2] A rich literature investigates how managers and market participants determine their discount rates (Graham and Harvey, 2001; Krüger et al., 2015; Gormsen and Huber, 2022; Decaire, 2023; Decaire et al., 2023).

49 countries between 2000 and 2023.[3] Importantly, TGR expectations are systematically different from the focal variable of prior literature, the IBES LTG measure of analysts' 3-5-year earnings growth forecasts. The average difference in TGR and LTG expectations is 10 percentage points (pp), as first shown in Decaire and Graham (2023). Morever, as we document, the correlation between both expectation series is noticeably weak ($\rho = 0.08$). The considerable disconnect between both series indicates important differences in their information content, and a limited capacity of the 3-5-year LTG forecasts in capturing truly long-run beliefs of financial market participants.

Second, to gain a comprehensive understanding of investors' (long-run) expectations, it is crucial to illuminate and uncover the determinants of the heterogeneity in beliefs prevalent across forecasters. Existing datasets on firm growth forecasts such as IBES lack any personally identifiable information about forecasters, such as their name, real-time location, age, gender, race, and education. Consequently, it is impossible to link the variation in forecasts across analysts to underlying forecaster characteristics and experiences.[4] In our dataset of TGR forecasts, we directly observe various pieces of identifiable information, including the full name of each forecaster and the name of forecaster's employer. Equipped with this information, we merge our dataset with the universe of individuals included on LinkedIn.[5] This allows us to obtain detailed data on forecaster backgrounds, such as employment history and educational background. This information, in turn, allows us to infer additional individual characteristics of interest, such as forecaster age, location of formative years, place of residence during formative years (high school and college), gender, and race. In total, we collect detailed personal information for 1,667 individuals located in 44 countries.

Third, the ideal dataset to make progress on understanding long-run expectations not only includes personally identifiable information on analysts but also rich cross-sectional variation in terms of covered firms, industries, and countries. Approximating this ideal dataset, we track analysts over several years, and most analysts in our data evaluate multiple, heterogeneous firms in any given year from different countries (e.g., US, UK, China, Australia,

[3] We present a detailed description of the construction of this new dataset in Section 3.

[4] For example, Bouchaud et al. (2019) are able to investigate variation in forecast stickiness across analysts as a function of the number of years an analyst is included on IBES or has provided forecasts for a specific firm or industry, but they are unable to link the variation to any personal characteristics of analysts.

[5] The LinkedIn data, containing more than 750 million unique individuals, is obtained from Revelio Labs.

Germany). The richness of the data also facilitates the quantification of the explanatory power of individuals' observable characteristics and environment. We simultaneously observe how forecasters evaluate domestic and foreign firms, and a subset of forecasters in our data switch employers, allowing us to tease apart individual and firm effects (Abowd et al., 1999).

We organize our analysis and findings into two main parts. In the first part of the paper, we establish that TGR expectations, beyond exhibiting systematic differences from IBES LTG expectations, contain substantial real economic information. Crucially, TGR expectations robustly forecast firms' realized long-run growth. We uncover an economically and statistically significant positive relation between analysts' TGR forecasts and actually realized firm growth over various horizons, with the estimated regression slope ranging between 0.5 and 1 depending on the examined horizon of realized firm growth.

In the cross-sectional average over time, average TGR expectations predict a significant share of future realized average firm growth (R^2 ranging between 0.34 and 0.60). Moreover, the correlation between analysts' TGR forecasts and the subjective discount rates they apply in the *same* reports is close to zero (Decaire and Graham, 2023), implying that long-term growth expectations contain independent information that is useful in forecasting realized firm growth.

We also find that forecasters' long-term TGR stock growth expectations are systematically below historically realized long-term growth rates in every year of our sample. This adds to the differences between the TGR expectation series in our analysis and LTG expectations studied in prior work, as the latter are systematically above historical growth rates (Nagel and Xu, 2022; Bordalo et al., 2023). One likely reason for the differing patterns is survivorship bias affecting historical growth series, especially over longer horizons, as also discussed in Decaire and Graham (2023).[6] We complement and refine this intuition by showing that analysts revise long-term expectations downward when a firm's long-term default risk increases.

In the second part of the paper, we investigate the dominant drivers of professional forecasters' long-term growth expectations. We first perform a variance decomposition using

[6] Close to 1 in 4 of public firms eventually go bankrupt, with an average lifespan of 9.4 years at bankruptcy. This statistic is taken from the universe of North America Compustat firms over the period 1950–2023/08. In this calculation, we include 3 types of Compustat firms: (i) bankrupted (02), (ii) liquidated (03), (iii) active, and exclude all other firms based on their mnemonic code DLRSN.

three fundamental sets of fixed effects (FE): (i) firm FEs (i.e., FEs for each firm for which forecasts are made), (ii) individual FEs (i.e, FEs for each forecasting analyst), and (iii) brokerage house FEs (i.e., FEs for each analyst employer). Jointly, these fixed effects explain more than 65% of the variation in long-term growth expectations in our data. Perhaps surprisingly, the brokerage house fixed effects make only a negligible contribution to the explained variation (approximately 2%), implying that organizational norms and protocols play a limited role in determining analyst expectations. By contrast, both firm fixed effects and analysts fixed effects contribute substantially to the explained variation. The significance of individual analyst fixed effects, after partialling out brokerage house effects, implies persistent heterogeneity in TGR expectations across forecasters. This finding is consistent with prior work documenting persistent individual heterogeneity in macro-finance beliefs of retail investors (Giglio et al., 2021).

Guided by these TGR variance decomposition results, we investigate further the factors influencing the persistent heterogeneity in long-run expectations across firms and forecasters, examining both firm-specific attributes and individual forecaster characteristics. With respect to firm characteristics, the explanatory power and importance of the firm fixed effect varies significantly over the firm's life cycle. It is particularly important in younger firms and gradually declines with firm age. As firms mature, firm country and industry factors increasingly account for a larger share of TGR expectations, reaching 60% and more for firms aged 70 years and older. This finding relates to Decaire (2023) showing that analysts systematically consider macroeconomic variables—GDP growth—when determining TGR forecasts, with macro-variable series explaining 92% of TGR expectations when averaged at the country-year level. Furthermore, we show that the within-firm, within-year dispersion in analyst TGR expectations declines close to monotonically in firm age, consistent with the existence of a firm life cycle component in influencing analysts' expectation formation.

We then turn our focus to forecaster characteristics and their ability to explain the large, persistent heterogeneity in TGR expectations across analysts. We formally estimate analyst fixed effects using a mover design (AKM method, Abowd et al. (1999); see Card et al. (2018) for a recent review of the labor literature using the AKM method), exploiting analysts who switch brokerage houses in the sample, and then regress the estimated fixed effects on forecaster observables. Forecaster demographics can explain as much as 20-30% of the variation in analyst fixed effects, which is substantial in comparison to prior work. For example, Giglio et al. (2021), like us, estimate individual fixed effects in macro-finance beliefs, in their surveys of retail investors, and find that respondent characteristics can only explain 3-10% of the individual fixed effects. One likely reason for our increased ability to explain forecaster expectation heterogeneity is the larger dissimilarity in forecaster characteristics and backgrounds in our sample, e.g., encompassing analysts from many different countries, compared to the more homogeneous Giglio et al. (2021) sample on observables, comprising wealthy, U.S. retail investors from Vanguard only.[7] Significant factors that contribute to the explained variation in our setting include the age (birth year) of forecasters, their race, and, indeed, their geographic location (country).

Finally, beyond investigating the persistent heterogeneity in TGR forecasts, we examine whether and how professional forecasters extrapolate from personally and locally experienced economic conditions, building on prior evidence documenting local extrapolation by, e.g., households in the U.S. housing market (Kuchler and Zafar, 2019). This analysis in particular exploits the richness of our dataset in terms of the variation in the location (country) of analysts forecasting the *same* firm. We find strong evidence of local extrapolation. Recent GDP growth in an analyst's country of residence strongly predicts their TGR expectations for firms located in *other* countries, controlling for GDP growth of the firm's country. This pattern is unlikely to be explained by common shocks to a cluster of neighboring countries affecting expectations, or special linkages between the analyst country and the firm country as the granular nature of our data allows us to include firm-country*analyst-country fixed effects. Instead, our evidence is consistent with cross-country extrapolation, as it is fully driven by observations where analyst countries are located at a considerable geographical distance from firm countries.

Overall, we present, to the best of our knowledge, the first analysis of the origins of

[7] Other prior work that uncovers robust statistical associations between demographics and expectations commonly finds relatively low explanatory power of demographics for the variation in expectations as well (e.g., Malmendier and Nagel, 2011; Bailey et al., 2019; Ben-David et al., 2018; Kuchler and Zafar, 2019; Das et al., 2020; D'Acunto et al., 2023). These papers also examine samples that compared to ours are more homogeneous along important dimensions, such as focusing on households from a single country (e.g., the U.S. or one of the Scandinavian countries).

professional forecasters' (very) long-run cash flow expectations, using a novel, international dataset on analyst terminal growth rate expectations in which we, crucially, observe forecaster identities and backgrounds. Our unique setting allows us to tease apart firm, industry, country, and individual-specific factors in shaping analysts' expectation formation and the heterogeneity therein.

Broadly speaking, we contribute to the literature on the macro-finance belief formation process of investors and financial market participants (e.g., Giglio et al., 2021), as well as the literature on the effect of personal characteristics, experiences, and extrapolation on beliefs and economic outlooks (e.g., Malmendier and Nagel, 2011, 2016; Kuchler and Zafar, 2019; cf. also the further literature referenced in footnote 7). By focusing on individual analysts' beliefs and backgrounds, we also add to the literature in behavioral corporate finance and in particular the less-developed strand that focuses on the behavior of "third parties," i.e., non-investors and non-managers (cf. Malmendier (2018) and Guenzel and Malmendier (2020) for recent surveys of the field of behavioral corporate finance). Furthermore, we advance the literature that studies investor and analyst expectations beyond very short horizons, yet typically examines LTG expectations from IBES, i.e., medium-term forecasting horizons (Nagel and Xu, 2022; De la O and Myers, 2023; Bordalo et al., 2023). Finally, we contribute to an emerging literature that studies the valuation practices of professional forecasters using directly observable valuation inputs (Decaire, 2023; Decaire and Graham, 2023; Decaire et al., 2023).

The remainder of the paper proceeds as follows. Section 2 introduces the institutional background. Section 3 introduces the methodology and data. Sections 4 and 5 discuss our results. Section 6 concludes.

2 Institutional Details

We collect our data on (very) long-run cash flow expectations from equity reports that professional analysts publish (i.e., the original documents). Hence, it is useful to first provide background on the analytical practices in the equity research industry. Among the methods used to perform valuation, financial textbooks (Berk and DeMarzo, 2019; Brealey et al., 2022), and business school curricula emphasize discounted cash flow models (DCF) and valuation multiples methods. Echoing these recommendations, these two approaches are the most common tools used by financial professionals (Graham and Harvey, 2001; Mukhlynina and Nyborg, 2018) to perform valuation, with one or both strategies being included in close to 100% of equity reports housed by the data provider, Refinitiv. Decaire and Graham (2023) also shows that the use of DCF models in equity reports has steadily increased over the past 20 years, accounting for approximately 40% of all reports including DCF analysis over the past 15 years. Although the strategies share similarities, our data collection focuses on reports produced with DCFs for two institutional reasons.

First, in contrast to valuation multiples that only disclose a single metric—the multiple—DCFs require analysts to report detailed modeling assumptions, allowing us to clearly distinguish the terminal growth rate used by analysts from the other parameters of the valuation model. Appendix Figure B.1 presents an example of a complete DCF model from an equity report.[8] This richness of the data guarantees that we never have to estimate or approximate any of the terminal growth rates. Precisely, our analysis is conducted entirely with data directly observed in the analyst reports.

Second, many past studies using analyst data have relied on commercial databases, such as IBES or Value Line, which collect and provide mainly short- and medium-term expectations. As we also discuss in detail in Section 4.1, the long-term growth estimates reported in these databases (e.g., LTG) do not reflect truly long-term expectations provided by analysts. LTG from IBES and Value line reflect forecasts made for a three- to five-year horizon, while our data capture analysts' *very* long-term expectations. The data limitations present in existing datasets have forced researchers to rely on potentially inexact proxies when determining terminal growth rates in their analysis. For example, Figure 2, which we discuss in more detail in Section 4.1, shows that the annual LTG from IBES averages 13.03%, with the interquartile range taking values between 5.50% and 17.0%, an order of magnitude larger compared to the average terminal growth rate in the equity reports of 2.2%, and an interquartile range between 1.5% and 3.0%. Consequently, if researchers directly relied on the annualized LTGs from IBES as a proxy for the long run, they would systematically overstate long-term growth

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

rate expectations.

We note that analysts disclose DCF modeling details in their equity reports on a voluntary basis. Studies have found that the extent of information disclosure of the DCF model assumptions is positively associated with report accuracy (Asquith et al., 2005; Hashim and Strong, 2018), and more detailed information disclosure leads to larger market reactions following changes in recommendations (Huang et al., 2023). By detailing their valuation thesis, informed analysts have the opportunity to differentiate their work from their uninformed rivals, gaining credibility in the process. In total, this suggests that our data differs advantageously from datasets that unconditionally collect earnings forecasts, as our data is likely to be sampled from a more informed subset of analysts.

3 Methodology and Data

3.1 TGR Forecasts from Analyst Equity Reports

We initially downloaded 157,549 equity reports with mentions of DCF from 55 major equity research firms. We restricted the time window to reports published in the first months of the calendar year (January 1^{st} to April 1^{st}) from 2000 to 2023, to ensure that our data items were systematically measured at a similar time point during the year. In cases where analysts published more than one report on the same firm during those months, we systematically kept the earliest publication of that calendar year to avoid duplicates for a given analyst-firm-year pair. This procedure resulted in 41,429 reports that contained the terminal growth rate numerical estimate, and—crucially for our goal of examining driver of the heterogeneity in long-run expectations across analysts—for which we could unambiguously identify the *analyst name* and *location* at the time of the report, the latter by using their landline country indicators.

We collected the terminal growth rate included in each of these reports in four steps. First, we pre-processed each document using a series of Python programs, such as pdf extraction functions and optical character recognition (OCR) packages, to identify all sections of text, tables, and figures containing the relevant information of interest for our purposes. Second, we converted these different elements into short text snippets. Third, for each variable collected, we used artificial intelligence, Open AI API, to extract the numerical value from these snippets. We conducted steps one to three on the Arizona State University High Performance Computing servers *Sol*, as these steps are computationally intensive and require a large number of processing nodes combined with significant storage capacity. Fourth, we exported to Excel the text snippets and the numerical values extracted by artificial intelligence, and manually verified the validity of each extracted value with the help of our research team. This last step of the data collection process is crucial for ensuring the integrity and high quality of the dataset. While artificial intelligence has been shown to be an efficient tool for text extraction Gilardi et al. (2023), and processes complex sentences with a high success rate, one may remain worried about error rates being above acceptable levels when left unsupervised.

3.2 Firms and Coverage

The 41,429 equity reports from 41 of the largest brokerage houses operating throughout the world cover 8,010 firms located in 49 countries from analysts located in 44 countries during the 2000-2023 period (cf. the summary statistics in Table 1, which we discuss in more detail in Section 3.4). The average forecasted firm owns assets with a book value of \$15.8 billion USD and has an investment rate of 5.55%. These magnitudes are comparable to the IBES universe, where the average firm has assets with a book value of \$15.2 billion USD, and an investment rate of 5.3%. Overall, this suggests that the firms in our sample are of comparable size and invest with similar intensity as those included in other broadly distributed commercial analyst datasets.

The average firm is included in the sample for 7.9 years, and it is followed by 7.2 analysts producing DCF reports. In terms of geographic coverage, 39% of firms have their headquarters located in Europe, 27% in North America (24% in the US), 19% in Asia, 12% in Oceania, 2% in South America, and 1% in Africa.

37% of the reports are produced by analysts based in Europe, 30% in North America (27% from the US), 18% in Asia, 12% in Oceania, 2% in South America, and 1% in Africa.

Our sample includes two dozen NAICS industry sectors (2-digit), with the eight largest broad sectors accounting for 84% of the total coverage: 35% for manufacturing (NAICS 31-32-33), 19% for information (NAICS 51), 8% for professional services (NAICS 54), 7% for retail trades (NAICS 44-45), 4% for mining and oil & gas (NAICS 12), 4% for transportation (NAICS 48-49), 5% for utilities (NAICS 22), and 4% for finance and insurance (NAICS 52).

Overall, these statistics suggest that our sample is comprehensive, representative, and comparable to its commercial counterparts.

3.3 Analyst Backgrounds from Universe of LinkedIn Data

We merge this unique dataset described in Section 3.1, containing identifiable information on forecasting analysts, with the universe of LinkedIn users obtained from Revelio Labs, which allows us to obtain additional (self-reported) personal characteristics on forecasters, including their educational background and (approximate) age.

In linking the datasets, we require the names across individuals in the TGR and LinkedIn datasets to match precisely. To further err on the side of caution in constructing the matched dataset, we also require the LinkedIn-provided employment history to match the analyst's employer in the equity reports,[9] as well as the name-employer matching to result in a unique LinkedIn user that is matched to the data.[10] This procedure leads to 1,667 uniquely matched analysts across the TGR and LinkedIn datasets (Panel A of Table 1) out of the 5,300 equity analysts included in our sample (31%).

3.4 Summary Statistics

Table 1 presents detailed summary statistics. As alluded to above, our dataset contains more than 40,000 TGR forecasts by over 5,300 analysts that make forecasts for approximately 8,000 unique firms (Panel A).

In Panel B, the average TGR forecast in the data is 2.2%, which is an order of magnitude smaller than the average IBES-based LTG expectation for the sample firms of 13.0%. (We will discuss the differences between TGR and LTG expectations further in Section 4.1.) Figure 1 plots the average TGR across firms and analysts over time, showing that average long-run expectations have somewhat declined over time, from around 2.8% at the beginning of the

[9] We account for various commonly used employer names (e.g., Bank of America or BofA) as well as accented characters (e.g., Societe Generale or Société Générale).

[10] That is, we drop "matches" of multiple LinkedIn users with the same name and who list the same employer in their LinkedIn biography.

sample in 2000 to closer to 2.0% towards the end of the sample. Also in Panel B, about 1 in 3 equity reports and TGR forecasts come from foreign analysts, i.e., analysts who forecast the long-run growth of a firm headquartered in a different country.

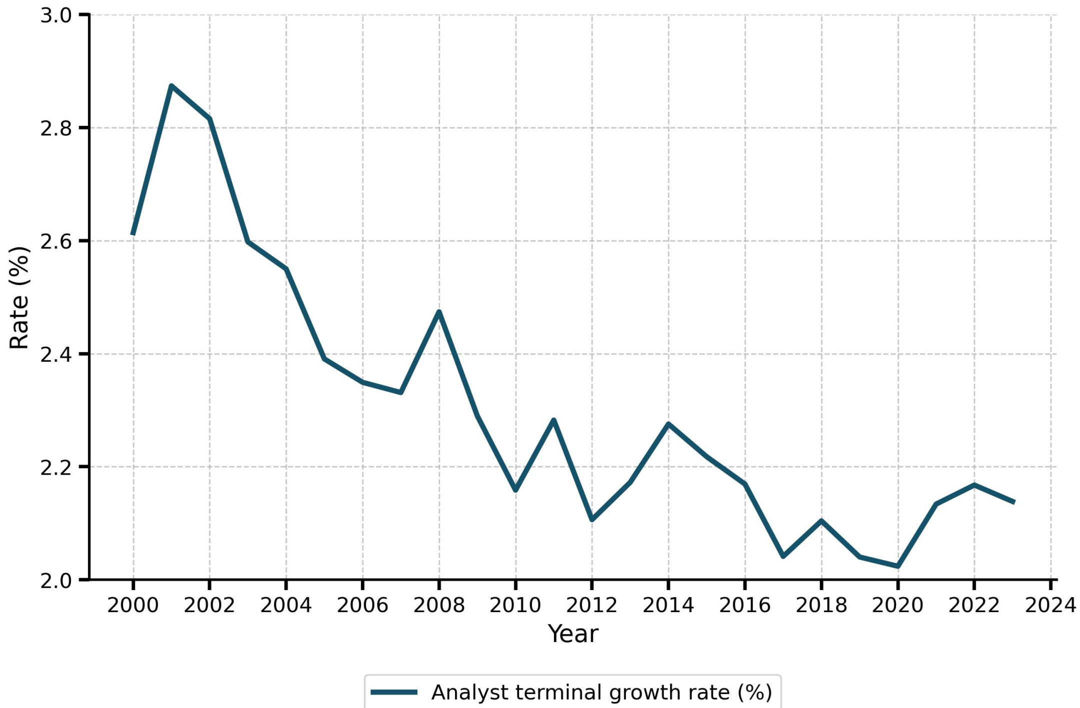

Figure 1: Average TGR expectations over time This figure plots the time trend of average terminal growth rates across analysts and firms over the sample period from 2000 to 2023.

Panel C contains demographic and other information about the sample analysts. Just under 20% of analysts are female. The vast majority of analysts are Caucasian (75%) as per the Revelio-based race prediction algorithm. The next largest group is Asian analysts (18%). 44% of analysts have a graduate degree (Master's and/or MBA). There is considerable variation in analyst age and birth years, with the 25th-percentile analyst born in the early 1970s and the 75th-percentile analyst born in the mid-1980s.

In terms of other analyst-related statistics, the average analyst in the sample contributes 8 reports and TGR forecasts. There are about 120 analysts on average who make forecasts for firms located in a given country, and 140 analysts per brokerage house.

Panels D and E present descriptive statistics on economic series for the countries in which forecasted firms and analysts (conditioning on foreign-based analysts) are located. There is meaningful variation in economic conditions of both firm and analyst countries. For example, the interquartile range (IQR) in firm-country real GDP and inflation is 2.2pp and 1.9pp, respectively. Similarly, the IQR in analyst-country GDP and inflation is 1.7pp and 1.4pp, respectively.

4 Economic Information Contained in TGR Expectations

This section establishes the economic importance of analysts' long-term cash flow expectations, in three steps. First, we show that terminal growth rate expectations contain distinct economic information relative to other expectation series used in prior work. In particular, we show that terminal growth rates shares limited overlap with the existing long-term expectation benchmark used in the literature, IBES LTG—a measure that captures analysts' expectations over a 3-5-year horizon. Second, we show that terminal growth rate expectations predict ex-post realized long-term firm earnings growth, known in hindsight. Finally, terminal growth expectations respond to increases in firms' default risk.

4.1 TGR Versus IBES LTG Expectations

We start this section by examining the relation between terminal growth rates and the IBES LTG variable, and establish that both variables share limited similarities. Panel B of Table 1 reports that the correlation between the two series is weak ($\rho = 0.08$). Contrasting the time trends in both variables, we find that the terminal growth rate yearly average has steadily declined over the sample period (Figure 1), whereas the average level of IBES LTG has remained constant. Further, comparing the levels of both series (Panel A of Figure 2), we observe a systematic and persistent gap between the two series, averaging 10.0 pp throughout the sample period, and showing that terminal growth rate estimates are substantially smaller than IBES LTG. Lastly, Panel B of Figure 2 shows a scatter plot representing the relation between IBES LTG and terminal growth rates. Consistent with the weak correlation presented in Panel B of Table 1, it is difficult to visually discern a clear relation between both variables, given their considerable degree of dispersion. The figure also clearly shows that IBES LTG exhibits substantially more volatility than the terminal growth rate. Table 1 confirms the visual inspection of the scatter plot and shows that the standard deviation of IBES LTG

(22.5 pp) is 17 times greater than that of the terminal growth rate (1.29 pp).

Adding to the differences between the TGR and LTG expectation series, in Appendix Figure B.2, we also find that forecasters' long-term TGR stock growth expectations are systematically below historically realized long-term growth rates in every year of our sample, whereas LTG expectations studied in prior work are systematically above historical growth rates (Nagel and Xu, 2022; Bordalo et al., 2023).

These differing patterns are likely explained, at least in part, with survivorship bias affecting realized growth series, especially over longer horizons, as also discussed in Decaire and Graham (2023). We further examine how TGR expectations respond to firms' default risk in Section 4.3.

Altogether, the evidence in this section establishes that TGR expectations are systematically different from other expectation series that target growth beyond the two-year horizon, such as the IBES LTG series. This implies that our understanding of how professional forecasters form long-term expectations about firms' growth potential has yet to be fully explored. Combined with the fact that Decaire (2023) finds that terminal growth rates are important determinants of expected price variations, the next parts of the paper aim at deepening our knowledge about how professional forecasters determine their *very* long-term expectations.

4.2 Predictive Power of TGR Expectations for Realized Growth Rates

In a first step to understand the properties of the terminal growth rate and to further validate this measure of analyst expectations, we study whether the terminal growth rate is a good predictor of firms' future long-term growth.

To design this test, we first reiterate that terminal growth rates are inputs from analysts' DCF models.[11] Decaire and Graham (2023) shows that the modal DCF model sets the explicit forecast horizon to be equal to three years and then applies a constant terminal growth rate to any subsequent cash flows. We note that this horizon has also been used in other contemporaneous studies (e.g., Hommel et al., 2023) that encounters methodological

[11] Decaire and Graham (2023) shows that DCF models are among the most common tools used by equity analysts when determining valuations, in tandem with valuation multiples (cf. also our discussion in Section 2).

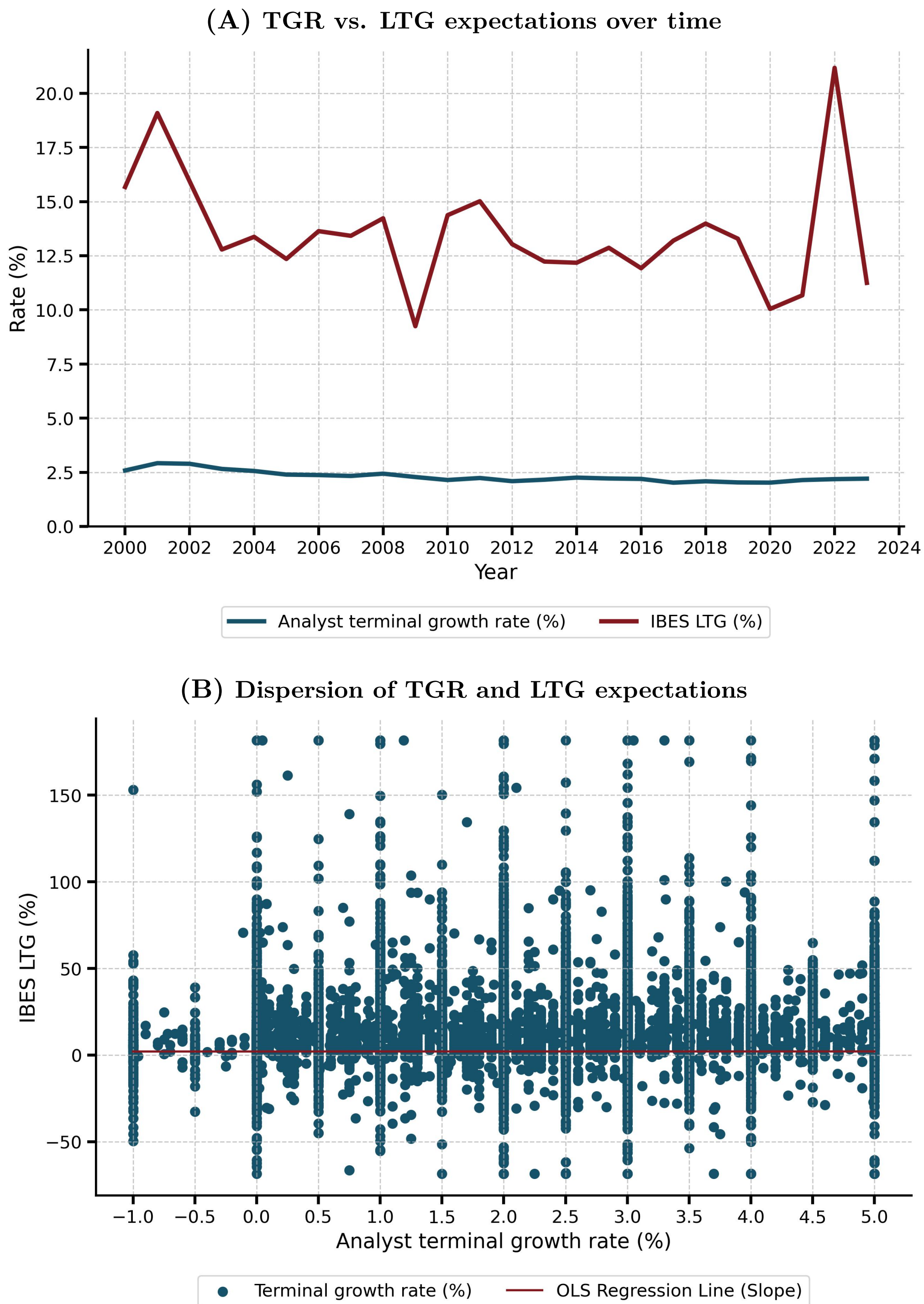

Figure 2: TGR versus IBES LTG expectations For Panel A, the x-axis is expressed in years, and the y-axis in percentage points. Panel A compares the time trend of IBES LTG expectations with analysts' terminal growth rates over the sample period. Panel B's x-axis represents analysts' terminal growth rates, and the y-axis corresponds to the firm-year LTG consensus (median) provided by IBES. Each blue dot denotes an observation. The red line is the slope from an OLS regression between IBES LTG and terminal growth rates. For illustration purposes and readability, we winsorize the LTG variable at the 0.1 and 99.9^{th} percentiles.

aspects similar to ours. Using this intuition, in our main specification, our goal is to capture growth expectations from period $t+4$ and onward, when the modal analyst starts applying the terminal growth rate in the DCF model.

Our main measure of realized growth is then the geometric average of the ex-post realized earnings growth from year $t+4$ to $t+8$, measured for each firm in our sample. Comparing the terminal growth rate with this ex-post measure of realized growth in Figure 3, we find that both series strongly comove together, but note differences in their respective levels (i.e., terminal growth rate $-$ ex-post realized growth $= -3.2$ pp). The fact that both series share a similar trend is reassuring, but the difference in levels calls for additional tests that we conduct at the end of this section.

To formalize the broad findings of a significant comovement in TGR expectations and realized firm growth rates from Figure 3, we run a linear regression where we consider three possible alternative ways to measure the ex-post realized growth. Specifically, we measure the average geometric earnings growth for each firm in our sample over the periods $t+1$ to $t+5$, $t+4$ to $t+8$, and $t+4$ to $t+13$. The last windows expand the horizon over which we measure realized growth, to account for a 10-year period. Panel A of Table 2 presents the results of this test. Focusing on our preferred specification, $t+4$ to $t+8$ in Column 2, we find that a one percentage point increase in the terminal growth rate is associated with a 0.70 percentage points increase in the ex-post realized growth. Further, focusing on the annual average growth measures across firms in Panel B, we find that annual average terminal growth rates explain a significant share of ex-post realized growth ($R^2 = 0.44$).

4.3 TGR Expectations and Default Risk

We now investigate plausible factors that can help explain the gap between ex-post realized growth and the TGR measure of long-term expectations by focusing on the firm's probability of default.

Naturally, and as alluded to above, ex-post realized returns can only be measured for surviving firms, those that did not go bankrupt over the sample period. However, ex-ante, analysts are likely to account for the probability of default, especially when forming expectations at a very long horizon. For example, Decaire and Graham (2023) document that

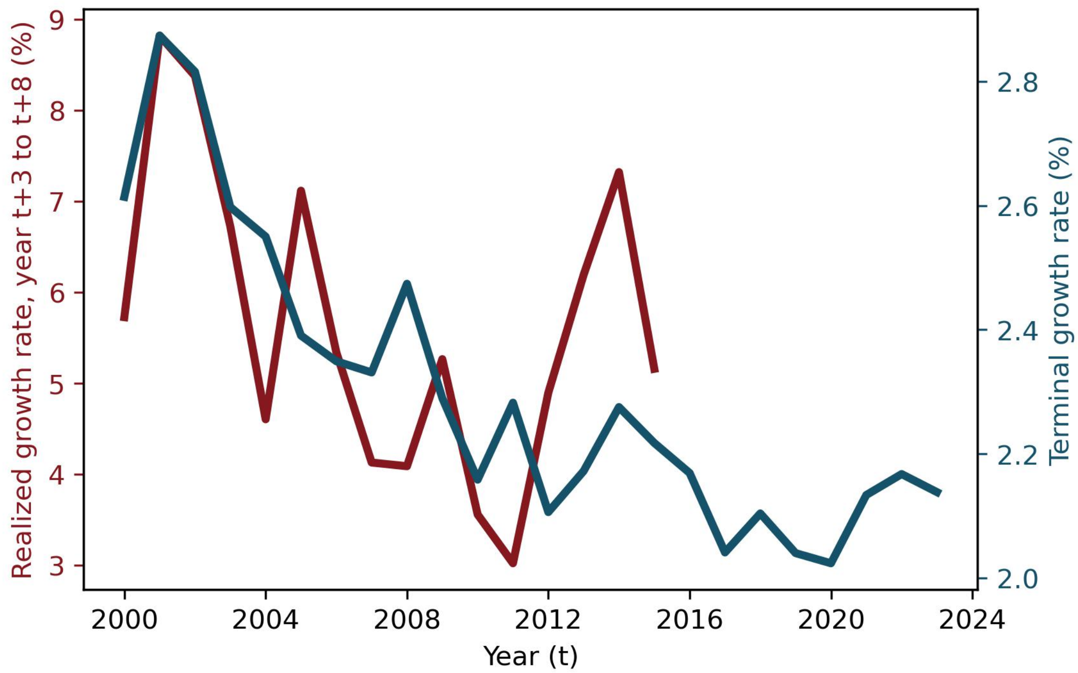

Figure 3: TGR expectations versus realized returns This figure compares the time trends of ex-post realized earnings growth at the $t+3$ to $t+8$ horizon with analyst terminal growth rates. Realized earnings growth corresponds to the geometric average realized from $t+3$ to $t+8$, averaged by year (t) in the sample. Terminal growth rate is the average terminal growth rate by year. The x-axis denotes years. The left-hand-side y-axis is associated with the ex-post realized returns, and the right-hand-side y-axis relates to the terminal growth rate.

going back to 1950, close to 1 in 4 firms included in Compustat North America went bankrupt or were liquidated. For those firms, bankruptcy occurred after 9.4 years of operation on average.[12] These large liquidation probabilities highlight the need to account for default risk when forming long-term expectations.

To formalize this intuition, we construct an ex-ante measure of firm probability of default following the naive Merton distance-to-default model discussed in Bharath and Shumway (2008) at two horizons, 10 and 20 years. Table 3 presents the results of this test. We include firm, country, and industry fixed effects in our specifications. This allows us to evaluate how different levels of default risk impact the terminal growth rate for firms operating in the same country and industry during the same year. We also include a firm age control, measured as the natural logarithm of the firm's post-IPO age, because our analysis below shows that

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

firm age is one of the main drivers of the terminal growth rate. Using this specification, we estimate a negative coefficient, indicating that analysts appear to apply a 0.21 pp discount, a 10% reduction compared to the sample average, to firms that have a probability of default above the sample median. Considering that, conditional on being in the *high* risk of default group (above the median), the average probability of default is equal to 5.8%, the 10% reduction in the terminal growth rate is commensurate.

Altogether, the negative association between default risk and analyst TGR expectations, even when holding firm age constant, helps explain the higher level of realized firm growth in Figure 3, and further indicates the information content of TGR expectations, as analysts actively revise their long-run forecasts in response to default risk variation.

5 Explaining Heterogeneity in TGR Expectations Across Firms and Analysts

Having established that terminal growth rates have different properties compared to other long-term variables studied in the existing literature, and that they contain information about the realization of firm earnings growth—making it a meaningful measure of expectations—we focus our efforts on understanding the key drivers of analysts' terminal growth rate choices and expectations. Specifically, we employ a variance decomposition of TGR beliefs, and link the (heterogeneity in) beliefs to a host of underlying firm as well as analyst characteristics.

5.1 Variance Decomposition

Table 4 decomposes the variation in TGR expectations across brokerage houses, analysts, and forecasted firms, using an ANOVA-based sequential variance decomposition. Panel A estimates the decomposition on the full sample (excluding singletons for which the fixed effect would fully explain the association variation). Panel B excludes firms with fewer than ten observations for robustness. In both panels, we include specifications with at least 10, 25, and 50 observations per forecaster, to address any potential concerns about overfitting.

We consistently find that the three sets of fixed effects explain a large portion, between 60% and 70%, of the variation in TGR expectations. that brokerage house fixed effects contribute only a very small share to the explained variation, whereas analyst fixed effects and firm fixed effects drive most of the explained variation. For example, in the largest sample in Column (1) of Panel A, brokerage house fixed effects contribute 2% of the explained variation, whereas analyst and firm fixed effects contribute 71% and 27%, respectively. Similarly, in the most narrow sample in Column (4) of Panel B, we estimate contributions of 15%, 52%, and 33%, respectively.

One limitation of the approach in Table 4 is that the ANOVA-based estimation is not indifferent to variations in the sequential inclusion order of the brokerage, analyst, and firm fixed effects. As an alternative approach, we estimate standard OLS regressions in which we include the various fixed effects one at a time, without any other control variables. In each case, we will estimate an *upper bound* for the amount of variation that can be explained by the inclusion of the given fixed effects. Intuitively, the included fixed effects may be correlated with other (omitted) variables that also affect TGR expectations (cf. the related discussion in Ayyagari et al., 2008). Using this approach, brokerage fixed effects alone can explain a very small share of only up to 1.4% of the total variation in TGR expectations. Analyst fixed effects alone can explain a much larger share of up to 49% of the TGR variation. Firm fixed effects alone can explain a similarly large share of up to 46% of the variation. Also noteworthy, brokerage and firm fixed effects jointly can explain up to 47% of the variation, whereas including in addition analyst fixed effects leads to an incremental R^2 of 0.20 (i.e., a total R^2 of 67%).[13] In other words, 20% is a *lower bound* for the variation in TGR expectations that can be explained directly by analyst fixed effects and indirectly by other variables (other than brokerage houses and firms) that analyst fixed effects predict.

Overall, the variance decomposition results highlight the importance of firm factors and individual forecasters in shaping professionals' long-run cash flow expectations. These findings motivate a deeper analysis of firm and analyst demographics and backgrounds for explaining the large and persistent heterogeneity in TGR expectations across firms and analysts.

[13] These estimates are for the largest sample corresponding to Column (1), Panel A of Table 4. Estimates for the other specifications and subsamples in Table 4 yield similar conclusions.

5.2 Firm Characteristics

It is well documented that as firms age and an entire industry becomes more mature, products become more standardized and opportunities for product innovation diminish (e.g., Klepper, 1996). Therefore, the most natural approach is to associate the heterogeneity in TGR expectations across firms with factors related to the firm life cycle.

We first relate TGR expectations to firm age in Figure 4, which shows that forecasters' TGR expectations monotonically decline with firm age. The average TGR in the sample is 2.5% for young firms aged 10 years and less, and declines to 0.5% for very old firms, reflecting diminishing growth opportunities with firm age. These magnitudes are obtained after controling for firm and year fixed effects. Columns (3) to (5) of Table 3 confirm that the decline in TGR expectations with increasing firm age is statistically significant.

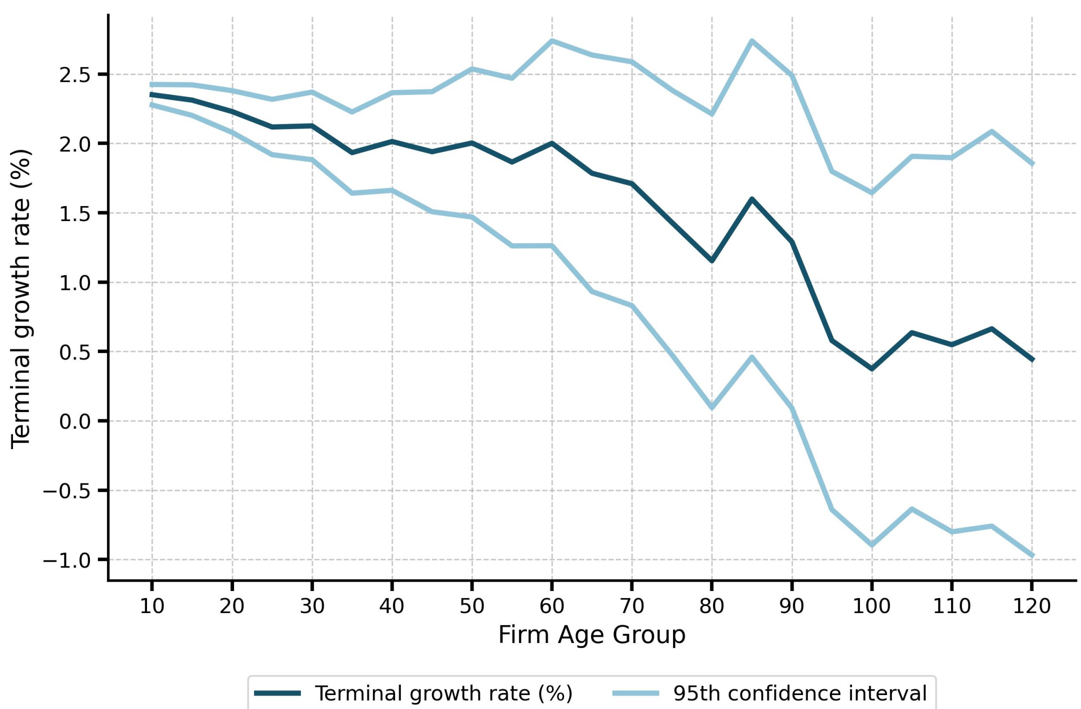

Figure 4: TGR expectations over firms' life cycle The figure plots analyst terminal growth rates over firms' life cycle. The solid blue line corresponds to Age group fixed effects obtained from the regression: $TGR_{i,j,t} = k + I_{\text{Age group}} + I_{\text{Firm}} + I_{\text{Year}} + \epsilon_{i,j,t}$, for which we add back the regression constant (k) to better illustrate the terminal growth rate level. The pale blue lines correspond to the $I_{\text{Age group}}$ regression estimate 95^{th} confidence interval, for which we add back the regression constant (k) for consistency with the other lines of the figure, and illustration purposes. The variable Firm Age Group captures firm age groups measured in 5-year increments. For example, Firm Age Group = 10 corresponds to firms that are 5 to 10 years old.

Motivated by this evidence, we then ask when the explanatory power and importance of firm fixed effects is most pronounced, and when it is weaker. Table 5 examines how the variation in TGR expectations that is explained by firm, industry, and firm-country fixed effects respectively, changes across the firm's life cycle. In the left column, we find that a firm's industry and country explain only a small portion of TGR expectations in young firms. These factors explain only 9% of the variation in very young firms aged 5 years or less. Even 20-25 years after a firm's IPO, industry and country explain only about 20% of TGR forecasts. In the right column, we find that in these young firms, firm fixed effects explain a large share of the variation in TGR expectations that is unaccounted for by industry and country factors, consistent with the evidence in Section 5.1. They account for up to 60% of unexplained variation in very recently IPOed firms, and up to about 50% for firms aged 20-25 years.

These patterns present for young firms reverse as firms mature. In old firms, the left column of Table 5 shows that a firm's industry and country can explain a much larger amount of the variation in TGR expectations, e.g., 50% for 60-year-old firms and up to 70% and more for 90+-year-old firms. Correspondingly, for mature firms, the incremental explanatory power of firm fixed effects over industry and country strongly diminishes, amounting to, e.g., only up to 14% and 1% for 60-year old and 90+-year-old firms, respectively.

As a bridging step between studying firm and analyst characteristics, we also examine how the within-firm-age dispersion of TGR expectations across analysts varies over the firm's life cycle. Dispersion in analyst TGR beliefs is largest in young firms, where the average absolute dispersion in TGR expectations in the sample is about 1 pp (Table 6). The TGR belief dispersion across forecasters declines as firms mature, shrinking by 34% for the most mature firms relative to the youngest firms. These patterns are consistent with analysts exhibiting greater variation in their access to or processing of information related to firm factors than in industry and country factors that impact their long-term expectations.

Overall, the evidence in this section indicates that the explanatory power of firm fixed effects documented in Section 5.1 is particularly pronounced in younger firms and gradually declines with firm age. As firms mature, firm country and industry factors increasingly account for a larger share of TGR expectations.

5.3 Analysts' Personal Characteristics and Backgrounds

Having established the importance of analyst fixed effects in Section 5.1, we next ask to what extent analyst observables can explain the persistent analyst heterogeneity, making use of the fact that in our data we observe forecaster identities which we match to their LinkedIn profiles.

Table 7 performs a sequential ANOVA decomposition of estimates of individual analyst fixed effects, which we obtain using a mover design—i.e., analysts moving brokerage houses in our sample, allowing us to separate analyst and employer fixed effects—following the literature in labor economics (Abowd et al., 1999). Jointly, analyst demographics can explain about 30% of the variation in analyst fixed effects, which is a larger amount relative to prior studies on retail investors (cf. Giglio et al., 2021) and households (cf. Malmendier and Nagel, 2011; Bailey et al., 2019; Ben-David et al., 2018; Kuchler and Zafar, 2019; Das et al., 2020; D'Acunto et al., 2023)), which typically finds that demographics can explain 10% or even much less of the belief variation.

A plausible explanation for our greater capability to explain heterogeneity in forecaster expectations is the greater diversity in forecaster characteristics and backgrounds within our sample. This sample includes analysts from various countries, in contrast to the more homogeneous samples in prior work that typically includes individuals from a single country, who oftentimes share additional commonalities (e.g., being affluent U.S. retail investors affiliated with Vanguard in the case of Giglio et al., 2021).

Demographic factors that stand out in Table 7 as being particularly related to the analyst fixed effects in our sample include analyst race, birth year (age), and location (country of residence). This is true both when we examine the full sample of analysts with identified individual fixed effects based on Abowd et al. (1999) in Column (1), when we separate the sample based on whether analysts have both foreign and domestic firm coverage (Column (2)), or when we exclude analysts with domestic coverage (Column (3)).

Table 8 further displays the coefficients on analyst observables when regressed, individually or jointly, on the individual analyst fixed effects. Consistent with Table 7, we observe significant improvements in the explained variation and statistical significance on the coefficients in particular with respect to analyst race characteristics (Column (2)), birth year (Column (4)), and analyst location (broad geographic region in Column (5) and analyst country in Column (6)).[14] The point estimates also reveal the directional relation between analyst demographics and persistent heterogeneity. For example, Asian analysts are more "optimistic" in the sense of having higher TGR expectations, whereas younger analysts born more recently tend to have lower TGR expectations.[15]

A natural question is why analysts from certain backgrounds, e.g., in terms of their geographic origins and exposures, have systematically higher or lower TGR expectations. In the next section, we explore how locally experienced economic conditions affect analysts' long-run expectations, including expectations for geographically distant firms.

5.4 Analysts' Personal Economic Environment and Extrapolative Expectations

Table 9 investigates the effect of personally, and locally, experienced economic conditions on forecasters' long-run expectations about firms, exploiting the richness in our data with respect to the location and country of firms and forecasting analysts.

In Columns (1) and (3), we find that recent GDP growth experienced by the forecasting analyst in their country of residence strongly predicts the analyst's long-run firm expectations, *controlling for* the recent economic performance in the country in which the firm is located.[16] This pattern points to substantial extrapolation by analysts from local factors when forming their TGR beliefs. This is in particular since the effects of home-country experiences are concentrated in forecasted firms that are located in geographically distant areas (Column (3)). Such a pattern is not predicted by a possible alternative mechanism that is unrelated to extrapolation and in which common shocks to a cluster of neighboring countries affect expectations.

[14] In total, analysts in Table 8 are located in 33 different countries, i.e., the country fixed effects in Column (3) are about 3 times as granular as the country region indicators in Column (5). Whether we include the indicators for White and Asian analysts in Columns (2) to (5) or race fixed effects (which further distinguish non-White and non-Asian analysts) makes little difference empirically.

[15] The large increase in the constant in Columns (4) and (5) arises from the fact that we include birth years without transforming them to be mean-zero.

[16] As Columns (2) and (4) show, the extrapolation mechanism appears to work through experienced macroeconomic productivity factors, as we find no evidence of extrapolation with respect to locally experienced inflation on long-run expectations.

Overall, the evidence in Table 9 extends the existing evidence on local extrapolation (e.g., Kuchler and Zafar, 2019), by documenting strong extrapolative effects across countries and economic environments, present in professional forecasters, and for long-run economic variables.

6 Conclusion

In this paper, we employ a new, large-scale dataset on terminal growth rate expectations for individual firms by professional forecasters, where we crucially observe forecaster identities and individual backgrounds, to study the origins and drivers of their very long-run cash flow expectations.

We establish a number of novel facts and findings. TGR expectations convey distinct economic insights compared to shorter-term forecasts like IBES long-term growth (LTG). They robustly forecast actual long-run firm growth and, in line with firm life cycle models, decline with firm age. There is persistent heterogeneity in TGR expectations across forecasters, particularly for less mature firms where country and industry factors do not predominate, and forecaster demographics play a substantial role in explaining this variation. Forecasters extrapolate from economic conditions in their country of residence when forming long-run expectations about firms in other, distant countries.

Among other things, our findings reinforce the conclusions drawn in prior work (e.g., Giglio et al., 2021) emphasizing the critical yet frequently unmodeled role of incorporating individual heterogeneity in belief formation. While earlier research has primarily focused on retail investors or households, our study uniquely highlights persistent individual heterogeneity in long-run beliefs among professional analysts. The fact that we identify economically important, persistent heterogeneity in long-run expectations in professional participants in financial markets magnifies the importance of incorporating such models in both macro-finance and corporate finance contexts.

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Table 1: Summary statistics This table reports summary statistics. The sample consists of 8,010 firms with observations from 41,429 equity reports in 2000–2023. Panel A describes the sample coverage. Panel B focuses on DCF variables associated with equity reports, Panel C provides information about the analysts included in the analysis, and Panels D and E examine economic data series. Variables definitions appear in Appendix A.

Panel A: Firms and Coverage						
		No. Firm			No. Obs	
Terminal growth rate sample		8,010			41,429	
Equity Analyst					5,304	
Equity Analyst (LinkedIn Matched)					1,667	
Brokerage house					41	
Panel B: Equity Reports	Mean	25^{th} Pct.	Median	75^{th} Pct.	Std. Dev.	No. Obs.
No. foreign reports	0.31	0.00	0.00	1.00	0.46	41,129
No. reports by country	845.49	11.00	240.00	581.00	2,140.80	49
Analyst terminal growth rate $(\text{TGR})_{i,j,t}(\%)$	2.22	1.50	2.00	3.00	1.31	41,429
$\text{TGR}_{i,j,t}(\%)$ (IBES Overlap)	2.21	1.50	2.00	3.00	1.29	25,615
IBES $\text{LTG}_{i,j,t}(\%)$	13.03	5.50	10.30	17.00	22.48	25,615
Correlation(IBES LTG, TGR)	0.08***					
Panel C: Analyst Information	Mean	25^{th} Pct.	Median	75^{th} Pct.	Std. Dev.	No. Obs.
Female	0.18	0.00	0.00	0.00	0.38	1,667
Asian	0.18	0.00	0.00	0.00	0.38	1,667
Black	0.03	0.00	0.00	0.00	0.18	1,667
Caucasian	0.75	1.00	1.00	1.00	0.43	1,667
Hispanic	0.03	0.00	0.00	0.00	0.18	1,667
Graduate degree (Masters and MBAs)	0.44	0.00	0.00	1.00	0.50	1,667
Birth year	1977.77	1971.00	1978.00	1985.00	9.64	1,020
No. Reports by Analyst	7.92	1.00	3.00	7.00	16.41	5,304
No. analyst by country	120.14	9.00	48.00	91.50	259.85	44
No. analyst by brokerage house	142.15	24.00	46.00	180.00	186.16	41
Panel D: Economic Data Series—All sample	Mean	25^{th} Pct.	Median	75^{th} Pct.	Std. Dev.	No. Obs.
Firm country						
Real GDP $\text{growth}_{i,j,t}$ (%)	2.55	1.55	2.29	3.74	3.36	38,370
$\text{Inflation}_{i,j,t}$ (%)	2.57	1.26	2.01	3.16	2.50	38,247
10-year Treasury $\text{yield}_{i,j,t}$ (%)	3.15	1.68	2.91	4.10	2.30	40,000
Panel E: Economic Data Series—Foreign reports	Mean	25^{th} Pct.	Median	75^{th} Pct.	Std. Dev.	No. Obs.
Analyst country						
Real GDP $\text{growth}_{i,j,t}$ (%)	2.01	1.45	2.29	3.12	3.70	12,296
$\text{Inflation}_{i,j,t}$ (%)	2.49	1.45	2.27	2.85	1.93	12,285
10-year Treasury $\text{yield}_{i,j,t}$ (%)	3.02	1.51	2.92	4.14	2.10	12,828
Firm country						
Real GDP $\text{growth}_{i,j,t}$ (%)	2.11	0.96	2.21	3.82	3.58	11,802
$\text{Inflation}_{i,j,t}$ (%)	2.43	0.90	1.83	3.06	2.75	11,686
10-year Treasury $\text{yield}_{i,j,t}$ (%)	3.02	0.97	2.75	4.11	2.76	11,830

Table 2: Realized long-term earnings growth rates versus analysts' expected TGRs In Panel A, this table decomposes ex-post realized earnings growth at different horizons based on analysts' terminal growth rates. The unit of observation is at the firm i, analyst j, and forecast year t levels. The sample period is 2000–2023. The dependent variables in Columns 1 to 3 are the geometric average of firms' earnings annual growth rates experienced by firm i for the 5-year periods $t+n$ to $t+n+4$, for different values of n. *Terminal growth rate*$_{i,j,t}$ is the terminal growth rate expectation by the analyst, measured in percentage points. In Panel B, we replicate the analysis from Panel A, but we average the geometric averages in each year across observations. The unit of observation is at the forecast year t level. Variable definitions appear in Appendix A. The regressions are estimated using ordinary least squares, and the standard errors (in parentheses) are heteroskedastic-consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Panel A: Firm level	$\Pi_{t+1}^{t+5}(1+g_{i,t})^{(1/5)}-1$	$\Pi_{t+4}^{t+8}(1+g_{i,t})^{(1/5)}-1$	$\Pi_{t+4}^{t+13}(1+g_{i,t})^{(1/10)}-1$
	(1)	(2)	(3)
Terminal growth rate (%)$_{i,j,t}$	1.02***	0.70***	0.53***
	(0.12)	(0.12)	(0.10)
Constant	4.42***	3.38***	2.93***
	(0.31)	(0.30)	(0.29)
Observations	20,812	17,116	9,367
F Statistics	70.03	36.66	28.58
R^2	0.01	0.00	0.01
Panel B: Sample average	$\frac{\sum_{j=1}^{J}\Pi_{t+1}^{t+5}(1+g_{j,t})^{(1/5)}-1}{J}$	$\frac{\sum_{j=1}^{J}\Pi_{t+4}^{t+8}(1+g_{j,t})^{(1/5)}-1}{J}$	$\frac{\sum_{j=1}^{J}\Pi_{t+4}^{t+13}(1+g_{j,t})^{(1/10)}-1}{J}$
	(1)	(2)	(3)
Average terminal growth rate (%)$_t$	4.18**	4.19***	1.91***
	(1.73)	(1.00)	(0.22)
Constant	-2.89	-4.49*	-0.40
	(3.90)	(2.49)	(0.51)
Observations	16	14	8
F Statistics	5.86	17.62	76.65
R^2	0.34	0.44	0.60

Table 3: TGR, firm age, and default risk This table presents the relation between firm age, default risk, and analyst terminal growth rates. 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, *Terminal growth rate*$_{i,j,t}$, is the terminal growth rate expectation by the analyst, measured in percentage points. Default risk variables are indicator variables equal to 1 if the firm probability of default is above their respective sample median, and 0 otherwise. The firm probability of default is estimated using the naive Merton distance-to-default model described in Bharath and Shumway (2008), using a 10- and 20-year horizon ($T = 10$ or 20), respectively. Age is the natural logarithm of firm age measured from the IPO year. Variable definitions appear Appendix A. The regressions are estimated using ordinary least squares, and the standard errors (in parentheses) are heteroskedastic-consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Dependent variable	Terminal growth rate$_{i,j,t}$				
	(1)	(2)	(3)	(4)	(5)
Default risk (10-year horizon)$_{i,j,t}$	-0.16***			-0.18***	
	(0.03)			(0.04)	
Default risk (20-year horizon)$_{i,j,t}$		-0.18***			-0.21***
		(0.03)			(0.04)
ln(Firm post-IPO age$_{i,j,t}$)			-0.14***	-0.17***	-0.17***
			(0.02)	(0.03)	(0.03)
Firm Country*Industry*Year FE	Yes	Yes	Yes	Yes	Yes
Observations	26,172	26,172	22,124	14,745	14,745
F Statistics	39.93	47.97	41.68	26.82	31.96
R^2	0.33	0.33	0.33	0.36	0.36

Table 4: ANOVA variance decomposition This table presents a variance decomposition of analyst terminal growth rates using ANOVA. For this analysis, we exclude from the sample firms, analysts, and brokerage houses with fewer than 2 observations in total, as for these observations, their respective fixed effects fully explain the associated variation in terminal growth rates. We also exclude brokerage houses that are not associated with equity analysts that switched between employers during the sample period (2000–2023), since it is not possible to distinguish between the effect of those brokerage houses and their analysts (Abowd et al., 1999). Panel A includes this entire subsample. Panel B excludes firms with fewer than 10 observations. To account for the fact that the sample used to conduct the analysis is unbalanced, as we do not observe a terminal growth rate estimate for every analyst-firm-year pair during the entire sample period, we estimate the sequential partial sum of squares. The adjusted partial R^2 is defined as: $1-(1-(\frac{Pss_i}{TSS})*\frac{N-1}{N-df_i-1})$, where i denotes a specific set of fixed effects (brokerage house, analyst, or firm). Variable definitions appear in Appendix A.

	Panel A: Anova			
	All sample	$\frac{Reports}{Analyst} \geq 10$	$\frac{Reports}{Analyst} \geq 25$	$\frac{Reports}{Analyst} \geq 50$
Brokerage house FE				
Share of total R^2 (%)	0.02	0.02	0.04	0.12
Adjusted Partial R^2	0.01	0.02	0.02	0.08
Analyst FE				
Share of total R^2 (%)	0.71	0.44	0.61	0.48
Adjusted Partial R^2	0.42	0.42	0.41	0.34
Firm FE				
Share of total R^2 (%)	0.27	0.21	0.35	0.40
Adjusted Partial R^2	0.04	0.06	0.06	0.09
Total R^2	0.67	0.67	0.69	0.72
Observations	35,719	26,565	17,733	8,504
	Panel B: Anova—Obs per firm $\geq$ 10			
	All subsample	$\frac{Reports}{Analyst} \geq 10$	$\frac{Reports}{Analyst} \geq 25$	$\frac{Reports}{Analyst} \geq 50$
Brokerage house FE				
Share of total R^2 (%)	0.03	0.04	0.06	0.15
Adjusted Partial R^2	0.02	0.02	0.04	0.10
Analyst FE				
Share of total R^2 (%)	0.78	0.73	0.67	0.52
Adjusted Partial R^2	0.42	0.42	0.41	0.34
Firm FE				
Share of total R^2 (%)	0.18	0.23	0.27	0.33
Adjusted Partial R^2	0.06	0.08	0.08	0.09
Total R^2	0.63	0.62	0.64	0.68
Observations	21,528	16,651	11,480	5,456

Table 5: TGR expectations over firms' life cycle This table evaluates the share of the second-stage dependent variable explained by the right-hand-side explanatory variables over firm life cycle. The unit of observation is at the firm i, analyst j, and forecast year t levels. The sample period is 2000–2023. Variable definitions appear in Appendix A. The regressions are estimated using ordinary least squares.

Stage 1: **Stage 2**:	None $TGR_{i,j,t} = I_{\text{Firm country}} + I_{\text{Industry}} + \epsilon_{i,j,t}$	$TGR_{i,j,t} = I_{\text{Firm country}} + I_{\text{Industry}} + \epsilon_{i,j,t}$ $\hat{\epsilon}_{i,j,t} = I_{\text{Firm}} + \upsilon_{i,j,t}$
	Stage 2 R^2	**Stage 2** R^2
0 <= Firm age < 5	0.09	0.60
5 <= Firm age < 10	0.09	0.55
10 <= Firm age < 15	0.10	0.53
15 <= Firm age < 20	0.14	0.52
20 <= Firm age < 25	0.18	0.54
25 <= Firm age < 30	0.24	0.51
30 <= Firm age < 35	0.18	0.46
35 <= Firm age < 40	0.19	0.62
40 <= Firm age < 45	0.20	0.43
45 <= Firm age < 50	0.38	0.37
50 <= Firm age < 55	0.32	0.41
55 <= Firm age < 60	0.25	0.23
60 <= Firm age < 65	0.56	0.14
65 <= Firm age < 70	0.57	0.34
70 <= Firm age < 75	0.64	0.11
75 <= Firm age < 80	0.45	0.16
80 <= Firm age < 85	0.60	0.16
85 <= Firm age < 90	0.28	0.02
90 <= Firm age < 95	0.72	0.01
95 <= Firm age < 100	0.84	0.00

Table 6: TGR expectation dispersion This table presents the results of the dispersion of terminal growth rate expectations over firms' life cycle. 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 corresponds to the absolute value of the difference between the analyst's estimate of the terminal growth rate and the industry (k) consensus for the firm age group in the forecast year t. The dependent variables are indicator variables equal to one if the firm age lies within the range associated with the indicator variable and 0 otherwise. Variable definitions appear in Appendix A. The regressions are estimated using ordinary least squares, and the standard errors (in parentheses) are heteroskedastic-consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Terminal Growth Rate dispersion	$\lvert \text{TGR}_{i,j,t} - \overline{TGR}^{\text{Age Group}}_{k,t} \rvert$	
	(1)	(2)
10 <= Firm age < $20_{i,j,t}$	-0.04**	-0.03*
	(0.02)	(0.02)
20 <= Firm age < $30_{i,j,t}$	-0.04*	-0.03
	(0.02)	(0.02)
30 <= Firm age < $40_{i,j,t}$	-0.13***	-0.14***
	(0.03)	(0.03)
40 <= Firm age < $50_{i,j,t}$	-0.23***	-0.23***
	(0.05)	(0.05)
50 <= Firm age < $60_{i,j,t}$	-0.24***	-0.23***
	(0.05)	(0.05)
60 <= Firm age < $70_{i,j,t}$	-0.14*	-0.13**
	(0.07)	(0.07)
70 <= Firm age < $80_{i,j,t}$	-0.06	-0.09
	(0.07)	(0.07)
80 <= Firm age < $90_{i,j,t}$	-0.41***	-0.37***
	(0.07)	(0.08)
90 <= Firm age < $100_{i,j,t}$	-0.33***	-0.34***
	(0.11)	(0.09)
Constant	0.99***	0.98***
	(0.01)	(0.01)
Year*Industry FE	No	Yes
Observations	23,824	23,824
F Statistics	11.66	9.53
R^2	0.01	0.06

Table 7: Analyst fixed effects decomposition This table shows the combined explanatory power of various fixed effects for terminal growth rates and presents a variance decomposition of analyst fixed effects in terminal growth rate expectations. For this analysis, we exclude from the sample firms, analysts, and brokerage houses with fewer than 2 observations in total, as for these observations, their respective fixed effects fully explain the associated variation in terminal growth rates. We also exclude brokerage houses that are not associated with equity analysts that switched between employers during the sample period (2000–2023), since it is not possible to distinguish between the effect of those brokerage houses and their analysts Abowd et al., 1999. In column 1, we use the entire subsample; column 2 restricts the analysis to firms that have both domestic and foreign coverage, and column 3 focuses on the foreign coverage for the firms included in column 2. Panel A shows the combined explanatory power of three primitive variables—firm, brokerage house, and analyst—for the terminal growth rate. The unit of observation is at firm i, analyst j, and forecast year t levels. Panel B performs a variance decomposition of the analyst fixed effects into 5 dependent variables using ANOVA. Gender is a binary variable equal to 1 if the analyst is female and 0 otherwise. Race is a categorical variable indicating White, Asian, Hispanic, and other races. Education is a binary variable equal to 1 if the analyst has a graduate degree and 0 otherwise. Birthyear and analyst country are a series birth year and country of residence indicators. To account for the fact that the sample used to conduct the analysis is unbalanced, as we do not observe a terminal growth rate estimate for every analyst-firm-year pair during the entire sample period, we estimate the sequential partial sum of squares. The adjusted partial R^2 is defined as: $1-(1-(\frac{Pss_i}{TSS})*\frac{N-1}{N-df_i-1})$, where i denotes a specific set of fixed effects (brokerage house, analyst, or firm). Variable definitions appear in Appendix A.

Panel A: Fixed effects	Terminal growth rate$_{i,j,t}$		
	All Sample	Has both foreign and domestic coverage	Exclude domestic coverage
	(1)	(2)	(3)
Constant	2.17***	2.17***	2.14***
	(0.00)	(0.00)	(0.00)
Firm FE	Yes	Yes	Yes
Brokerage FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Observations	6,668	2,759	1,355
R^2	0.69	0.71	0.72
Panel B: ANOVA decomposition	**Analyst FE**		
	All Sample	Has both foreign and domestic coverage	Exclude domestic coverage
	(1)	(2)	(3)
Gender FE			
Share of total R^2 (%)	0.00	0.01	0.00
Adjusted Partial R^2	0.00	0.00	-0.01
Race FE			
Share of total R^2 (%)	0.09	0.04	0.06
Adjusted Partial R^2	0.02	0.01	0.02
Education FE			
Share of total R^2 (%)	0.15	0.01	0.01
Adjusted Partial R^2	0.04	-0.01	-0.01
Birthyear FE			
Share of total R^2 (%)	0.19	0.46	0.37
Adjusted Partial R^2	-0.04	0.00	-0.03
Analyst country FE			
Share of total R^2 (%)	0.58	0.47	0.31
Adjusted Partial R^2	0.12	0.06	0.08
Total R^2	0.31	0.29	0.43
Observations	479	318	153

Table 8: Analyst fixed effects by analyst demographics This table explores the sign and magnitude associated with observable analyst characteristics in explaining analyst fixed effects. For this analysis, we exclude from the sample firms, analysts, and brokerage houses with fewer than 2 observations in total, as for these observations, their respective fixed effects fully explain the associated variation in terminal growth rates. We also exclude brokerage houses that are not associated with equity analysts that switched between employers during the sample period (2000–2023), since it is not possible to distinguish between the effect of those brokerage houses and their analysts (Abowd et al., 1999). The unit of observation is at the analyst j level. Female is a binary variable equal to 1 if the analyst is female and 0 otherwise. White is a binary variable equal to 1 if the analyst is white, and 0 otherwise. Asian is a binary variable equal to 1 if the analyst is Asian, and 0 otherwise. Graduate degree is a binary variable equal to 1 if the analyst has a graduate degree, and 0 otherwise. We focus the country binary variables on the most populated regions of our sample. The regressions are estimated using ordinary least squares, and the standard errors (in parentheses) are heteroskedastic-consistent. Variable definitions appear in Appendix A. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Dependent variable	Analyst FE					
	(1)	(2)	(3)	(4)	(5)	(6)
I_j^{Female}	0.04	-0.09	-0.09	-0.06	0.10	0.10
	(0.22)	(0.22)	(0.22)	(0.22)	(0.21)	(0.19)
I_j^{White}		-0.27	-0.27	-0.29	-0.19	
		(0.29)	(0.29)	(0.29)	(0.30)	
I_j^{Asian}		0.68*	0.68*	0.72**	-0.33	
		(0.36)	(0.36)	(0.36)	(0.38)	
$\mathrm{I}_j^{Graduate\ degree}$			-0.02	-0.06	0.03	0.04
			(0.13)	(0.13)	(0.13)	(0.13)
Birth year$_j$				-0.02**	-0.01*	
				(0.01)	(0.01)	
I_j^{UK}					0.06	
					(0.18)	
$\mathrm{I}_j^{LatinAmerica}$					0.60	
					(0.60)	
$\mathrm{I}_j^{SoutheastAsia}$					1.15	
					(0.71)	
$\mathrm{I}_j^{Scandinavia}$					-0.49**	
					(0.25)	
$\mathrm{I}_j^{Germany}$					-0.44*	
					(0.24)	
I_j^{India}					2.81***	
					(0.49)	
I_j^{Canada}					1.02**	
					(0.46)	
$\mathrm{I}_j^{Australia}$					0.12	
					(0.18)	
$\mathrm{I}_j^{MiddleEast}$					0.62**	
					(0.29)	
$\mathrm{I}_j^{EastAsia}$					0.56**	
					(0.28)	
I_j^{Russia}					-0.96***	
					(0.34)	
Constant	0.06	0.18	0.20	33.14**	23.31*	0.03
	(0.07)	(0.29)	(0.30)	(14.13)	(13.63)	(0.10)
Race FE	No	No	No	No	No	Yes
Analyst Country FE	No	No	No	No	No	Yes
Observations	475	475	475	475	475	475
R^2	0.00	0.06	0.06	0.07	0.21	0.31

Table 9: Analyst–firm distance, analyst local economic conditions, and extrapolation This table explores the effect of analyst local economic conditions on their terminal growth rate expectations. 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, *Terminal growth rate*$_{i,j,t}$, is equal to the terminal growth rate expectation by the analyst, measured in percentage points. The 10-year average real GDP growth series, for both the firm and the analyst's country, are taken from the World Bank data series. They are measured as the trailing 10-year average. The 10-year average inflation rates, for both the firm and the analyst's country, are constructed from data from the World Bank. They are measured as the trailing 10-year average. *Far* is a binary variable equal to 1 if the geographic distance between the analyst's country and the firm's country is above the sample median, and 0 otherwise. We measure the distance between countries as the shortest distance between the two countries' capitals. Variable definitions appear in Appendix A. The regressions are estimated using ordinary least squares, and the standard errors (in parentheses) are heteroskedastic-consistent and clustered at the firm level. Significance levels are shown as follows: * = 10%, ** = 5%, *** = 1%.

Dependent variable	Terminal growth rate$_{i,j,t}$			
	(1)	(2)	(3)	(4)
10-year average real GDP growth (Firm)$_{i,j,t}$	0.09***		0.09***	
	(0.02)		(0.02)	
10-year average real GDP growth (Analyst)$_{i,j,t}$	0.09***		-0.04	
	(0.03)		(0.05)	
10-year average inflation rate (Firm)$_{i,j,t}$		0.00		0.00
		(0.00)		(0.00)
10-year average inflation rate (Analyst)$_{i,j,t}$		-0.00		-0.00
		(0.00)		(0.00)
10-year average real GDP growth (Analyst)$_{i,j,t} * I^{far}_{i,j,t}$			0.15***	
			(0.05)	
10-year average inflation rate (Analyst)$_{i,j,t} * I^{far}_{i,j,t}$				0.02
				(0.03)
Analyst country*firm country FE	Yes	Yes	Yes	Yes
Observations	11,675	11,575	11,675	11,575
F Statistics	29.82	0.02	21.26	0.12
R^2	0.15	0.14	0.15	0.14

Appendix A Variable Definitions

Table A.1: Variable Definitions

Subscript t indicates the forecast year, i indicates a firm, j indicates a contributor, and c identifies a country.

Variable	**Definition**
10-year average inflation rate (Analyst)$_{i,j,t}$	The 10-year rolling average of the analyst's country inflation rate, obtained from the World Bank.
10-year average inflation rate (Firm)$_{i,j,t}$	The 10-year rolling average of the firm's headquarters' country inflation rate, obtained from the World Bank.
10-year average real GDP growth (Analyst)$_{i,j,t}$	The 10-year rolling average of the analyst's country real GDP growth rate, obtained from the World Bank.
10-year average real GDP growth (Firm)$_{i,j,t}$	The 10-year rolling average of the firm's headquarters' country real GDP growth rate, obtained from the World Bank.
Default risk (10-year horizon)$_{i,j,t}$	A binary variable equal to 1 if the firm probability of default is above the sample median, and 0 otherwise. The probability of default is measured following the naive Merton's distance-to-default model discussed in Bharath and Shumway (2008), using a horizon of 10 years (T=10).
Default risk (20-year horizon)$_{i,j,t}$	A binary variable equal to 1 if the firm probability of default is above the sample median, and 0 otherwise. The probability of default is measured following the naive Merton's distance-to-default model discussed in Bharath and Shumway (2008), using a horizon of 20 years (T=20).
Firm age	The firm post-IPO year age.
$I^{far}_{i,j,t}$	A binary variable equal to 1 if the distance between the analyst's country capital and the firm's country capital is above the sample median, and 0 otherwise. The pairwise distance is measured as the shortest distance between both cities using their centroid GPS coordinates.
LTG (IBES)$_{i,j,t}$	The consensus measure (median) of the LTG variable provided by the Institutional Brokers' Estimate System (IBES), for the firm and the beginning of the calendar year.
Terminal growth rate (TGR)$_{i,j,t}$	The terminal growth rate$_{i,j,t}$ used by equity analysts in their DCF models, measured from the equity reports.
Terminal growth rate dispersion	The absolute value of the difference between analysts' terminal growth rate, and the average terminal growth rate measured for each age group-industry-year subsets: $\lvert TGR_{i,j,t} - \overline{TGR}^{\text{Age Group}}_{k,t} \rvert$.

Appendix B Supplementary Figures

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 B.1: 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.*

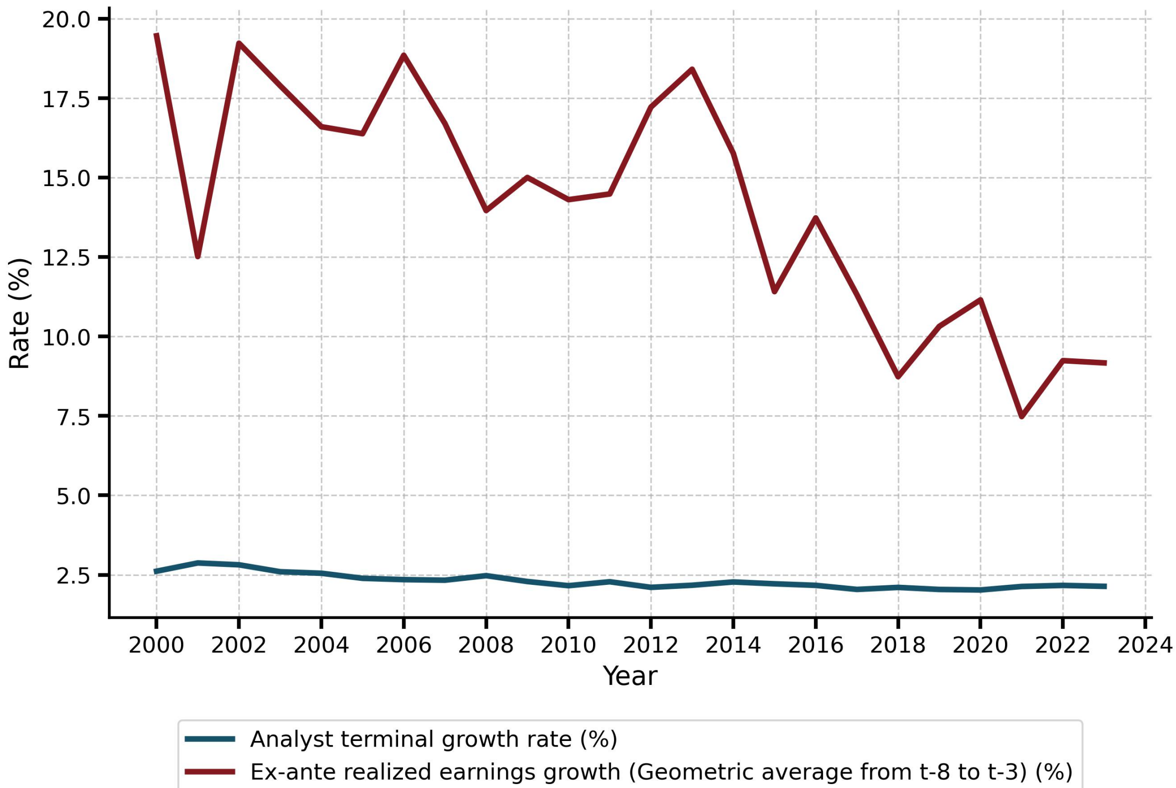

Figure B.2: TGR expectations versus historical returns This figure compares the time trends of historically realized earnings growth at the $t-8$ to $t-3$ horizon with analyst terminal growth rates. Realized earnings growth corresponds to the geometric average realized from $t-8$ to $t-3$, averaged by year (t) in the sample. Terminal growth rate is the average terminal growth rate by year. The x-axis denotes years. The y-axis corresponds to rates, in percentages (%).