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Analysts' Cultural Long-Term Orientation and Their Information Production

Orientation culturelle à long terme des analystes et production d'information

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ABSTRACT

We study how analysts' inherited cultural attitudes to time orientation affect their production of long-term information and the profitability of their stock recommendations. We find that analysts from long-term-oriented cultures exhibit a longer forecast horizon and issue more long-term forecasts. They also produce more accurate long-term forecasts and ask more long-term-focused questions during conference calls, eliciting greater long-term disclosure from managers. In addition, they are more likely to use discounted valuation models that explicitly incorporate expectations about firms' long-term prospects. Further, their stock recommendations are more profitable, consistent with their production of long-term information enhancing valuation. Our findings highlight the role of cultural long-term orientation in shaping analysts' information production in capital markets.

JEL Classification: G15, G24, G41, J15, O31

RÉSUMÉ

Nous examinons de quelle façon les attitudes culturelles acquises des analystes en matière d'orientation temporelle influencent leur production d'information à long terme et la rentabilité de leurs recommandations boursières. Nous établissons que l'horizon de prévision des analystes issus de cultures orientées sur le long terme est plus étendu et que ceux-ci font davantage de prévisions à long terme. Ils produisent aussi des prévisions à long terme plus précises et posent plus de questions en ce sens lors des conférences téléphoniques, ce qui pousse les gestionnaires à divulguer davantage d'information à long terme. En outre, ces analystes sont plus susceptibles d'utiliser des modèles d'évaluation actualisés qui intègrent explicitement les attentes concernant les perspectives à long terme des entreprises. Leurs recommandations boursières sont également plus rentables, ce qui est cohérent avec le fait que leur production d'information à long terme améliore l'évaluation. Nos observations mettent en lumière l'influence de l'orientation culturelle à long terme dans la production d'information des analystes sur les marchés boursiers.

1 | Introduction

Long-term orientation (hereafter LTO) in capital markets refers to the prioritization of investments and strategies that create sustainable value over extended time horizons, rather than focusing on short-term performance. A global McKinsey survey of more than 1000 board members and C-suite executives found that 86% believe that adopting a longer-time perspective enhances innovation and produces sustainable value for investors (Barton and Wiseman 2013). Yet, despite the importance of this topic, empirical research on the determinants of LTO in capital markets and its associated benefits remains limited. We attempt to bridge this gap by examining the production of long-term information by financial analysts, a key group of information intermediaries in capital markets. Specifically, we study how analysts' inherited cultural LTO influences their production of long-term information and the profitability of their stock recommendations.

Inherited cultural attitude toward LTO refers to the extent to which individuals prioritize future rewards and emphasize long-term outcomes over immediate gains (e.g., Geert Hofstede and Bond 1988; Gert Jan Hofstede et al. 2002; Geert Hofstede and Minkov 2010).[1] Prior research finds that LTO influences business leaders' focus on long-term performance (Geert Hofstede et al. 2002), consumers' intertemporal purchasing decisions (Bearden et al. 2006), and CEOs' tendencies to pursue acquisitions outside their firms' core business (Ferris et al. 2013). In the context of financial analysts, producing long-term information can enhance their reputation among institutional clients and lead to higher compensation and better career prospects (e.g., Groysberg et al. 2011; B. Jung et al. 2012). These economic incentives may reinforce the effects of cultural LTO on analysts' investment in the production of long-term information. We therefore posit that analysts from higher-LTO cultures (higher-LTO analysts) will place greater emphasis on analyzing firms' longer-term prospects and produce more long-term information. Further, to the extent that this long-term emphasis improves the quality of their valuation models and inputs, we also expect their stock recommendations to be more profitable.

We conduct our analysis using data on 3797 unique analysts in the United States from 2000 to 2014. To measure each analyst's LTO, we draw on Hofstede's cultural index of LTO[2] and assign each analyst a score based on the ancestral origins associated with the analyst's surname. Ancestral countries are identified using historical US immigration data that link surnames to national origins (e.g., Pan et al. 2017). Following prior research (J. Jung et al. 2019), we measure analyst's LTO using the weighted average of Hofstede's cultural indices of LTO for countries that are associated with the analyst's surname. We further provide survey evidence and cross-sectional analysis on cultural decay that validate this LTO measure.

To capture analysts' production of long-term information, we examine the issuance of long-term earnings forecasts, the accuracy of long-term earnings forecasts, and the content of analysts' questions during earnings conference calls. We measure the issuance of long-term forecasts using both the weighted average horizon across all of an analyst's earnings forecasts and the sum of indicator variables capturing the issuance of different types of long-term earnings forecasts (forecasts more than 2 years ahead, including long-term growth [LTG] forecasts). Our regressions include an extensive set of controls, including other prominent cultural attributes, a host of analyst-level and firm-level characteristics, hand-collected information on analysts' educational and professional achievements from LinkedIn, and year, brokerage, and firm fixed effects.

We find that analysts from higher-LTO cultures provide forecasts with longer horizons and are more likely to issue long-term forecasts. Our results are also economically meaningful: moving from the lowest to the highest regional mean of LTO is associated with a 4.0% increase in the weighted forecast horizon and a 7.6% increase in the likelihood of issuing long-term forecasts, relative to their respective sample means. Furthermore, our results are robust to the inclusion of firm × year interacted fixed effects and hold in additional tests using an international setting of non-US analysts.

If higher-LTO analysts invest more in gathering long-term information, we also expect them to issue more accurate long-term forecasts. Consistent with this expectation, we find that higher-LTO analysts produce more accurate 2- and 3-year-ahead earnings forecasts as well as LTG earnings forecasts. In contrast, we find no evidence that their 1-year-ahead earnings forecast accuracy differs from that of lower-LTO analysts. These findings suggest that cultural LTO enhances the production of long-term information, rather than general information.

To further examine analysts' information production, we conduct a textual analysis of the Q&A sections of earnings conference call transcripts. This setting allows us to observe the extent to which an analyst's questions focus on a firm's long-term prospects, thereby providing direct evidence on the relation between LTO and analysts' information gathering. We find that higher-LTO analysts are more likely to ask long-term-oriented questions during conference calls. Moreover, managers respond by disclosing more long-term information about the firm's prospects in turn. These findings suggest that higher-LTO analysts not only seek more long-term information themselves but also induce corporate managers to disclose more long-term information.

To corroborate our findings based on earnings forecasts and conference call analyses, we use a hand-collected sample of analyst reports to examine the relation between analysts' LTO and the valuation models they use. We retrieve a random sample of 200 firm-level matched pairs of full analyst reports—that is, 200 issued by higher-LTO analysts and 200 by lower-LTO analysts—covering the same firms, allowing for a within-firm comparison. We find that higher-LTO analysts are more likely to employ sophisticated discounted valuation models, such as discounted cash flow (DCF) or residual income models, which explicitly incorporate expectations about a firm's long-term performance. Regression analysis further shows that higher-LTO analysts are less likely to rely on heuristic models, such as price-to-earnings ratios.

We next examine the capital market benefits of analysts' long-term information production by evaluating the profitability of stock recommendations. Following Barber et al. (2001), we use a calendar-time portfolio approach to estimate the abnormal returns associated with recommendations from higher- versus lower-LTO analysts. We sort stocks into five portfolios based on the consensus recommendation level, rebalance weekly abnormal returns, and compute monthly abnormal returns using a six-factor model. We find that the recommendations issued by higher-LTO analysts are more profitable. The hedge portfolio constructed using recommendations from higher-LTO analysts earns monthly abnormal returns that are 30 basis points higher than those using recommendations from lower-LTO analysts. Cross-sectional tests further reveal that the incremental profitability is more pronounced among firms with greater sales or asset volatility, lower book-to-market ratios, or more intangible assets. For these firms, long-term performance is both more important and harder to predict. These findings suggest that cultural LTO not only enhances the production of long-term information but also boosts the value of stock recommendations, particularly among firms where long-term information is most valued.

Our study provides new insights into how LTO shapes information production in capital markets. While both practitioners and academics have long highlighted the tension between short-term market pressures and long-term value creation, prior research has largely focused on corporate short-termism and its consequences (e.g., Malmendier and Tate 2005; Brochet et al. 2015; Sampson and Shi 2023). Much less is known about the determinants of long-term information production by capital market intermediaries. Our evidence shows that analysts' culturally inherited LTO is systematically associated with greater production of long-horizon information and more informative research. A key takeaway from our findings is that differences in analysts' LTO help explain why some analysts produce and transmit more long-term information to the market than others.

Our findings also have practical implications for capital market participants. For investment banks and brokerage houses, our results suggest that analyst heterogeneity in LTO may matter for how analysts are allocated across firms, industries, and stages of the firm life cycle. Analysts with stronger LTO may be particularly well suited to covering firms where long-horizon information is especially valuable, such as high-growth, innovation-intensive, or high-uncertainty firms. Our findings further suggest that analyst evaluation and incentive systems that emphasize short-term performance metrics may undervalue analysts whose competitive advantage lies in producing long-horizon research.

For investors, our results suggest that analyst reports differ not only in their information content but also in the time horizon of the information they produce. Investors seeking long-term insights may benefit from placing greater weight on analysts with higher LTO. More broadly, our findings suggest that investors may better interpret analyst outputs not only through the lens of firm fundamentals but also through differences in analysts' information production styles.

Our study also contributes to the growing literature on the role of analysts' inherited cultural traits in forecasting behavior. Prior studies have examined cultural similarity between analysts and CEOs (Brochet et al. 2019; Frijns and Garel 2021), cultural diversity among analysts (Merkley et al. 2020), and analysts' cultural individualism (Cao et al. 2024). We add to this literature by identifying cultural LTO as an important determinant of analysts' information production choices. Specifically, we show that analysts with higher LTO are more likely to seek and generate long-term insights, elicit disclosure of long-term information from managers, rely on long-horizon valuation models, and provide more valuable recommendations.

Finally, our findings deepen our understanding of analysts' influence on managerial disclosures. While prior research has primarily focused on analysts' effects on managers' short-term disclosures (Brochet et al. 2015; Chapman and Green 2018), we document that analysts with stronger LTO tend to elicit more long-term disclosures from managers. This evidence suggests that analyst coverage does not uniformly amplify short-term pressure. Rather, differences in analysts' orientation can shape the nature of the information managers provide to the market. Taken together, our results highlight the importance of analyst heterogeneity in understanding the dynamics of information production and communication in capital markets.

2 | Related Research and Hypotheses

2.1 | Extant Research on the Role of Culture on Managers and Analysts

A large economics literature finds that inherited cultural values affect various economic preferences and outcomes at both the individual and the country level (see Fernández 2011 for a review). Economists model individuals as economic agents who make choices in an economic and institutional environment, given their preferences and beliefs. As such, researchers can treat prior beliefs and values, that is, inherited cultural values, as parameters associated with an economic agent's utility function, while maintaining the standard economic assumption that each individual seeks to maximize their utility function (Guiso et al. 2006).

In line with this economic research, accounting and finance research has found that inherited cultural values affect managers' behavior. For example, Pan et al. (2017, 2020) find that CEOs from more uncertainty-avoiding cultures invest less in R&D, make fewer acquisitions, and hold more cash. Brochet et al. (2019) find that CEOs from more individualistic cultures use a more optimistic tone in their language and make more self-references in conference calls. In a cross-country setting, Brochet et al. (2023) find that firms with a more long-term-oriented investor base use more long-term-oriented disclosures in annual reports.

The literature on analysts' cultural background is more recent and growing. Bhagwat and Liu (2020) find an inverted-U relationship between inherited trust values and forecast accuracy, consistent with analysts from low (high) trust cultures underweighting (overweighting) public information. Merkley et al. (2020) find that greater cultural diversity among analysts is associated with more accurate consensus forecasts. Brochet et al. (2019) show that analysts extract more useful information from managerial disclosure when they share similar cultural backgrounds with managers (see also Frijns and Garel 2021). Cao et al. (2024) find that individualistic analysts issue bolder forecasts and recommendations and that their coverage reduces price synchronicity. While this literature is growing, little is known about how analysts' cultural time orientation affects long-term information production and related capital market outcomes. We fill this void.

2.2 | Hypotheses

Long-term and short-term-oriented cultures reflect different ways of approaching the future. Cultural LTO captures the extent to which individuals prioritize future outcomes over immediate rewards (Bearden et al. 2006; Geert Hofstede and Minkov 2010). In this sense, LTO serves as a time-based cultural trait that influences how economic agents perceive and respond to forward-looking opportunities and risks.

Applied to financial analysts, we expect cultural LTO to shape both preferences and attentional focus. Analysts from higher-LTO cultures are more likely to value and attend to long-term outcomes, enhancing their motivation and ability to gather and process long-term information. This attentiveness may foster greater willingness to invest in the effort-intensive task of analyzing firms' long-term fundamentals, particularly when long-horizon insights are difficult to obtain. Furthermore, the effect of cultural LTO is likely reinforced by analysts' economic incentives, as producing long-term information—such as multiyear earnings forecasts or long-horizon valuation analyses—can increase the perceived value of analysts' research to institutional clients and improve their recommendations (B. Jung et al. 2012). The resulting reputational gains and improved recommendations, in turn, are linked to tangible outcomes such as higher compensation and career advancement (Groysberg et al. 2011). Thus, we expect analysts from long-term-oriented cultures to produce more long-term information about the firms they cover:

Hypothesis 1 (H1). *Analysts' cultural LTO is positively related to the production of long-term information.*

However, this hypothesis is not a foregone conclusion. Analysts work in a highly competitive and commercially driven environment, where market pressures and firm-level incentives can weaken or even override cultural preferences for time orientation. Prior research shows that analysts' information production is shaped by incentives to support investment banking relationships (e.g., Lin and McNichols 1998), generate trading commissions (e.g., Irvine 2004; Cowen et al. 2006), curry favor with firm management (e.g., Chen and Matsumoto 2006; Ke and Yu 2006), cater to institutional investors (e.g., Firth et al. 2013), or exploit personal trading opportunities (e.g., Chan et al. 2018). Furthermore, structural frictions may constrain the supply and demand for long-term-oriented analysis. For example, producing long-horizon forecasts requires significant time and effort, which may not be immediately rewarded by clients or employers. Labor market frictions, such as limited supply and coverage capacity (Bradley, Gokkaya, and Liu 2017), can constrain brokers' ability to hire long-term-oriented analysts and efficiently allocate them across firms. These forces highlight that the influence of cultural LTO operates within a broader ecosystem of economic constraints and institutional trade-offs.

Next, we consider the role of analysts' LTO in enhancing the value of their stock recommendations. Higher-LTO analysts are more likely to invest in understanding the long-term drivers of firm value. This includes identifying and analyzing information that goes beyond near-term earnings and relates to sustainable advantages, growth potential, and strategic positioning. For example, in platform- or subscription-based industries (e.g., Zoom, Uber, and Netflix), analysts may emphasize long-term lease commitments, global user growth, or customer retention rates. They may also dig deeper into structural trends—such as geographic market penetration or technological adoption—that influence multiyear prospects. This investment in analyzing long-term fundamentals gives analysts deeper insight into the opportunities and challenges firms face in the years ahead. In turn, their better understanding of firms' long-term prospects enhances the quality of their valuation models and inputs, leading to more valuable stock recommendations:

Hypothesis 2 (H2). *Analysts' cultural LTO is positively related to the value of their stock recommendations.*

3 | Sample, Variable Measurement, and Regression Model

3.1 | Sample

We start with analyst forecast data from I/B/E/S, retaining analysts' 1-year-ahead forecasts of annual earnings for US firms. For each firm-year for which an analyst issues at least one such forecast, we also collect the analyst's earnings forecasts of different horizons. To mitigate measurement error in identifying analyst ethnicity, we exclude analysts associated with multiple names. We then merge the analyst forecast sample with Compustat, CRSP, and FactSet to obtain information on firm fundamentals, stock prices, and institutional ownership, respectively. We also utilize data on conference call transcripts from Capital IQ, firm managers from ExecuComp and BoardEx, analyst reports from Refinitiv Eikon, and analyst biographical information from LinkedIn.[3] After requiring nonmissing values for variables used in our main analyses, our final sample contains 223,195 firm-year-analysts from 3797 unique analysts and 5230 unique firms in the United States over the period 2000–2014.[4]

3.2 | Measuring Analysts' Cultural LTO

To measure analysts' cultural LTO, we first use analysts' surnames to identify their countries of origin by tracking down the nationalities of US immigrants who shared the same surname and entered the United States through the port of New York between 1820 and 1957.[5] That is, we use the distribution of the US immigrants' nationalities sharing the same surname as a proxy for the analyst's countries of origin.[6] Once we identify the countries of origin of an analyst, we compute the level of the analyst's LTO, *Long-term orientation*, by taking the weighted average of Hofstede's cultural indices of LTO for countries associated with the analyst's surname.[7] The weight for each country is the fraction of the US immigrants sharing the same surname who reported the country as their nationality (e.g., J. Jung et al. 2019).[8] We provide detailed definitions for all variables in the Appendix.

Hofstede's cultural index of LTO has been validated by prior research through surveys and large-sample empirical analyses. For example, Geert Hofstede et al. (2002, 791) survey junior managers and professionals in 12 countries and find that LTO index is positively associated with valuing "profits 10 years from now" and the *un*importance of "this year's profits." The LTO construct has also been linked to long-term investments, such as national savings rates (Read 1993) and real estate investments (de Mooij 2004), and less to short-term behaviors, such as compulsive buying (Bearden et al. 2006) and noncore acquisitions (Ferris et al. 2013). It has been further validated by successive rounds of the World Values Survey (WVS) (Geert Hofstede et al. 2010).

We also validate the LTO construct by surveying a random sample of 200 US residents via Amazon Mechanical Turk. Of Hofstede's two LTO dimensions, that is, "respect for tradition" and "planning for the future," the latter is most relevant to our setting. We supplement the original eight survey questions of Bearden et al. (2006) with two additional questions to better capture planning (see Supporting Information S1). Using principal component analysis, we extract two factors, with the first capturing planning and the second tradition. The first factor is significantly positively correlated with Hofstede's LTO indices for survey respondents' ancestral countries of origin.

Panel A of Table 1 presents the sample distribution of the US equity analysts' countries of origin and the mean value of *Long-term orientation* for countries by geographic region. A total of 115 countries of origin associated with the surnames of our sample analysts are regrouped into nine different geographic regions, following standard area codes identified by the UN (UN Statistics Division 1999). We assign each analyst to a single country that accounts for the largest fraction of the nationalities of US immigrants sharing the same surname. This approach enables us to classify analysts into nine mutually exclusive geographic regions. On average, countries in Eastern Asia (Latin America and the Caribbean) have the highest (lowest) value of *Long-term orientation*: 91.67 (21.90). The largest (smallest) fraction, 46.77% (0.16%), of the US equity analysts in our sample have Northern European (Latin American and the Caribbean) countries as their origin.[9]

3.3 | Measuring Analysts' Issuance of Long-Term Forecasts

We construct two variables to capture analysts' issuance of long-term earnings forecasts. The first is the weighted average of the forecast horizons of an analyst's earnings forecasts for a firm in a year (*Weighted forecast horizon*).[10] The second is the sum of indicator variables for the analyst's issuance of each type of long-term earnings forecasts for a firm in a year (*LT issuance*). We define analysts' long-term earnings forecasts as their earnings forecasts with a horizon longer than 1 year, including 2- to 7-year-ahead earnings forecasts, as well as LTG earnings forecasts.[11]

Panel B of Table 1 reports the distribution of earnings forecasts by horizon. By construction, all firm-year-analyst observations have 1-year-ahead forecasts. Virtually all (99.76%) also have at least one 2-year-ahead earnings forecast in our sample. The proportion of firm-year-analysts with at least one particular type of long-term earnings forecast decreases dramatically as the forecast horizon lengthens: 41.88% for 3-year-ahead earnings forecasts, 8.36% for 4-year-ahead earnings forecasts, and 0.38% for 7-year-ahead earnings forecasts. About one-third of our sample (28.05%) has at least one LTG earnings forecast.

3.4 | Regression Model

We estimate the following OLS regression model at the analyst-firm-year level to examine the relation between analysts' LTO and their production of long-term earnings information:

$$\begin{aligned} \textit{Weighted forecast horizon}_{ijt}/\textit{LT issuance}_{ijt} = \alpha_0 + \beta_1\, &\textit{Long-term orientation}_{ijt} + \Sigma\, \gamma' \textit{Controls for culture}_{ijt} \\ &+ \Sigma\, \delta' \textit{Controls for analyst and firm}_{ijt} \\ &+ \textit{Year, Brokerage, Firm fixed effects} + \varepsilon_{ijt}. \end{aligned} \tag{1}$$

TABLE 1 | Distributions of US equity analysts' countries of origin and earnings forecasts.

Panel A: The distribution of the US equity analysts' countries of origin by geographic region

			Sample composition			
			Individual analysts		Firm-year-analysts	
Geographic region	**Two most common countries of origin**	**Regional mean of *Long-term orientation***	**No.**	**Percent**	**No.**	**Percent**
Eastern Asia	China, Japan	91.67	120	3.16	6067	2.72
Eastern Europe	Russia, Poland	64.00	195	5.14	12,257	5.49
Latin America and the Caribbean	Mexico, Colombia	21.90	6	0.16	158	0.07
Northern America	USA, Canada	31.00	505	13.30	29,452	13.20
Northern Europe	Great Britain, Ireland	49.70	1776	46.77	103,408	46.33
Southern Asia	India, Iran	38.33	62	1.63	3066	1.37
Southern Europe	Italy, Spain	55.36	355	9.35	21,950	9.83
Western Asia	Turkey, Arab countries	34.83	10	0.26	652	0.29
Western Europe	Germany, France	70.43	768	20.23	46,185	20.69
Total			3797	100	223,195	100

Panel B: The distribution of earnings forecasts by forecast horizon

		Firm-year-analysts with at least one issuance	
Forecast horizon	**Horizon window**	**No.**	**Percent**
Short-term earnings forecasts	1 quarter (1-quarter-ahead earnings forecasts)	220,901	98.97
	2 quarters	208,310	93.33
	3 quarters	200,735	89.94
	4 quarters	189,924	85.09
	1 year (1-year-ahead earnings forecasts)	223,195	100.00
Long-term earnings forecasts	2 years (2-year-ahead earnings forecasts)	222,658	99.76
	3 years	93,478	41.88
	4 years	18,653	8.36
	5 years	10,305	4.62
	6 years	2848	1.28
	7 years (7-year-ahead earnings forecasts)	838	0.38
	LTG earnings forecasts	62,614	28.05

Note: This table reports the distributions of US equity analysts' countries of origin and the horizons of their earnings forecasts over the sample period from 2000 to 2014. In Panel A, each analyst is assigned to a single country that accounts for the largest fraction of US immigrants who share the analyst's surname. A total of 115 countries, representing the inferred origins of the sample analysts, are grouped into nine geographic regions (see Section 3.2). For each region, we report the two most common countries of origin and the mean of Hofstede's index of LTO for countries in the region. Only countries with nonmissing LTO values are considered. In Panel B, we classify earnings forecasts as short-term or long-term earnings forecasts, depending on whether the forecast horizon exceeds 1 year. Our sample analysts have at least one long-term earnings forecast issued for a firm in a year. A forecast of a particular horizon is counted for a firm-year if it is issued between the firm's prior and current annual earnings announcement dates.

We use both measures of analysts' production of long-term information, as described in Section 3.3, as the dependent variable in Equation (1). Our key variable of interest, *Long-term orientation*, is the weighted average of Hofstede's indices of LTO for analyst *i*'s countries of origin reflected in their surname. We expect a positive coefficient on *Long-term orientation*.

We include the following four sets of control variables. The first set includes other cultural dimensions: Hofstede's cultural dimensions of *Individualism*, *Indulgence*, *Masculinity*, *Power distance*, and *Uncertainty avoidance* (Geert Hofstede et al. 2010); *Cultural optimism* (Gallagher et al. 2013); and *Societal trust* (Bhagwat and Liu 2020). The second set includes analyst and firm characteristics, including *All star*, *Book-to-market*, *Brokerage size*, *Female analyst*, *Firm size*, *Firm-specific experience*, *General experience*, *Institutional ownership*, *Intangibles*, *Capital expenditures*, *Leverage*, *Momentum*, *Number of analysts following*, *Number of firms*, *Number of forecast items*, *Number of industries*, *Return on assets*, and *Segments* (e.g., Chan et al. 2018; J. Jung et al. 2019). The third set of variables controls for an individual analyst's biographical characteristics, including indicator variables for the following: *Education in USA*, *Academic major in business*, *Academic major in STEM*, *MBA degree*, *CPA or CFA*, *Related industry experience*, *Favorable surname*, and *No profile on LinkedIn*. We hand-collect this set of variables from analysts' profiles on LinkedIn and complement the data using Revelio. Of the 3797 unique individual analysts in our sample, 1556 (41.0%) have a LinkedIn profile. Untabulated analysis shows that *Long-term orientation* is not significantly different between subsamples of analysts with and without LinkedIn profiles. All continuous variables are winsorized at the 1% and 99% levels. Detailed definitions are in the Appendix.

In addition to the above control variables, our fourth set of control variables includes firm, broker, and year fixed effects, which mitigate confounding effects of, for example, an analyst's employer, workplace, or other time-invariant firm characteristics and time trends. We also include firm × year interacted fixed effects, which allow us to compare analysts following the same firm in the same year and thereby substantially mitigate correlated omitted variable concerns. We cluster standard errors by both firm and year (Petersen 2009).

4 | Results

4.1 | Descriptive Statistics

Panel A of Table 2 reports descriptive statistics for the variables in Equation (1). We report summary statistics based on our sample of 223,195 firm-year-analyst observations. Our primary variable of interest, *Long-term orientation*, has a mean and median of 50.4 and 46.4, respectively.[12] For other indicator variables of analyst characteristics, their distributions are in line with those in prior research (e.g., Kumar 2010; J. Jung et al. 2019). For example, 11.7% of our sample observations are from *All star* analysts, and 11.3% are from female analysts.[13] In Panel B of Table 2, we report summary statistics for LinkedIn variables using a subsample of 1556 unique analysts who have LinkedIn profiles. Conditional on having LinkedIn profiles, 74.0% of our sample analysts have an undergraduate degree from a US university (*Education in USA*), 44.1% have a business major (*Academic major in business*), 35.3% have an MBA degree (*MBA degree*), and 17.6% have a CPA license or a CFA designation (*CPA or CFA*).[14]

4.2 | Issuance of Long-Term Forecasts

Panel A of Table 3 reports the results of estimating Equation (1) using *Weighted forecast horizon* as the dependent variable. Consistent with our expectation, the coefficient on *Long-term orientation* is positive and significant across all four columns with varying sets of control variables and fixed effects, indicating that higher-LTO analysts have a longer forecast horizon. The result is also economically meaningful. For example, the result in Column 4 indicates that moving from the lowest to the highest LTO regional mean is associated with a 4% increase in the weighted forecast horizon relative to its sample mean.[15] It also shows that a one-standard-deviation increase in *Long-term orientation* is associated with an increase in the weighted forecast horizon by 3.7% of its standard deviation.[16] The magnitude of this effect is comparable to that of a change in other major analyst characteristics, such as whether an analyst is an all-star analyst in a year (*All star* = 1.3%), the number of years an analyst has followed a firm (*Firm-specific experience* = −7.7%), and the number of industries an analyst covers in a year (*Number of industries* = −3.8%).[17]

TABLE 2 | Descriptive statistics.

Panel A: Full sample ($N = 223{,}195$ firm-year-analysts)					
Variable	**Mean**	**SD**	**P1**	**Median**	**P99**
Long-term orientation	50.420	13.525	28.571	46.368	83.000
Weighted forecast horizon	1.739	0.365	1.200	1.636	3.143
LT issuance	1.843	0.952	1.000	2.000	5.000
Cultural optimism	7.517	0.491	6.218	7.724	8.240
Individualism	76.205	12.710	26.334	78.771	89.435
Indulgence	55.954	13.313	25.662	62.727	69.000
Masculinity	61.563	8.249	23.879	64.155	71.714
Power distance	41.958	10.569	30.636	37.469	78.259
Societal trust	33.621	6.066	21.019	32.417	56.984
Uncertainty avoidance	51.888	15.520	32.245	45.750	90.729
All star	0.117	0.322	0.000	0.000	1.000
Book-to-market	0.493	0.439	−0.232	0.399	2.927
Brokerage size	64.060	56.671	1.000	47.000	252.000
Female analyst	0.113	0.317	0.000	0.000	1.000
Firm size	14.678	1.719	10.974	14.605	18.848
Firm-specific experience	4.541	3.529	1.000	3.000	17.000
General experience	10.427	5.981	1.000	9.000	27.000
Institutional ownership	0.570	0.363	0.000	0.695	1.000
Intangibles	0.188	0.197	0.000	0.122	0.749
Capital expenditures	0.061	0.063	0.003	0.040	0.337
Leverage	0.218	0.197	0.000	0.193	0.865
Momentum	0.216	0.644	−0.793	0.114	3.276
Number of analysts following	18.288	10.754	2.000	16.000	49.000
Number of firms	16.115	6.832	3.000	15.000	38.000
Number of forecast items	2.177	0.787	1.000	2.000	4.000
Number of industries	3.784	2.291	1.000	3.000	11.000
Return on assets	0.020	0.154	−0.768	0.049	0.257
Segments	2.501	2.165	0.000	1.000	9.000
Education in USA	0.391	0.488	0.000	0.000	1.000
Academic major in business	0.219	0.414	0.000	0.000	1.000
Academic major in STEM	0.081	0.273	0.000	0.000	1.000
MBA degree	0.185	0.388	0.000	0.000	1.000
CPA or CFA	0.105	0.306	0.000	0.000	1.000
Related industry experience	0.051	0.219	0.000	0.000	1.000
Favorable surname	0.252	0.434	0.000	0.000	1.000
No profile on LinkedIn	0.478	0.500	0.000	0.000	1.000

(Continues)

TABLE 2 | (Continued)

Panel B: Subsample of analysts whose LinkedIn profiles are successfully found (N = 1556 unique analysts)					
Variable	**Mean**	**SD**	**P1**	**Median**	**P99**
Education in USA	0.740	0.439	0	1	1
Academic major in business	0.441	0.497	0	0	1
Academic major in STEM	0.152	0.359	0	0	1
MBA degree	0.353	0.478	0	0	1
CPA or CFA	0.176	0.381	0	0	1
Related industry experience	0.098	0.298	0	0	1
No profile on LinkedIn	0.000	0.000	0	0	0

Note: This table presents descriptive statistics for the variables used in our main analyses. Panel A reports summary statistics based on the full sample of 223,195 firm-year-analyst observations from 2000 to 2014. Panel B reports summary statistics for LinkedIn-related variables, based on a subsample of 1556 unique analysts for whom LinkedIn profiles are successfully identified (i.e., *No profile on LinkedIn* = 0). All continuous variables are winsorized at the 1% and 99% levels. Variable definitions are provided in the Appendix.

Panel B of Table 3 reports the results of estimating Equation (1) using *LT issuance* as the dependent variable. For parsimony of presentation, we suppress the tabulation of all control variables.[18] Similar to the results in Panel A, the coefficient on *Long-term orientation* is positive and significant across all four columns, indicating that higher-LTO analysts are more likely to issue long-term earnings forecasts. In terms of economic significance, moving from the lowest to the highest LTO regional mean is associated with a 7.6% increase in *LT issuance* relative to its sample mean; and a one-standard-deviation increase in *Long-term orientation* increases *LT issuance* by 2.8% of its standard deviation, comparable to that of a change in other major analyst characteristics, such as *All star* (1.9%), *Firm-specific experience* (−3.7%), and *Number of industries* (−3.1%).

Despite the comprehensive set of controls included, concerns about potential correlated omitted variables can still arise from the analyst selection issue. For example, more long-term-oriented firms that invest more heavily in innovation may cater to higher-LTO analysts, creating a positive correlation between analysts' LTO and firm innovation. Given that analysts produce more long-term information for firms with more innovation (Bae et al. 2017), this may generate a spurious positive relation between analysts' LTO and their production of long-term information. Although the controls for firm characteristics such as intangibles and growth and firm fixed effects may mitigate this concern to some extent, firm innovation could vary over time, and these existing controls and fixed effects may fail to fully address this concern.

To further mitigate such concerns, we implement an even more stringent fixed effects control structure by replacing all firm controls with firm × year fixed effects. This interactive fixed effect structure controls for all time-variant and time-invariant firm characteristics and essentially compares analysts with different time orientations within the same firm-year.[19] The results are reported in Panel C of Table 3. We find that our results on both weighted forecast horizons and the issuance of long-term earnings forecasts continue to hold.[20,21] Taken together, the effect of LTO on analysts' issuance of long-term forecasts is robust to both time-varying and time-invariant firm characteristics. In addition, the cultural effect we document goes beyond what can be predicted by analysts' higher educational training, their professional skills and achievements, and them having surnames originating from countries favored by Americans.[22]

To further corroborate our inferences based on US analysts, we also conduct an analysis of non-US analysts. If our results based on US analysts are indeed attributable to cultural beliefs, then we should observe that non-US analysts' forecasting behavior is also aligned with their level of cultural LTO. We use I/B/E/S international data on analyst forecasts for non-US firms to construct a non-US sample. We assign cultural values to analysts using two different approaches: the first approach assigns cultural values to analysts based on the country location of the headquarters of the firms they cover, not on their names (thus not based on their ancestral country of origin), and the second approach assigns cultural values based on their surnames. These two approaches complement each other in providing support for our main inferences. To mitigate potential measurement error, particularly for the first approach of assigning the same country-level cultural values to all analysts covering firms in the same country, our non-US tests are confined to ethnically homogeneous countries whose percentage of international migrants relative to their total population is lower than the corresponding percentage for the United States in the same year.

TABLE 3 | Tests of issuance of long-term earnings forecasts.

Panel A: The weighted average of earnings forecast horizons				
Dep. var.:	***Weighted forecast horizon***			
	(1)	**(2)**	**(3)**	**(4)**
Long-term orientation	0.001**	0.001***	0.001***	0.001**
	(2.044)	(3.073)	(3.007)	(2.058)
Controls for culture				
Cultural optimism	0.010	0.015	0.012	−0.008
	(0.755)	(1.063)	(0.843)	(−0.692)
Individualism	−0.000	−0.000	0.000	−0.000
	(−0.252)	(−0.286)	(0.093)	(−0.652)
Indulgence	0.001**	0.001***	0.001***	0.001***
	(2.306)	(4.678)	(4.549)	(4.251)
Masculinity	0.001*	0.001**	0.001**	0.000
	(1.693)	(2.385)	(2.222)	(0.690)
Power distance	0.000	0.001	0.001	0.000
	(0.973)	(1.280)	(1.417)	(0.093)
Societal trust	0.001	0.000	0.000	0.000
	(0.822)	(0.510)	(0.728)	(0.553)
Uncertainty avoidance	0.000	0.001***	0.001***	0.000
	(0.819)	(3.045)	(3.009)	(0.427)
Controls for analyst and firm				
All star		0.064***	0.065***	0.015***
		(5.021)	(4.914)	(2.587)
Book-to-market		−0.002	−0.002	−0.005
		(−0.463)	(−0.429)	(−0.996)
Brokerage size		−0.000***	−0.000***	−0.001**
		(−5.489)	(−5.886)	(−2.102)
Female analyst		0.003	0.006	0.008
		(0.387)	(0.802)	(1.302)
Firm size		0.022***	0.022***	0.019***
		(5.693)	(5.703)	(5.173)
Firm-specific experience		−0.009***	−0.009***	−0.008***
		(−9.231)	(−9.110)	(−9.731)
General experience		−0.001***	−0.001***	−0.000
		(−3.755)	(−3.540)	(−1.572)
Institutional ownership		−0.039***	−0.038***	−0.037***
		(−3.586)	(−3.506)	(−3.532)
Intangibles		−0.011	−0.012	−0.012
		(−0.699)	(−0.746)	(−0.793)
Capital expenditures		0.032	0.031	0.020
		(0.792)	(0.764)	(0.548)

(Continues)

Panel A: The weighted average of earnings forecast horizons				
Dep. var.:	***Weighted forecast horizon***			
	(1)	**(2)**	**(3)**	**(4)**
Leverage		−0.006	−0.004	−0.009
		(−0.274)	(−0.214)	(−0.442)
Momentum		0.007**	0.007**	0.007**
		(2.104)	(2.088)	(2.094)
Number of analysts following		−0.002***	−0.002***	−0.002***
		(−4.156)	(−4.115)	(−4.754)
Number of firms		0.001*	0.001	0.000
		(1.782)	(1.559)	(0.662)
Number of forecast items		0.098***	0.099***	0.115***
		(22.485)	(22.771)	(25.901)
Number of industries		−0.010***	−0.009***	−0.006***
		(−8.327)	(−8.159)	(−5.620)
Return on assets		−0.032**	−0.032**	−0.030*
		(−2.076)	(−2.075)	(−1.936)
Segments		−0.002*	−0.002*	−0.001
		(−1.783)	(−1.886)	(−1.414)
Education in USA			0.003	0.003
			(0.496)	(0.750)
Academic major in business			−0.009	−0.010*
			(−1.453)	(−1.877)
Academic major in STEM			−0.012	0.002
			(−1.327)	(0.256)
MBA degree			−0.012**	−0.014**
			(−2.050)	(−2.498)
CPA or CFA			0.032***	0.023***
			(5.077)	(3.736)
Related industry experience			0.011*	0.011
			(1.771)	(1.313)
Favorable surname			0.004	0.000
			(0.797)	(0.043)
No profile on LinkedIn			−0.034***	−0.028***
			(−4.752)	(−4.881)
Year FE	Yes	Yes	Yes	Yes
Brokerage FE	No	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	223,195	223,195	223,195	223,195
Adj. R^2	0.210	0.262	0.265	0.339

(Continues)

TABLE 3 | (Continued)

Panel B: The likelihood of issuing long-term earnings forecasts				
Dep. var.:	***LT issuance***			
	(1)	**(2)**	**(3)**	**(4)**
Long-term orientation	0.002*	0.003***	0.003***	0.002**
	(1.957)	(3.297)	(3.150)	(2.147)
Controls and FE	Identical to the corresponding column in Panel A			
Observations	223,195	223,195	223,195	223,195
Adj. R^2	0.153	0.248	0.250	0.322

Panel C: Including firm × year fixed effects				
Dep. var.:	***Weighted forecast horizon***		***LT issuance***	
	(1)	**(2)**	**(3)**	**(4)**
Long-term orientation	0.001***	0.001**	0.003***	0.002**
	(3.268)	(2.265)	(3.221)	(2.253)
Control variables	Yes	Yes	Yes	Yes
Brokerage FE	No	Yes	No	Yes
Firm × year FE	Yes	Yes	Yes	Yes
Observations	223,195	223,195	223,195	223,195
Adj. R^2	0.296	0.375	0.279	0.354

Note: This table presents OLS regression results testing analysts' production of long-term earnings information. The dependent variables are the weighted average of the horizons of annual earnings forecasts (*Weighted forecast horizon*) in Panel A, the likelihood of issuing long-term earnings forecasts (*LT issuance*) in Panel B, and both measures in Panel C. Long-term earnings forecasts include 2- to 7-year-ahead earnings forecasts and LTG earnings forecasts. The variable of interest is *Long-term orientation*, measured as the weighted average of Hofstede's indices of LTO for an analyst's inferred countries of origin, based on US immigration records. Control variables in Panel B are identical to those in the corresponding columns of Panel A. Control variables in Panel C are identical to those in Column 4 of Panel A, excluding variables that do not vary within a firm-year due to collinearity (i.e., *Book-to-market*, *Firm size*, *Institutional ownership*, *Intangibles*, *Capital expenditures*, *Leverage*, *Momentum*, *Number of analysts following*, *Return on assets*, and *Segments*). All continuous variables are winsorized at the 1% and 99% levels. Variable definitions are provided in the Appendix. *t*-statistics based on standard errors clustered by firm and year are presented in parentheses.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 presents the results of the non-US analyst sample. We exclude control variables not available for the non-US analyst sample (*All star*, *Female analyst*, *Segments*, and LinkedIn-related variables) from this set of analyses. Instead, we additionally include *GDP growth* and *GDP per capita* (both GDP data from the World Bank) to control for country characteristics. Control variables that do not vary within a firm-year (e.g., *Book-to-market*, *Firm size*, *Intangibles*) are excluded in Columns 3 and 6, when we use firm × year fixed effects together with broker fixed effects. We cluster standard errors by firm and year. Columns 1 and 4 of Table 4 present results using country-level cultural values, and Columns 2, 3, 5, and 6 present the results using analyst-level cultural values. Consistent with our results for US analysts, we find positive and significant coefficients on *Long-term orientation* for both dependent variables of *Weighted forecast horizon* and *LT issuance*.

In untabulated tests, we also explore whether the results vary across different generations of immigrants. Prior research suggests that the impact of inherited cultural values is likely to be the strongest for early generation immigrants and tends to attenuate over successive generations (e.g., Guiso et al. 2006, 2008; Malmendier and Nagel 2011). To test this, we construct an indicator variable *High gen immigrant*, that equals 1 if an analyst has an American-sounding full name and a US bachelor's degree, and 0 otherwise, and interact this indicator variable with *Long-term orientation* in Equation (1).[23] The coefficients on *Long-term orientation* × *Higher gen immigrant* are significantly negative across all specifications, consistent with the attenuation of the impact of analysts' inherited cultural LTO over generations (Fernández 2011).

TABLE 4 | Cross-country tests using non-US analysts.

Dep. var.:	***Weighted forecast horizon***			***LT issuance***		
Level of cultural measures:	**Country**	**Analyst**	**Analyst**	**Country**	**Analyst**	**Analyst**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Long-term orientation	0.001**	0.001**	0.000**	0.002***	0.002***	0.001***
	(2.521)	(2.488)	(2.364)	(2.749)	(2.753)	(3.052)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes	No
Broker FE	No	No	Yes	No	No	Yes
Industry FE	Yes	Yes	No	Yes	Yes	No
Country FE	No	Yes	No	No	Yes	No
Firm × Year FE	No	No	Yes	No	No	Yes
Observations	401,821	422,856	427,360	401,821	422,856	427,360
Adj. R^2	0.146	0.157	0.495	0.185	0.194	0.487

Note: This table presents OLS regression results testing the production of long-term earnings information by non-US analysts. The sample includes 427,360 non-US firm-year-analyst observations from 2000 to 2014. The tests are restricted to ethnically homogeneous countries, where the proportion of international migrants relative to the total population is lower than that of the United States in the same year. The dependent variables are *Weighted forecast horizon* and *LT issuance*. Long-term earnings forecasts include 2- to 7-year-ahead earnings forecasts and LTG earnings forecasts. The variable of interest is *Long-term orientation*. In Columns 1–4, *Long-term orientation* is measured using Hofstede's index of LTO for the non-US country in which the headquarters of a firm that an analyst follows is located. In Columns 2, 3, 5, and 6, *Long-term orientation* is based on Hofstede's indices of LTO for an analyst's inferred countries of origin, identified using US immigration records linked to the analyst's surname. Control variables for cultural characteristics (*Cultural optimism*, *Individualism*, *Indulgence*, *Masculinity*, *Power distance*, *Societal trust*, and *Uncertainty avoidance*) are constructed analogously to *Long-term orientation* using the relevant cultural indices. Control variables for analyst and firm characteristics include *Book-to-market*, *Brokerage size*, *Firm size*, *Firm-specific experience*, *General experience*, *Institutional ownership*, *Intangibles*, *Capital expenditures*, *Leverage*, *Momentum*, *Number of analysts following*, *Number of firms*, *Number of forecast items*, *Number of industries*, *Return on assets*, and *Favorable surname*. Control variables for country characteristics include *GDP per capita* and *GDP growth*. In Columns 3 and 6, we exclude control variables that do not vary within a firm-year due to collinearity (i.e., *Book-to-market*, *Firm size*, *Institutional ownership*, *Intangibles*, *Capital expenditures*, *Leverage*, *Momentum*, *Number of analysts following*, *Return on assets*, *GDP per capita*, and *GDP growth*). All continuous variables are winsorized at the 1% and 99% levels. Industry fixed effects are based on two-digit SIC codes. Variable definitions are provided in the Appendix. *t*-statistics based on standard errors clustered by firm and year are presented in parentheses.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

4.3 | Accuracy of Long-Term Forecasts

To the extent that higher-LTO analysts invest more in collecting and analyzing long-term information, they should be better positioned to produce higher-quality long-term forecasts. We examine this empirically by estimating forecast accuracy of different forecast horizons in the following regression:

$$\begin{aligned} \textit{Forecast accuracy}_{ijt} = \alpha_0 + \beta_1 \textit{ High LTO}_{ijt} + \Sigma\, \gamma' \textit{Controls for culture}_{ijt} + \Sigma\, \delta' \textit{Controls for analyst}_{ijt} \\ + \textit{Brokerage fixed effects}, \textit{Firm} \times \textit{Year fixed effects} + \varepsilon_{ijt}. \end{aligned} \tag{2}$$

We calculate individual analyst-level forecast accuracy across multiple horizons, from 1 to 7 years ahead, as well as for LTG forecasts. When an analyst issues multiple forecasts for the same horizon, we use the analyst's most recent forecast issued prior to the firm's earnings announcement date in the current year. Forecast accuracy for earnings forecasts is measured as −1 multiplied by the absolute difference between the analyst's forecasted EPS and the firm's actual EPS for the respective horizon, scaled by stock price 2 trading days prior to the forecast date. For LTG forecasts, accuracy is computed as −1 multiplied by the absolute difference between the forecasted and actual LTG rate of earnings. Since LTG forecasts are expressed as percentages, this metric does not require scaling by stock price. Following prior studies (e.g., Bradshaw et al. 2006), the actual LTG rate is computed as the geometric growth rate implied by the equation:

$$EPS\,(t) = EPS\,(0) \times (1+r)^t, \tag{3}$$

where r is the actual (realized) LTG rate. EPS (0) is the initial actual EPS for the current year, and EPS (t) is the last available EPS observed within a 5-year period. We require that EPS (0) and EPS (t) are at least 3 years apart.[24]

We define an indicator variable, *High LTO*, for analysts with LTO scores greater than the sample median. The regression includes the same control variables and fixed effects as in Column 4 of Panel C of Table 3, excluding those that do not vary within a firm-year (e.g., *Firm size* and *Book-to-market*). We include brokerage and firm × year fixed effects, and additionally include *Past Accuracy* to control for the analyst's past forecasting performance.

Results are presented in Table 5. Due to limited sample sizes for longer-horizon forecasts, we pool 4- to 7-year-ahead earnings forecasts and report their combined results in Column 4.[25] Consistent with our prediction that higher-LTO analysts' investment in long-term information gathering and analysis will enable them to produce more accurate long-term forecasts, the coefficients on *High LTO* for 2- and 3-year-ahead earnings forecasts, as well as that for LTG forecasts, are all significantly positive at the 5% level or better. The coefficient on *High LTO* for 1-year-ahead earnings forecasts is insignificant, consistent with the view that LTO is more relevant for long-term forecasting.

4.4 | Analysts' Questions in Conference Call Q&A

Conference calls are an important information exchange platform between managers and analysts. We employ a textual analysis of the Q&A section of conference call transcripts to provide more direct evidence of the relation between analysts' LTO and their information gathering as well as managers' responses to their questions. We obtain speaker-level transcripts of conference call data between 2008 and 2014 from the Capital IQ database.[26] We measure the time horizon of an analyst's questions, *Analyst question horizon*, as the ratio of long-term-oriented keywords to short-term-oriented keywords in the analyst's questions during the Q&A section of a firm's quarterly earnings conference call. Following Brochet et al. (2015), long-term-oriented keywords are long-term (or long term), long-run (or long run), year(-s or annual[-ly]), look(-ing) ahead, and outlook; and short-term-oriented keywords are short-run (or short run), short-term (or short term), day(-s or daily), week(-s or -ly), month(-s or -ly), and quarter(-s or -ly). Similarly, we measure the time horizon of a manager's responses to the same analyst's questions, *Manager response horizon*, as the ratio of long-term-oriented to short-term-oriented keywords in the manager's responses to the analyst's questions during the same conference call Q&A section.

TABLE 5 | Analyst forecast accuracy.

Dep. var.:	***Forecast accuracy***				
Forecast type:	***X*-year-ahead earnings forecast**				**LTG forecasts**
***X*=**	**1**	**2**	**3**	**4 to 7**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
High LTO	−0.000	0.003**	0.006**	0.914	0.306***
	(−1.029)	(1.972)	(2.135)	(0.961)	(2.581)
Control variables	Yes	Yes	Yes	Yes	Yes
Brokerage FE	Yes	Yes	Yes	Yes	Yes
Firm×year FE	Yes	Yes	Yes	Yes	Yes
Observations	203,560	202,812	84,416	26,291	39,635
Adj. R^2	0.756	0.922	0.934	0.296	0.921

Note: This table presents OLS regression results testing individual analyst-level forecast accuracy across multiple horizons, from 1 to 7 years ahead, as well as for LTG forecasts. For each horizon, we use the analyst's most recent forecast issued prior to the firm's earnings announcement date. The dependent variable is *Forecast accuracy*, measured using Equations (2) and (3). The variable of interest is *High LTO*, an indicator equal to 1 if an analyst's *Long-term orientation* is above the sample median, and 0 otherwise. In Column 4, we pool 4- to 7-year-ahead earnings forecasts and report the combined results. Control variables are identical to those in Table 3, Panel C, Column 4, excluding those that do not vary within a firm-year due to collinearity (i.e., *Book-to-market*, *Firm size*, *Institutional ownership*, *Intangibles*, *Capital expenditures*, *Leverage*, *Momentum*, *Number of analysts following*, *Return on assets*, and *Segments*). We additionally control for *Past accuracy* and include brokerage fixed effects and firm×year fixed effects. All continuous variables are winsorized at the 1% and 99% levels. Variable definitions are provided in the Appendix. t-statistics based on standard errors clustered by firm and year are reported in parentheses.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

To examine the relation between analysts' LTO and their questions as well as managerial responses in conference calls, we estimate a modified version of Equation (1) by replacing the dependent variables with *Analyst question horizon* and *Manager response horizon*, respectively. We augment our baseline regression model of Equation (1) by adding the following eight call-specific control variables: *Horizon in the presentation section*, *Number of words in the call*, *Tone of the call*, *Number of participants in the call*, *Quarterly loss*, *Negative quarterly earnings surprise*, *End-of-year call*, and *Days since fiscal quarter end*. When we test the time horizon in a manager's responses to the analyst's questions (*Manager response horizon*), we further control for the cultural background of the actual responding manager (e.g., CEO, CFO, or IR manager) by including *Manager long-term orientation*, *Manager individualism*, *Manager indulgence*, *Manager masculinity*, *Manager power distance*, and *Manager uncertainty avoidance*, as well as three CEO characteristics: *CEO duality*, *CEO tenure*, and *Female CEO*.[27] Control variables that do not vary within a firm-conference call are dropped in Columns 2 and 4, when we use firm × year-quarter fixed effects together with broker fixed effects. We cluster standard errors by firm and year-quarter.

For our conference call tests, we use a sample of 58,204 firm-quarter-analysts. We report the results in Table 6. We examine the time horizon of an analyst's questions in Columns 1 and 2 and a manager's responses to the analyst's questions in Columns 3 and 4. The coefficients on *Long-term orientation* across all four columns are significantly positive, suggesting that higher-LTO analysts ask more long-term-oriented questions and that managers respond to their questions by offering more long-term information.[28] In terms of control variables, we find that most of the coefficients for call-specific control variables are significant (see Supporting Information S1 for all coefficients on control variables). For example, based on the result in Column 1, *Horizon in the presentation section* (i.e., a ratio of long-term-oriented to short-term-oriented keywords used in the presentation section prior to the Q&A section) has a positive and significant coefficient, suggesting that analysts are more likely to ask long-term-oriented questions when the firm provides more long-term information in its presentation section. *Number of participants in the call* has a negative and significant coefficient, suggesting that analysts are less likely to ask long-term-oriented questions when more people participate in the call. *Negative quarterly earnings surprise* also has a negative and significant coefficient, suggesting that analysts seek more information on short-term outcomes when a firm has bad earnings news in the quarter. *End-of-year call* has a positive and significant coefficient, suggesting that analysts ask more about a firm's long-term prospects during its year-end (fourth quarter) conference call.

Notably, we find that an analyst's LTO continues to have a positive and significant relation to the analyst's question horizon and manager response horizon when we include firm × year-quarter fixed effects. This shows that higher-LTO analysts ask more long-term-oriented questions and that managers provide more long-term information in their responses when we compare analysts participating in the same conference call for a given firm-quarter, thereby controlling for all call-specific characteristics as well as time-varying firm characteristics. Overall, the results based on the Q&A sections of conference calls provide more direct evidence in support of our hypothesis that higher-LTO analysts produce more long-term information.

In untabulated analyses, we examine the relationship between analysts' LTO and the informativeness of their post-call forecasts. To assess the informativeness, we estimate the market reaction to analysts' 2-year-ahead earnings forecast revisions issued immediately after conference calls. We define *Forecast revision* as the change in an analyst's 2-year-ahead earnings forecasts for the same fiscal year, scaled by the stock price 2 trading days prior to the forecast date. To ensure relevance, we restrict the sample to each analyst's first forecast revision issued within 30 days following the call. The dependent variable is the absolute value of cumulative abnormal returns over the (0,+1) trading day window surrounding the forecast revision date, |*CAR(0,+1)*|, where trading day 0 is the revision date. Abnormal returns are calculated using the Fama-French three-factor model plus the momentum factor (Carhart 1997), via Eventus. Our key independent variable is the analyst's LTO (*Long-term orientation*). The regression model includes analyst-, firm-, and call-level controls, as well as fixed effects for year-quarter, brokerage house, and firm as in Column 1 of Table 6. Additional control variables include the magnitude of the forecast revision (|*Forecast revision*|), the number of days until the target fiscal year-end (*Days until fiscal year end*), and the absolute value of the most recent quarterly earnings surprise (|*Quarterly earnings surprise*|). We find a positive and significant coefficient on *Long-term orientation*, suggesting that higher-LTO analysts who participated in the call issue more informative long-term forecast revisions following the call. Our results are robust to additionally controlling for the magnitude of the analyst's concurrent revision of 1-year-head earnings forecasts.

4.5 | Analysts' Valuation Models

To corroborate our findings based on earnings forecast and conference call analyses, we hand-collect a random sample of 400 full analyst reports to examine the relation between analysts' LTO and the valuation models they use.

TABLE 6 | Tests of analysts' questions and managers' responses in the Q&A sections of conference calls.

Dep. var.:	*Analyst question horizon*		*Manager response horizon*	
	(1)	(2)	(3)	(4)
Long-term orientation	0.003**	0.003**	0.005**	0.005***
	(1.962)	(2.277)	(2.423)	(3.053)
Controls for culture, analyst, and firm	Yes	Yes	Yes	Yes
Controls for conference call	Yes	No	Yes	No
Controls for responding manager and CEO	No	No	Yes	No
Year-quarter FE	Yes	No	Yes	No
Brokerage FE	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Firm × year-quarter FE	No	Yes	No	Yes
Observations	57,363	58,204	50,854	58,204
Adj. R^2	0.057	0.115	0.078	0.164

Note: This table presents OLS regression results testing the effect of analysts' LTO on the time horizon of analysts' questions (Columns 1 and 2) and managers' responses to their questions (Columns 3 and 4) during the Q&A sections of firms' quarterly earnings conference calls. In Columns 1 and 2, the dependent variable is *Analyst question horizon*, defined as the ratio of long-term-oriented to short-term-oriented keywords in an analyst's questions during the Q&A section (see Section 4.4). In Columns 3 and 4, the dependent variable is *Manager response horizon*, defined as the ratio of long-term-oriented to short-term-oriented keywords in a manager's responses to the analyst's questions during the same Q&A section (see Section 4.4). A manager's response is identified as the instance in which a manager speaks immediately after an analyst's question. The variable of interest is *Long-term orientation*, measured as Hofstede's indices of LTO for an analyst's inferred countries of origin, identified through US immigration records. Control variables for culture, analyst, and firm characteristics are identical to those in Table 3, Panel A, Column 4. In Columns 1 and 3, we additionally control for conference call characteristics, including *Horizon in the presentation section*, *Number of words in the call*, *Tone of the call*, *Number of participants in the call*, *Quarterly loss*, *Negative quarterly earnings surprise*, *End-of-year call*, and *Days since fiscal quarter end*. Column 3 further includes control variables for the cultural background of the responding manager (e.g., CEO, CFO, or IR manager), including *Manager long-term orientation*, *Manager individualism*, *Manager indulgence*, *Manager masculinity*, *Manager power distance*, and *Manager uncertainty avoidance*, as well as CEO characteristics, including *CEO duality*, *CEO tenure*, and *Female CEO*. In Columns 2 and 4, control variables that do not vary within a firm-conference call are excluded due to collinearity. All continuous variables are winsorized at the 1% and 99% levels. We use Capital IQ to obtain conference call transcripts between 2008 and 2014. Variable definitions are provided in the Appendix. *t*-statistics based on standard errors clustered by firm and year-quarter are presented in parentheses.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Specifically, we begin by randomly selecting 200 I/B/E/S recommendation observations associated with higher-LTO analysts—defined as those with LTO scores above the sample median. To strengthen identification, for each report from a higher-LTO analyst, we randomly draw a report for the same firm from a lower-LTO analyst (LTO score at or below the sample median). This procedure yields a random sample of 200 firm-level matched pairs (400 reports in total), enabling a within-firm comparison of valuation model usage across analysts with differing levels of LTO. Using information on firm name, analyst name, recommendation date, and rating, we locate and download the corresponding full analyst reports from Refinitiv Eikon. After downloading all 400 analyst reports, we read each report to identify the type of valuation models used to justify the price target. We also collect the names of all authors on the report to construct variables for analyst team-level characteristics.

The results are reported in Table 7. Panel A shows the number and percentage of analyst reports that use market multiples, such as P/E (price/earnings) and EV/EBITDA, to justify price targets. We find that 95.5% (= 191/200) of higher-LTO analysts' reports and 98.0% (= 196/200) of lower-LTO analysts' reports use market multiples for company valuation. The difference is not statistically significant (chi-square = 1.99, *p*-value = 15.9%). This result indicates that virtually all analysts use market multiples in valuation.

In Panel B, we compare the number and percentage of analyst reports that use sophisticated discounted valuation models (e.g., DCF and residual income models), which explicitly incorporate expectations of firms' long-term performance. Interestingly, we find that 31.5% (= 63/200) of higher-LTO analysts' reports use such valuation models

TABLE 7 | Comparison of analysts' valuation models: evidence from analysts' reports.

Panel A: Number (%) of analyst reports using market multiples (e.g., P/E and EV/EBITDA)		
	High LTO reports	**Low LTO reports**
	(1)	**(2)**
	191 (95.5%)	196 (98.0%)
Test for equality of two proportions (1)–(2):	−2.5% (Chi-square = 1.99, p = 15.9%)	

Panel B: Number (%) of analyst reports using discounted models (e.g., DCF and residual income model)		
	High LTO reports	**Low LTO reports**
	(1)	**(2)**
	63 (31.5%)	41 (20.5%)
Test for equality of two proportions (1)–(2):	11.0%** (Chi-square = 6.29, p = 1.2%)	

Panel C: Analysts' choice of justifications for price targets in their reports				
Dep. var.:	***Market multiples*** **(e.g., P/E and EV/EBITDA)**		***Discounted models*** **(e.g., DCF and residual income)**	
	(1)	**(2)**	**(3)**	**(4)**
High LTO report	−0.075**	−0.099***	0.221*	0.286***
	(−2.023)	(−2.610)	(1.857)	(2.811)
Controls for culture	Yes	Yes	Yes	Yes
Controls for analyst, firm	No	Yes	No	Yes
Controls for valuation uncertainty and analyst team	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	400	400	400	400
Adj. R^2	0.006	0.042	0.042	0.109

Note: This table presents summary statistics and OLS regression results testing the effect of analysts' LTO on their choice of valuation models for price targets in their research reports, using a random sample of 400 analyst reports. The random sample consists of 200 randomly drawn matched pairs (200 High LTO reports and 200 Low LTO reports), each from the same firm. A report is classified as a High (Low) LTO report if it is issued by an analyst whose *Long-term orientation* is higher than (equal to or lower than) the sample median. *Long-term orientation* is measured as Hofstede's indices of LTO for an analyst's inferred countries of origin, identified through US immigration records. Panel A reports the number and percentage of High LTO versus Low LTO reports that use market multiples (e.g., P/E and EV/EBITDA) to justify price targets. Panel B reports the number and percentage of High LTO versus Low LTO reports that use discounted models (e.g., DCF and residual income models) to justify price targets. Panel C presents OLS regression results. The dependent variables are *Market multiples*, an indicator variable equal to 1 if a report uses a market multiple to justify a price target, and 0 otherwise; and *Discounted models*, an indicator variable equal to 1 if a report uses a discounted valuation model, and 0 otherwise. The variable of interest is *High LTO report*. Control variables for culture, analyst, and firm characteristics are identical to those in Column 4 of Panel A, Table 3. Additional control variables for valuation uncertainty include *Past earnings management*, *Past cash flow volatility*, and *Past loss*. Additional control variables for analyst team characteristics include *Analyst team report*, *Team diversity in education*, *Team diversity in experience*, and *Team diversity in gender*. All continuous variables are winsorized at the 1% and 99% levels. Industry fixed effects are based on two-digit SIC codes. Analyst reports are retrieved from Refinitiv Eikon. Variable definitions are provided in the Appendix. t-statistics based on standard errors clustered by firm and year are presented in parentheses.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

compared with 20.5% (= 41/200) for lower-LTO analysts' reports. The difference of 11.0% is statistically significant at the 5% level (two-tailed).

In Panel C, we run OLS regressions with the dependent variable *Market multiples* or *Discounted models*, indicators for using market multiples and discounted models, respectively. The variable of interest is *High LTO report*, an indicator for a higher-LTO analyst's report. In Columns 2 and 4, we include all controls for culture, analyst, and firm characteristics used in Column 4 of Panel A, Table 3. In addition, we add *Past earnings management*, *Past cash flow volatility*, and *Past loss* to control for earnings quality and firm risk (e.g., Huang et al. 2023) and *Analyst team report*, *Team diversity in education*, *Team diversity in experience*, and *Team diversity in gender* to control for analyst team-level characteristics (e.g., Fang and Hope 2021). We include year and two-digit SIC industry fixed effects,[29] and we cluster standard errors by firm and year.

In Columns 1 and 2, the dependent variable is *Market multiples*. We find negative and significant coefficients on *High LTO report* in both columns, suggesting that higher-LTO analysts are less likely to use market multiples such as P/E and EV/EBITDA to justify target prices. In Columns 3 and 4, when the dependent variable is *Discounted models*, we find positive and significant coefficients on *High LTO report* in both columns. The results suggest that higher-LTO analysts are more likely to use sophisticated discounted valuation models that require inputs for firms' long-term performance. In terms of control variables, we find a positive and significant coefficient on *Analyst team report* (i.e., an indicator variable equal to 1 if a report is associated with more than one author, and 0 otherwise) in Column 4, consistent with prior findings that analyst teams are more likely to use DCF models (Fang and Hope 2021). Overall, the evidence provides additional support to the hypothesis that analysts' cultural LTO is positively related to the use and production of long-term information.[30]

4.6 | Profitability of Stock Recommendations

We use a calendar-time hedge portfolio return approach to examine the profitability of stock recommendations. First, we classify analysts into High LTO versus Low LTO analyst groups in equal size based on the sample median of LTO. Following Barber et al. (2001), at the end of each Monday, we calculate the mean recommendation (level) for each firm. The consensus is calculated separately for High LTO and Low LTO analyst groups. Based on the consensus recommendation, a firm is assigned to one of five portfolios and remains in the same portfolio until the following Monday when the consensus is recalculated.[31] Using the I/B/E/S five-point rating scale (1 = *strong buy*, 2 = *buy*, 3 = *hold*, 4 = *sell*, and 5 = *strong sell*), we calculate the mean consensus and assign firms to one of the following five portfolios: P5 (most favorable), for which consensus ≤ 1.5; P4, for which $1.5 <$ consensus < 2; P3, for which $2 \leq$ consensus < 2.5; P2, for which $2.5 \leq$ consensus < 3; and P1 (least favorable), for which consensus ≥ 3.[32]

Following prior research (e.g., Barber et al. 2001; Cohen et al. 2010), we calculate a monthly return for each portfolio by compounding the portfolio's value-weighted daily returns over the trading days of each month. Then, for each combination of an analyst group and a portfolio (e.g., High LTO analysts × P1 [most favorable]), we estimate the following monthly time-series regression to compute the abnormal return (estimated intercept, α) using the Fama-French six-factor model (Fama and French 2018):

$$R_p - R_f = \alpha + \beta(R_M - R_f) + s \cdot SMB + h \cdot HML + r \cdot RMW + c \cdot CMA + m \cdot MOM + \varepsilon. \tag{4}$$

In the model, $(R_p - R_f)$ represents the portfolio excess return, $(R_M - R_f)$ is the market excess return, *SMB* is the size factor, *HML* is the value factor, *RMW* is the profitability factor, *CMA* is the investment factor, and *MOM* is the momentum factor. The estimated intercept, α, captures the monthly abnormal return, adjusted for the six factors.

In Panel A of Table 8, we report monthly abnormal returns (%) of the five portfolios, separately for High LTO and Low LTO analyst groups. The results show that portfolios of the most favorable stocks (P5) and the least favorable stocks (P1) generate significantly positive and negative abnormal returns in the subsample of High LTO analysts. In contrast, using stock recommendations from Low LTO analysts, we only find significant and negative abnormal returns for P1 (least favorable stocks). The hedge portfolio return for High LTO analysts' stock recommendations amounts to 61 basis points *per month*, which translates into a nontrivial annualized return of 7.3%, compared with 31 basis points per month for Low LTO analysts' stock recommendations. The difference in hedge portfolio returns between High LTO and Low LTO analyst groups is statistically significant and amounts to 30 basis points *per month*. These results suggest that High LTO analysts issue more profitable stock recommendations than Low LTO analysts.

We further conduct cross-sectional tests to explore whether the incremental value of recommendations associated with LTO is stronger among firms where long-term information is more valuable. Higher-LTO analysts engage more in gathering and analyzing long-term information, so their long-term forecasts are more accurate (see Table 5), resulting in more profitable recommendations. This is especially true for firms facing higher levels of uncertainty about future performance and for firms with rapid growth and large amounts of intangible assets that contain, for example, brand values and patents, which are not well captured on balance sheets.

TABLE 8 | Calendar-time portfolio returns for stock recommendations.

Panel A: Full sample analysis

Level of mean consensus	**High LTO analysts (1)**	**Low LTO analysts (2)**	**High LTO − Low LTO (3)**
Monthly abnormal return (six-factor alpha, %):			
P5 (most favorable)	0.397**	0.120	0.277*
	(2.294)	(0.710)	(1.959)
	[568, 360, 1172]	[587, 399, 1182]	
P4	0.186	0.122	0.065
	(1.098)	(0.610)	(0.413)
	[225, 110, 418]	[235, 110, 410]	
P3	0.132	0.231*	−0.099
	(0.833)	(1.659)	(−1.451)
	[1017, 778, 1229]	[1042, 832, 1339]	
P2	0.088	0.120	−0.032
	(0.541)	(0.769)	(−0.384)
	[483, 319, 636]	[478, 332, 635]	
P1 (least favorable)	−0.216**	−0.191**	−0.025
	(−2.440)	(−2.297)	(−0.359)
	[962, 687, 1267]	[949, 666, 1242]	
P5 − P1	0.613***	0.311	0.302**
	(3.097)	(1.626)	(2.410)

Panel B: Subsample analysis for volatile firms

Subsamples:	***Sales volatility***		***Asset volatility***		***Earnings volatility***	
	High (1)	**Low (2)**	**High (3)**	**Low (4)**	**High (5)**	**Low (6)**
High LTO − Low LTO (corresponds to P5 − P1, Panel A, Column 3)	0.308**	0.183	0.285**	0.158	0.270*	0.250**
	(2.193)	(1.042)	(1.985)	(1.181)	(1.943)	(2.136)

Panel C: Subsample analysis for growth-oriented, intangible-heavy firms

Subsamples:	***Book-to-market***		***Intangibles***		***Innovation***	
	High (1)	**Low (2)**	**High (3)**	**Low (4)**	**High (5)**	**Low (6)**
High LTO − Low LTO (corresponds to P5 − P1, Panel A, Column 3)	0.049	0.404**	0.219**	0.247	0.178	0.230
	(0.301)	(2.197)	(2.028)	(1.084)	(0.784)	(1.391)

Note: This table presents monthly abnormal returns (in percentages) from calendar-time portfolios formed based on analysts' mean consensus recommendations and their LTO. *Long-term orientation* is measured as Hofstede's indices of LTO for an analyst's inferred countries of origin, identified through US immigration records. Analysts are classified as High (Low) LTO analysts if their *Long-term orientation* score is above or equal to (below) the sample median. At the end of every Monday, we compute the mean consensus recommendation for each stock using I/B/E/S five-point rating scale (1 = *strong buy*, 2 = *buy*, 3 = *hold*, 4 = *sell*, and 5 = *strong sell*) and assign the stock into one of five portfolios based on the consensus: P5 (most favorable), for which consensus ≤ 1.5; P4, for which 1.5 < consensus < 2; P3, for which 2 ≤ consensus < 2.5; P4, for which 2.5 ≤ consensus < 3; and P1 (least favorable), for which 3 ≤ consensus. The stock remains in the same portfolio until the following Monday, when the consensus is recalculated and the stock is moved between portfolios, as necessary (i.e., weekly rebalancing). The calculation of the consensus and the portfolio formation are done separately for High LTO versus Low LTO analysts. Portfolio returns are value weighted. Following Barber et al. (2001), daily returns for each portfolio are compounded over trading days of the month to calculate a monthly return. We estimate the monthly time-series regression in Equation (4) to compute the Fama-French six-factor alpha (estimated intercept, α). Panel A presents the full sample results. In square brackets, we report the average, minimum, and maximum number of firms per month for each portfolio. Panel B presents results for subsamples split by *Sales volatility*, *Asset volatility*, and *Earnings volatility*. Panel C reports results for subsamples split by *Book-to-market*, *Intangibles*, and *Innovation*. All subsamples are constructed annually using the sample median of each firm characteristic, measured in December of year $t-1$. Variable definitions are provided in the Appendix. t-statistics based on standard errors clustered by calendar month are presented in parentheses.
***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

We capture uncertainty of future performance using three proxies: *Sales volatility*, *Asset volatility*, and *Earnings volatility*. We capture growth-oriented and intangible-heavy firms using three proxies: *Book-to-market*, *Intangibles*, and *Innovation* (i.e., number of patents filed by a firm in a year). In December of year $t-1$, firms are split into two subsamples based on the yearly median value of the most recent firm characteristics available to the market. We repeat the same analysis in Panel A separately for each subsample and report the results in Panels B and C of Table 8. For brevity, we only report the difference in hedge portfolio returns between the High and Low LTO analyst groups, which corresponds to the value for "P5 – P1" in Column 3 of Panel A.

Consistent with our expectations, we find that the superior performance of High LTO analysts' recommendations is stronger for firms with more volatile performance (in Panel B) and for firms that are growth-oriented or intangible-heavy (in Panel C). Hedge portfolio returns using High LTO analysts' recommendations are 31, 29, and 27 basis points *per month* higher than those using Low LTO analysts' recommendations in the high sales, asset, and earnings volatility subsamples, respectively. In contrast, we find no significant difference in the low volatility subsamples. Panel C shows stronger results in two of three subsamples: firms that are growth-oriented or intangible-heavy.[33] Taken together, these results indicate that higher-LTO analysts issue more profitable recommendations, especially for firms with greater uncertainty or value tied to long-term performance.

5 | Conclusions

We examine how analysts' inherited cultural orientation toward time—specifically, LTO—influences their production of long-term information and the value of their stock recommendations. We find that higher-LTO analysts issue forecasts with longer horizons and are more likely to produce long-term estimates. They also produce more accurate long-term forecasts, but not necessarily more accurate short-term forecasts, suggesting a specific comparative advantage in long-horizon forecasting. To more directly assess information gathering, we analyze earnings call Q&A sections and find that higher-LTO analysts ask more long-term-focused questions, prompting managers to disclose more long-term information in response.

We further hand-collect data on analysts' valuation models from analyst reports and find that higher-LTO analysts are more likely to use discounted valuation models that explicitly incorporate long-term assumptions. Importantly, consistent with the notion that higher-LTO analysts are better equipped to incorporate long-term information into valuations, stock recommendations from higher-LTO analysts generate higher abnormal returns, particularly for firms with greater sales or asset volatility, lower book-to-market ratios, and more intangible assets—settings where long-term forecasting is especially valuable.

Our study contributes to three strands of literature. First, we advance the emerging literature on LTO in capital markets by identifying a determinant of long-horizon information production—analysts' inherited cultural values—and documenting its economic benefits. While prior research has focused largely on the costs of corporate short-termism, we provide new evidence on the drivers and value of LTO among key information intermediaries. Second, we contribute to the growing literature on the influence of inherited cultural attributes on financial decision-making. Finally, we offer new insights into how analyst behavior influences managerial disclosure. Our findings show that long-term-oriented analysts can elicit more long-term information from management, suggesting that not all analyst coverage contributes to short-termism.

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Data Availability Statement

All data used are from public and commercially available sources cited in the article.

Endnotes

[1] Geert Hofstede, along with others, developed a cultural index of LTO; this index is hereafter referred to as Hofstede's index.

[2] See Endnote 1.

[3] See, example, Bradley, Gokkaya, and Liu (2017), Bradley, Gokkaya, Liu, and Xie (2017), Andres et al. (2024), and Li and Wang (2025) for prior research that has used LinkedIn data.

[4] Our sample period ends in 2014 due to data availability constraints. Historical US immigration records (from www.ancestry.com) and supplementary analyst identity data are only available through 2014. We thank Alok Kumar for generously sharing his data on analyst first names and name-based foreignness scores, which fully covers our sample period. According to our correspondence, first names were manually collected using the I/B/E/S Broker Translation File (discontinued after 2009) and sources such as Nelson's directory, Yahoo Finance, Factiva, and Google (Kumar 2010). The foreignness scores were calculated via online surveys, following the methodology outlined in Kumar et al. (2015). We use a vintage version of I/B/E/S downloaded in May 2015 to obtain analysts' surnames.

[5] Following J. Jung et al. (2019, app. A), we trim the original immigration records by regrouping immigrants' nationalities into a standardized set of 115 countries of origin and correcting minor typographic errors in the records.

[6] As a robustness check, we also infer an analyst's country of origin using an alternative classification based on OnoMap, which assigns individuals to the most likely ancestral origin based on full names, drawing on databases such as telephone directories and electoral registers (e.g., Mateos et al. 2011; Ellahie et al. 2017). In untabulated tests, we repeat our main analyses using country classifications inferred via OnoMap and find similar results.

[7] Geert Hofstede et al. (2010) provide the full list of LTO scores for 93 countries in their tab. 7.4.

[8] For example, surname Yamamoto is associated with a total of four countries. In order of dominance, Japan, Great Britain, Germany, and France account for the nationality of 99.5%, 0.3%, 0.1%, and 0.1% of US immigrants whose surname is Yamamoto. Therefore, our weighted measure of *Long-term orientation* for analyst Yamamoto is calculated as 0.995×88 (Japan's LTO) $+ 0.003 \times 51$ (Great Britain's LTO) $+ 0.001 \times 83$ (Germany's LTO) $+ 0.001 \times 63$ (France's LTO), which corresponds to 87.86.

[9] Some analysts have North American countries as their countries of origin. This occurs as the US historical immigration records are based on nationalities reported by passengers entering the United States between 1820 and 1957, a period that includes or precedes the founding of the United States (1776) and Canada (1867). The average cultural value of LTO for North American countries is 31.00, as reported in Panel A of Table 1.

[10] Suppose Analysts A and B each issue 10 forecasts for a firm in a year. Analyst A issues ten 1-year-ahead forecasts, whereas Analyst B issues seven 1-year-ahead forecasts and three 2-year-ahead forecasts. The weighted average of forecast horizons for Analyst A is calculated as $(10/10) \times 1$, which equals 1 year. The weighted average of the forecast horizons for Analyst B is calculated as $(7/10) \times 1 + (3/10) \times 2$, which equals 1.3 years.

[11] One potential concern is that I/B/E/S may be incomplete with regard to long-term forecasts. If I/B/E/S omits more long-term forecasts from lower-LTO analysts than for higher-LTO analysts, this could bias our findings. To address this, we follow B. Jung et al. (2012) to cross-check I/B/E/S data against analysts' reports in two random samples: 100 reports from higher-LTO analysts and 100 reports from lower-LTO analysts. I/B/E/S indeed misses some long-term forecasts and growth forecasts (7.8% for 3-year-ahead and 9.9% for LTG). However, missing rates are somewhat higher for higher-LTO analysts than for lower-LTO analysts (11.1% vs. 4.9% for 3-year-ahead and 13.9% vs. 5.7% for LTG). Thus, this I/B/E/S incompleteness issue is likely to bias against our findings.

[12] Hofstede's index of LTO is assigned to a country on a relative scale of 0 (lowest) to 100 (highest).

[13] Identifying the country of origin from surnames may be problematic for a female analyst who changes her surname to her husband's surname. Our results are robust to excluding female analysts (untabulated).

[14] Because analysts often list their licenses and certifications in different sections of their LinkedIn profiles (e.g., education, employer, and job title), we augment our hand-collected LinkedIn data with the Revelio database, which provides LinkedIn records. We find that 17.6% of our sample analysts hold a CPA license or a CFA designation. This figure is somewhat lower than the 23% for CFA (3% for CPA) reported in Andres et al. (2024) (see also De Franco and Zhou 2009). In addition to differences in sample composition, variation in the timing of LinkedIn data retrieval may also affect summary statistics. For example, we find that the number of user profiles in Revelio can fluctuate significantly across monthly updates (e.g., user counts can drop by as much as 24% between months).

[15] It is calculated as $(91.67 - 21.90)$ (Table 1) $\times 0.001$ (coefficient on *Long-term orientation*)/1.739 (mean of *Weighted forecast horizon*) $= 0.040$.

[16] It is calculated as 0.001 (coefficient on *Long-term orientation*) $\times 13.525$ (standard deviation of *Long-term orientation*)/0.365 (standard deviation of *Weighted forecast horizon*) $= 0.037$.

[17] For *All star*, it is calculated as 0.015 (its coefficient) $\times 0.322$ (its standard deviation)/0.365 (standard deviation of *Weighted forecast horizon*) $= 0.013$. For *Firm-specific experience*, it is calculated as -0.008 (its coefficient) $\times 3.529$ (its standard deviation)/0.365 (standard deviation of *Weighted forecast horizon*) $= -0.077$. For *Number of industries*, it is calculated as -0.006 (its coefficient) $\times 2.291$ (its standard deviation)/0.365 (standard deviation of *Weighted forecast horizon*) $= -0.038$.

[18] We provide full regression tables with all coefficients on control variables in the Supporting Information S1.

[19] In untabulated tests, we examine the relation between analysts' LTO and firm characteristics. We estimate OLS regression models in which the dependent variables are (1) *%High LTO analysts*, the fraction of analysts with above-median LTO following a firm in a given year, and (2) *Mean analyst LTO*, the average LTO of all analysts covering a firm-year. Independent variables include *Book-to-market*, *Firm size*, *Institutional ownership*, *Intangibles*, *Capital expenditures*, *Leverage*, *Momentum*, *Number of analysts following*, *Return on assets*, *Segments*, *R&D spending* (a ratio of R&D expenses to operating expenses), *Innovation* (the number of patents filed by a firm in year), *Sales volatility*, and *CEO long-term orientation*. We include year fixed effects. We find preliminary evidence that higher-LTO analysts tend to cover firms with low book-to-market ratios and higher R&D spending. However, we emphasize that these results should be interpreted with caution, as the associations become insignificant once firm fixed effects are included.

[20] We further test the robustness of our results by excluding female analysts and restricting our sample to analysts with American-sounding first names but non-US cultural last names. We define American-sounding first names as those among the top 100 most popular US baby first names from 1917 to 2016, based on data from the US Social Security Administration (www.ssa.gov). Non-US cultural surnames are identified as those for which the largest share of US immigrants bearing the surname originated from a non-US country. We reestimate Equation (1) using the specification in Column 4, Panel C, of Table 3. We find that our results remain robust.

[21] In untabulated tests, we follow J. Jung et al. (2019) and construct *CEO-Analyst cultural distance* (the mean absolute difference in all six of Hofstede's cultural indices between a CEO and an analyst) as well as *CEO-Analyst LTO distance* (the absolute difference between a CEO's LTO and an analyst's LTO). Although our sample size decreases substantially from 223,195 to 185,723, we find that our results remain qualitatively the same.

[22] In untabulated tests, we compare the proportion of covered firms for which each analyst issues at least one long-term forecast. While nearly all analysts issue 2-year-ahead forecasts for most firms, higher-LTO analysts are modestly more likely to issue longer-horizon (3- to 7-year-ahead) forecasts than lower-LTO analysts (mean = 0.468 vs. 0.444; median = 0.471 vs. 0.434). We also conduct a "style" analysis, following Bamber et al. (2010), and find that analyst fixed effects related to long-term forecasting are significantly associated with LTO. However, the explanatory power of this analysis is very low, pointing to the role of other first-order determinants.

[23] We obtain foreignness scores for the full names of our sample analysts from Alok Kumar, who constructed the scores following Kumar et al. (2015). To identify analysts with US educational backgrounds, we rely on LinkedIn data. If an analyst does not list a bachelor's degree from a US institution, we assume the analyst did not receive such a degree (i.e., *Education in USA* = 0). Our approach may introduce measurement error if analysts with a US degree chose not to disclose such information on LinkedIn and are thus misclassified as recent immigrants. However, such misclassification is likely to bias against finding a difference between recent and nonrecent immigrants.

[24] Results are similar if we compute the actual LTG rate using (1) the slope coefficient from an OLS regression of log(*actual EPS*) on year, excluding nonpositive EPS values; or (2) the arithmetic mean of yearly EPS growth rates over the next 5 years (e.g., Bradshaw et al. 2006).

[25] The individual sample sizes for 4- to 7-year-ahead forecasts are 15,485, 8198, 2065, and 543, respectively. In untabulated tests, we estimate the regression separately for each sample and find no significant results.

[26] Capital IQ provides data on speaker-level transcripts of the Q&A sections of conference calls from 2008.

[27] If multiple managers respond to an analyst's questions during a call, we use the average of the responding managers' cultural values. CEO data are obtained from ExecuComp and BoardEx.

[28] In untabulated tests, we examine the relation between the horizon of an analyst's questions and the horizon of managers' responses to this analyst's questions. The results confirm that managers do provide more long-term-focused responses when analysts ask more long-term-oriented questions.

[29] We use industry fixed effects mainly due to the small sample size. To ensure that our results are not sensitive to this choice (Bratten and Larocque 2024), we also use firm fixed effects and find similar results (untabulated).

[30] To evaluate whether higher-LTO analysts consistently apply sophisticated models across firms, we conduct a follow-up analysis. From the 400-report sample, we randomly select 10 reports authored by higher-LTO analysts that used a sophisticated valuation model. For each of these analysts, we then retrieve one additional report for every other firm covered by the same analyst in the same year. This procedure yields 146 additional reports across the 10 analysts. We find that 89.6% of these follow-up reports also used a sophisticated valuation model, suggesting that higher-LTO analysts tend to use such models consistently across most of the firms they cover.

[31] Our results are robust to different rebalancing frequency (daily and monthly).

[32] If analysts use different rating scales, I/B/E/S converts their ratings into its five-point format. Using the five-point scale allows us to form five portfolios in line with those used in prior studies (e.g., Barber et al. 2001). Furthermore, similar to Barber et al. (2001), we set the portfolio cutoffs so that only the lowest portfolio captures firms with unfavorable consensus ratings, such as hold or sell. This approach balances the need for sufficient statistical power with the goal of achieving meaningful separation across recommendation levels.

[33] In untabulated analysis, we find similar cross-sectional results on analysts' long-term forecast accuracy: the positive effect of LTO on long-term forecast accuracy is concentrated in firms with high sales volatility and high intangible assets—settings where long-term forecasting is more difficult and potentially more valuable.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** care70058-sup-0001-supinfo.docx.

Appendix

Variable Definitions

Variable	Definition
Key test variables: LTO and analysts' information horizons	
Long-term orientation	The weighted average of Hofstede's cultural indices of LTO, calculated based on the analyst's inferred countries of origin. These countries are identified by matching the analyst's surname to the nationalities of US immigrants who entered through the port of New York between 1820 and 1957. For countries with nonmissing Hofstede's indices, weights are assigned according to the frequency with which each nationality is associated with the surname in the immigration records. (*Source:* Hofstede, I/B/E/S, US immigration records)
LT issuance	The sum of issuance indicators for an analyst's long-term earnings forecasts for a firm in a year. For each type of long-term forecast (i.e., 2- to 7-year-ahead earnings forecasts and LTG forecasts), issuance is defined as an indicator that equals 1 if the analyst issues at least one forecast of that type for a firm in a year, and 0 otherwise. (*Source:* I/B/E/S)
Weighted forecast horizon	The weighted average of the forecast horizons in an analyst's annual earnings forecasts for a firm in a year. Forecasts for 1- to 7-year-ahead earnings are assigned horizons of 1–7 years, respectively. Long-term earnings growth forecasts are assigned a horizon of 3 years. Each horizon is weighted by the frequency with which the analyst issues forecasts of that specific horizon for a firm in a year. (*Source:* I/B/E/S)
Cultural dimension variables	
Cultural optimism	The weighted average of optimism scores from Gallagher et al. (2013), based on the analyst's inferred countries of origin. The variable is constructed using the same surname-nationality matching and weighting procedures described for *Long-term orientation*. (*Source:* Gallagher et al. (2013), I/B/E/S, US immigration records)
Individualism	The weighted average of Hofstede's cultural indices of individualism, based on the analyst's inferred countries of origin. The variable is constructed using the same surname-nationality matching and weighting procedures described for *Long-term orientation*. (*Source:* Hofstede, I/B/E/S, US immigration records)

Variable	Definition
Indulgence	The weighted average of Hofstede's cultural indices of indulgence, based on the analyst's inferred countries of origin. The variable is constructed using the same surname-nationality matching and weighting procedures described for *Long-term orientation*. (*Source:* Hofstede, I/B/E/S, US immigration records)
Masculinity	The weighted average of Hofstede's cultural indices of masculinity, based on the analyst's inferred countries of origin. The variable is constructed using the same surname-nationality matching and weighting procedures described for *Long-term orientation*. (*Source:* Hofstede, I/B/E/S, US immigration records)
Power distance	The weighted average of Hofstede's cultural indices of power distance, based on the analyst's inferred countries of origin. The variable is constructed using the same surname-nationality matching and weighting procedures described for *Long-term orientation*. (*Source:* Hofstede, I/B/E/S, US immigration records)
Societal trust	The weighted average of WVS trust scores, based on the analyst's inferred countries of origin. The variable is constructed using the same surname-nationality matching and weighting procedures described for *Long-term orientation*. A trust score is measured as the percentage of survey participants responding "Most people can be trusted" to the WVS question: "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?" For each country, we use the average of trust scores from three different WVS waves (2000–2004, 2005–2009, and 2010–2014), spanning our sample period. (*Source:* I/B/E/S, US immigration records, WVS)
Uncertainty avoidance	The weighted average of Hofstede's cultural indices of uncertainty avoidance, based on the analyst's inferred countries of origin. The variable is constructed using the same surname-nationality matching and weighting procedures described for *Long-term orientation*. (*Source:* Hofstede, I/B/E/S, US immigration records)
Firm-level variables	
Book-to-market	The ratio of a firm's book value of equity to its market value of equity in a year. (*Source:* Compustat, CRSP)
Capital expenditures	The ratio of capital expenditures to total assets for a firm in a year. (*Source:* Compustat)
Earnings volatility	The standard deviation of earnings before extraordinary items over the past 3 years. (*Source:* Compustat)
Firm age	The number of years for which a firm's stock price has appeared in CRSP. (*Source:* CRSP)
Firm size	The natural logarithm of a firm's market capitalization (in thousands) in a year. (*Source:* CRSP)
Institutional ownership	The average percentage of shares held by 13F institutional investors across the four quarters of a firm in a year. (*Source:* CRSP, FactSet)
Intangibles	The ratio of intangible assets to total assets for a firm in a year. (*Source:* Compustat)
Leverage	The ratio of total debts (short-term and long-term) to total assets for a firm in a year. (*Source:* Compustat)
Momentum	The 12-month cumulative return for a firm in the preceding year. (*Source:* CRSP)
Number of analysts following	The number of analysts following a firm in a year. (*Source:* I/B/E/S)
Return on assets	The ratio of net income to total assets for a firm in a year. (*Source:* Compustat)
Segments	The number of reported business segments for a firm in a year. (*Source:* Compustat)
Analyst-level variables	
Academic major in business	An indicator that equals 1 if an analyst holds a bachelor's degree in business or economics, and 0 otherwise. (*Source:* LinkedIn)
Academic major in STEM	An indicator that equals 1 if an analyst holds a bachelor's degree in science, technology, engineering, or mathematics, and 0 otherwise. (*Source:* LinkedIn)
All star	An indicator that equals 1 if an analyst is elected as an all-star analyst by the *Institutional Investor* magazine in a year, and 0 otherwise. (*Source:* I/B/E/S, Institutional Investor)

Variable	Definition
Brokerage size	The number of analysts working for a brokerage firm in a year. (*Source:* I/B/E/S)
CPA or CFA	An indicator that equals 1 if an analyst is a certified public accountant (CPA) or a chartered financial analyst (CFA), and 0 otherwise. (*Source:* LinkedIn)
Education in USA	An indicator that equals 1 if an analyst holds a bachelor's degree from a university in the United States, and 0 otherwise. (*Source:* LinkedIn)
Favorable surname	An indicator that equals 1 if an analyst has a surname that belongs to the top quartile of surname favorability in a year, and 0 otherwise. Following J. Jung et al. (2019), surname favorability is measured as the weighted average of favorability ratings for an analyst's countries of origin, identified through the nationalities of US immigrants with the same surname. The favorability rating is the percentage of people who answered "very favorable" or "mostly favorable" to Gallup's survey question: "I'd like your overall opinion of some foreign countries. Is your overall opinion of the following country very favorable, mostly favorable, mostly unfavorable, or very unfavorable?" The most recent favorability ratings available prior to each earnings announcement date are used. Countries with nonmissing ratings are assigned weights based on the frequency with which the US immigrants with the same surname reported those nationalities. (*Source:* Gallup, I/B/E/S, US immigration records)
Female analyst	An indicator that equals 1 if an analyst is female, and 0 otherwise. (*Source:* I/B/E/S, Nelson's directory)
Firm-specific experience	The number of years an analyst has issued 1-year-ahead earnings forecasts for a firm. (*Source:* I/B/E/S)
General experience	The number of years an analyst has appeared in I/B/E/S. (*Source:* I/B/E/S)
MBA degree	An indicator that equals 1 if an analyst holds an MBA degree, and 0 otherwise. (*Source:* LinkedIn)
No profile on LinkedIn	An indicator that equals 1 if an analyst does not have a LinkedIn profile, and 0 otherwise. (*Source:* LinkedIn)
Number of firms	The number of firms an analyst follows in a year. (*Source:* I/B/E/S)
Number of forecast items	The number of forecast items an analyst issues for a firm in a year, out of the following four items: earnings, cash flows, LTG, and target price. (*Source:* I/B/E/S)
Number of industries	The number of two-digit SIC industries an analyst follows in a year. (*Source:* CRSP, I/B/E/S)
Related industry experience	An indicator that equals 1 if an analyst follows a firm in a year that belongs to the same industry as any of the analyst's previous employers, and 0 otherwise. Industries are defined using 24 industry groups based on the four-digit Global Industry Classification System (GICS) codes. Up to four employers prior to the analyst's entry to the financial industry are considered. (*Source:* CRSP, LinkedIn)
Country-level variables	
GDP growth	The percentage change (%) in GDP per capita for the country in which the headquarters of a firm that an analyst follows is located, in a year. (*Source:* World Bank)
GDP per capita	The natural logarithm of GDP per capita in current US dollars for the country in which the headquarters of a firm that an analyst follows is located, in a year. (*Source:* World Bank)
Additional variables for forecast accuracy tests	
Forecast accuracy	For earnings forecasts, accuracy is measured as −1 times the absolute difference between the analyst's forecasted EPS and the firm's actual EPS for the respective horizon, scaled by the stock price 2 trading days before the forecast date. For LTG forecasts, accuracy is computed as −1 times the absolute difference between the forecasted and actual LTG rate of earnings. The actual LTG rate is calculated as the geometric growth rate implied by the equation: $EPS(t) = EPS(0) \times (1 + r)^{t}$, where r is the actual (realized) LTG rate, EPS (0) is the initial actual EPS for the current year, and EPS (t) is the last available EPS observed within a 5-year window. We require that EPS (0) and EPS (t) be at least 3 years apart. For each horizon, we use the analyst's most recent forecast issued prior to the firm's earnings announcement date. (*Source:* I/B/E/S, CRSP)

Variable	Definition
Past accuracy	Lagged accuracy of an analyst's 1-year-ahead earnings forecast. It is measured as −1 times the absolute difference between the analyst's forecasted EPS and the firm's actual EPS for the previous fiscal year, scaled by the stock price 2 trading days before the forecast date. We use the analyst's most recent 1-year-ahead earnings forecast issued prior to the firm's earnings announcement date for that year. (*Source:* I/B/E/S, CRSP)
Additional variables for conference call tests	
Analyst question horizon	The ratio of long-term-oriented to short-term-oriented keywords in an analyst's questions during the Q&A section of a firm's quarterly earnings conference call. Following Brochet et al. (2015), long-term-oriented keywords are long-term (or long term), long-run (or long run), year(-s or annual[-ly]), look(-ing) ahead, and outlook. Short-term-oriented keywords are short-run (or short run), short-term (or short term), day(-s or daily), week(-s or -ly), month(-s or -ly), and quarter(-s or -ly). (*Source:* I/B/E/S, Capital IQ)
Days since fiscal quarter end	The number of days between a firm's fiscal-quarter-end date and the date of its corresponding conference call. (*Source:* Capital IQ, Compustat)
End-of-year call	An indicator that equals 1 if the earnings conference call is for a firm's fiscal fourth quarter (Q4), and 0 otherwise. (*Source:* Capital IQ, Compustat)
Horizon in the presentation section	The ratio of long-term-oriented to short-term-oriented keywords in the presentation section of a firm's quarterly earnings conference call, based on keyword classifications from Brochet et al. (2015). (*Source:* Capital IQ)
Manager individualism	The manager-level counterpart of *Individualism*, calculated using the actual responding manager's (e.g., CEO, CFO, or IR manager) surname instead of the analyst's. (*Source:* Capital IQ, Hofstede, US immigration records)
Manager indulgence	The manager-level counterpart of *Indulgence*, calculated using the actual responding manager's surname instead of the analyst's. (*Source:* Capital IQ, Hofstede, US immigration records)
Manager long-term orientation	The manager-level counterpart of *Long-term orientation*, calculated using the actual responding manager's surname instead of the analyst's. (*Source:* Capital IQ, Hofstede, US immigration records)
Manager masculinity	The manager-level counterpart of *Masculinity*, calculated using the actual responding manager's surname instead of the analyst's. (*Source:* Capital IQ, Hofstede, US immigration records)
Manager power distance	The manager-level counterpart of *Power distance*, calculated using the actual responding manager's surname instead of the analyst's. (*Source:* Capital IQ, Hofstede, US immigration records)
Manager response horizon	The ratio of long-term-oriented to short-term-oriented keywords in a manager's responses to the analyst's questions during the Q&A section of a firm's quarterly earnings conference call. A manager's response is inferred as the instance of a manager speaking immediately after an analyst's question. Following Brochet et al. (2015), long-term-oriented keywords are long-term (or long term), long-run (or long run), year(-s or annual[-ly]), look(-ing) ahead, and outlook. Short-term-oriented keywords are short-run (or short run), short-term (or short term), day(-s or daily), week(-s or -ly), month(-s or -ly), and quarter(-s or -ly). (Source: I/B/E/S, Capital IQ)
Manager uncertainty avoidance	The manager-level counterpart of *Uncertainty avoidance*, calculated using the actual responding manager's surname instead of the analyst's. (*Source:* Capital IQ, Hofstede, US immigration records)
Negative quarterly earnings surprise	An indicator that equals 1 if a firm's actual quarterly earnings is below the analyst consensus forecast for the conference call quarter. The consensus is defined as the median of the most recent quarterly earnings forecasts issued by analysts in the 90 days prior to the earnings announcement date. (*Source:* I/B/E/S)
Number of participants in the call	Natural logarithm of the number of participants in a firm's quarterly earnings conference call. (*Source:* Capital IQ)
Number of words in the call	Natural logarithm of the total word count in a firm's quarterly earnings conference call. (*Source:* Capital IQ)

Variable	Definition
Quarterly loss	An indicator that equals 1 if a firm reports negative earnings for the quarter of the conference call, and 0 otherwise. (*Source:* Compustat)
Tone of the call	The tone of a firm's quarterly earnings conference call, calculated as the number of positive keywords minus the number of negative keywords, scaled by the total number of positive and negative keywords used in the call. The list of positive and negative keywords is based on Loughran and McDonald (2011). (*Source:* Capital IQ)
CEO-level variables	
CEO duality	An indicator that equals 1 if the CEO also serves as the chair of the firm's board, and 0 otherwise. (*Source:* BoardEx, ExecuComp)
CEO tenure	The number of years since the individual became the firm's CEO. (*Source:* BoardEx, ExecuComp)
Female CEO	An indicator that equals 1 if the CEO is female, and 0 otherwise. (*Source:* BoardEx, ExecuComp)
Additional variables for valuation model tests	
Analyst team report	An indicator that equals 1 if an analyst report lists more than one author, and 0 otherwise. (*Source:* Refinitiv Eikon)
Discounted models	An indicator that equals 1 if an analyst's research report uses a discounted valuation model (e.g., DCF and residual income models) as a justification for a price target, and 0 otherwise. (*Source:* I/B/E/S, Refinitiv Eikon)
Market multiples	An indicator that equals 1 if an analyst's research report uses a market multiple (e.g., P/E, P/Sales, or EV/EBITDA) as a justification for a price target, and 0 otherwise. (*Source:* I/B/E/S, Refinitiv Eikon)
Past cash flow volatility	The standard deviation of a firm's quarterly operating cash flows, scaled by its total assets, calculated over the past 5 years ending in the preceding year. (*Source:* Compustat)
Past earnings management	Abnormal accruals for a firm in the preceding year, estimated using the Modified Jones Model (Dechow et al. 1995). (*Source:* Compustat)
Past loss	An indicator that equals 1 if a firm reports negative earnings in the preceding year, and 0 otherwise. (*Source:* Compustat)
Team diversity in education	A Herfindahl-based index capturing the diversity of undergraduate majors among the authors of an analyst report. It is calculated as 1 minus the sum of the squared proportions of authors whose degrees fall into one of three categories: (1) business and economics, (2) quantitative fields (e.g., math, engineering, and physics), and (3) other fields (e.g., history and English). (*Source:* Refinitiv Eikon, LinkedIn)
Team diversity in experience	The standard deviation of the authors' sell-side industry experience, scaled by the mean experience. Experience is defined as the number of years since each author entered the sell-side industry. (*Source:* Refinitiv Eikon, LinkedIn)
Team diversity in gender	An indicator that equals 1 if both male and female authors are listed on an analyst report, and 0 otherwise. (*Source:* Refinitiv Eikon, LinkedIn)
Additional variables for calendar-time portfolio return tests	
Asset volatility	The standard deviation of total assets over the past 3 years. (*Source:* Compustat)
Earnings volatility	The standard deviation of earnings before extraordinary items over the past 3 years. (*Source:* Compustat)
Innovation	The number of patents filed by a firm in a year. (*Source:* Kim and Valentine 2021)
Sales volatility	The standard deviation of sales revenues over the past 3 years. (*Source:* Compustat)

Note: This table provides variable definitions and data sources.