Analysts' cultural preferences: A new approach based on culture of firms under coverage

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This version: January 15, 2025

Abstract

Different from the traditional approach based on national culture, we innovatively uncover analysts' cultural preferences from the cultural values of firms in analysts' research portfolios. Using our new measure with analyst-year variations, we document a positive role played by analyst culture. We find that analysts with stronger culture issue more accurate earnings forecasts and profitable recommendations, and their forecasts are less optimistic or hasty. Furthermore, analyst culture influences firms under coverage in that cultural diversity in the analyst-base improves firms' information environment.

Keywords: Analyst cultural preference; Forecasting performance; Firm information environment; Cultural diversity

***EFM* classification:** 530, 710, 750

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1. Introduction

Sell-side financial analysts are crucial information producers in financial markets. Prior literature documents that national culture (Hofstede, 1983) of analysts' country of origin influences the quality of analysts' information production (Du et al., 2017; Cao et al., 2024) and the information environment of firms under coverage (Merkley et al., 2020). We innovatively adopt a bottom-up approach by measuring an analyst's cultural preference from the corporate culture of firms (Li et al., 2021, LMSY hereafter) under her research coverage. Our approach aligns with prior literature that quantifies mutual funds' ESG preference based on fund holdings (Cao et al., 2023).

Our measure of analyst cultural preference has two main advantages over the traditional measure based on national culture. First, our measure is micro-based, which shares certain aspects of information with the conventional macro-based measure yet contains richer information. Our validation results show that analysts' cultural preferences are only partly inherited from their culture of origin and are also acquired through their education and professional experience. Second, national culture is rather sticky, lacking time-series variations. In comparison, our measure varies from year to year as analyst's coverage changes or corporate culture of firms under coverage changes.

Our approach is motivated by the fact that analysts' coverage decisions are significantly influenced by their cultural preferences. We adopt the procedures below to construct a clean measure of cultural preference to reflect analysts' autonomous coverage decisions. (1) Given considerable variations in corporate cultural values across industries (Loughran et al., 2009; Li et al., 2021), we demean firms' cultural scores at the industry average level to obtain industry-adjusted corporate culture. (2) We aggregate industry-adjusted corporate cultural values across firms within an analyst's coverage portfolio in each analyst-year to obtain the analyst culture score. (3) To separate the voluntary aspect of analyst coverage decisions, we further demean the analyst culture score at the brokerage level. As such, positive cultural values assigned to an analyst indicate an above average preference for a specific cultural value. (4) We observe considerable variations in the dispersion of cultural values across analysts' research portfolios. We argue that an analyst who exclusively covers high-integrity firms in her portfolio is more indicative of a reliable cultural preference, compared to one who covers a range of firms with varying integrity values, even if the mean integrity levels are comparable. To capture this, we calculate the standard deviation of cultural scores among firms in an analyst's stock portfolio, with a lower standard deviation indicating a more reliable cultural preference from the analyst. (5) For each analyst's research portfolio, we normalize the average cultural value (after industry and brokerage adjustments from step 3) by dividing it by the standard deviation from step 4. This allows us to assign greater weight to analysts who exhibit a consistent preference for a specific cultural value.

We proceed with a series of tests to validate our cultural preference measure for analysts. We first compare our research portfolio-based measure with the national culture of the analysts' country of origin. To achieve this, we utilize two dictionaries, namely Ancestry.com and forebears.io, to match the surnames of analysts to their countries of origin (Cao et al., 2024). Our findings reveal a negative association between the value of *teamwork* in LMSY's corporate culture and the value of *individualism* in Hofstede (1983)'s national culture, consistent with Ramamoorthy and Flood (2004). In other words, our research portfolio-based culture measure exhibits similarities with the analysts' inherited national culture. The second validation test is motivated by Chen et al. (2017), who find that firms in countries characterized by high *individualism* and/or low *uncertainty-avoidance* tend to be more innovative. We find consistent evidence that analysts originated from countries with a high *individualism* culture and/or low *uncertainty-avoidance* culture exhibit a preference for firms with higher corporate cultures of *innovation*. Notably, our panel regression results show that a substantial portion of observed variations in our research portfolio-based analyst's preference is attributable to their professional experience and features of the brokerage house. This implies that national cultural heritage is just one of a multitude of factors in shaping analysts' cultural preferences.

After the validation, we proceed to investigate the impact of coverage-based analysts' cultural preferences on analysts' forecasting performance. Previous literature shows that firms with strong corporate culture have a positive impact on firms' performance (Li et al., 2021; Graham et al., 2022). Analysts are affiliated with brokerage houses as financial firms that specialize in information production. In the same vein, we argue that analysts with strong cultural preferences possess a self-imposed moral constraint, leading them to behave ethically and issue high-quality research reports. Therefore, we hypothesize that an analyst's cultural preference positively impacts her forecast performance.

According to LMSY, it is difficult to attribute business outcomes to specific cultural values. The high correlation among the five dimensions of corporate cultural values could lead to multicollinearity issues in the multivariate regression. Thus, we employ a principal component (PC) analysis and extract the first two PCs with eigenvalues higher than one: *PC1* indicates the overall strength of firm culture, and *PC2* measures firm tendency to prioritize growth and customer satisfaction over moral considerations. Our results show that analysts with a higher *PC1* issue more accurate forecasts and more profitable recommendations, and their forecasts are less optimistic or hasty. In addition, analysts with a higher *PC2* are more likely to issue optimistic, bold, and/or hasty forecasts. Our results echo the evidence documented in Cao et al. (2024) that analysts originating from individualistic national culture are more inclined to issue bold forecasts.

As important financial intermediaries, analysts collect, process, and produce information on firms under coverage. Merkley et al. (2020) document that analysts from different national cultural clusters bring diverse perspectives, beliefs, and skills to the information production, which improves the accuracy of consensus analyst forecasts. In a similar spirit, we hypothesize that diversity in analyst culture improves the information environment of firms under coverage, although the specific cultural dimension that enhances firm value remains uncertain (LMSY).

We measure the cultural diversity of the analyst-base using our measure of five-dimensional cultural preferences. We count the number of corporate culture dimensions covered by attentive analysts, and analysts ranked in the top 25% in a specific cultural dimension are defined as attentive. To alleviate the potential endogeneity concerns, we exclude the focal firm when calculating the analyst's portfolio cultural score. Empirically, we regress accuracy of consensus analyst forecasts (Merkley et al., 2020) and analysts' forecast dispersion (Drake et al., 2024) on the cultural diversity count using firm-year observations. Our findings reveal that firms followed by analyst-bases with diverse cultural preferences exhibit better information environment in that their consensus forecasts are more accurate, and analyst forecasts are more dispersed. Such evidence lends further support to the beneficial role played by analyst's culture.

In the last empirical test, we explore how cultural similarity between analysts and covered firms influences analysts' coverage decisions and forecast performance. Prior studies show that financial analysts perform better when making forecasts for firms in their ethic culture region (Du et al., 2017) and revise their forecasts more strongly to managers who share the same cultural background (Brochet et al., 2018). Our findings extend the prior literature by quantifying the cultural similarity between analysts and covered firms from all five cultural dimensions. Consistent with prior literature, we find that an analyst is more likely to cover a firm into her research portfolio if the firm's culture values align with her cultural preference after controlling for various determinants influencing observed analyst-firm pairings (Liang et al., 2008). Furthermore, we observe improved forecast accuracy and recommendation profitability when the cultural distance between analysts and covered firms is shortened.

Overall, our paper contributes to the literature in four perspectives. First of all, our study adds evidence to the broad literature exploring the impact of culture on financial market. Motivated by the five-dimensional Hofstede (1983) model of national culture, a substantial body of literature suggests that culture has a significant impact on various corporate decisions (Shao et al., 2013; Ahern et al., 2015; Boubakri and Saffar, 2016; El Ghoul and Zheng, 2016; Brochet et al., 2018), and ultimately, firm performance (Frijns et al., 2016). Our study, in particular, originates from a recent study by LMSY that constructs text-based corporate culture at the firm level. Our results pinpoint the value added by culture of financial analysts, which echoes the beneficial role of corporate culture documented by prior studies (Li et al., 2021; Graham et al., 2022). Financial intermediaries, as a distinct category of firms, may augment their value through the subtle influence of culture's "invisible hand."

Second, we propose a new approach to quantify the culture preference of financial analysts and show robust evidence that our new bottom-up approach is superior to the traditional top-down approach. Our results echo prior studies rely on the culture of analyst's country of origin to proxy for analyst cultural preference (Merkley et al., 2020; Cao et al., 2024) yet provide richer and direct implications. Our bottom-up approach has the potential to quantify the cultural preferences of other financial intermediaries such as mutual fund managers, investment bankers, commercial banks, and venture capitalists. Even the personal cultural preferences of firm managers or board members can be quantified based on the corporate culture of firms that they have been involved with.

Third, a growing literature reveals that analyst backgrounds and attributes, such as gender (Kumar, 2010), political contributions (Jiang et al., 2016), ethnicity (Du et al., 2017), and cultural trust beliefs (Bhagwat and Liu, 2020), influence their forecasting styles and performances. Our study adds to this literature by highlighting the influence of culture on analysts' research outputs. In particular, by principal component analysis, we find that analysts with strong culture have superior forecasting performance, and analysts who prioritize growth over morality are more inclined to opportunistic behaviors such as issuing optimistic, bold, or hasty forecasts. Such multifaceted evidence is made available due to the rich information contained in our new measure of analysts' cultural preferences.

Finally, our research documents additional evidence that cultural preferences of analysts have substantial influence on the firms under coverage. Our paper is relevant to Merkley et al. (2020) and Du et al. (2017), who measure cultural diversity and proximity based on analysts' ethnic origin, which is invariant over time. We extend this line of research by developing new measures of cultural diversity and similarity based on our new approach, which can and does change over time and across covered firms. In this way, our approach shed new light on the role of financial analysts in information production.

The remainder of this study is organized as follows. Section 2 discusses the methodology to construct our new measure of analyst cultural preference. Section 3 presents its impact on analysts' forecasting performance. Section 4 shows the impact of cultural diversity on the information environment of the covered firms. Section 5 presents the impact of cultural similarity on analyst forecasting performance. Section 6 concludes the paper.

2. Data and methodology

2.1 Data

As we quantify analysts' cultural preferences from the corporate culture values of firms under analysts' coverage, our primary data are corporate culture values at firm-year level from LMSY. Based on the transcripts of question-and-answer sessions in annual earnings conference calls disclosed by listed firms, LMSY score corporate culture for the five most recurring culture values: *integrity*, *teamwork*, *innovation*, *respect*, and *quality*. LMSY count the frequency of culture-related words and phrases. The culture dictionary is generated by the word embedding model, which is one of the latest machine learning techniques in textual analysis. The updated data of LMSY have 74,391 firm-year observations, which cover 8,995 unique firms and span the period from 2001 to 2021.[1] Such a large sample allows for a comprehensive analysis of analysts' cultural preferences across analysts and over time.

We collect analyst forecasts from I/B/E/S. Consistent with prior studies (Clement and Tse, 2005; Cao et al., 2024), we focus on one-year-ahead earnings forecasts exclusively. An analyst issues at least one earnings forecast for a specific firm in a given year to define "coverage." We require an analyst to cover at least two firms within a year. Firm-level characteristics and stock returns are obtained from COMPUSTAT and CRSP. Table 1 shows the definitions of variables used in this study.

[Insert Table 1 here]

2.2 Measuring analysts' cultural preferences

We calculate analyst cultural preference using the updated corporate cultural values from LMSY. Panel A of Table IA1 presents the summary statistics for each dimension of corporate cultural values. The culture of *Innovation* has the highest scores among the five dimensions, indicating that it is mentioned most frequently by managers during earning conference calls.[2] We observe considerable variations in cultural scores across industries. Panel B of Table IA1 highlights the top 10 industries for each cultural value categorized by Fama and French (1997) 48 industries. Interestingly, the tobacco industry, traditionally regarded as "sin" industries, ranks highly in *Integrity*. This aligns with Loughran et al. (2009)'s finding that managers in sin

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[1] We obtain the original and updated version of corporate culture data from Kai Li's website https://sites.google.com/view/kaili/finance-publications.

[2] Our summary statistics differ from Table 3 in LMSY, as we use the updated data of corporate culture in this study. In the update from 2018 to 2021, LMSY expand the size of dictionary, automate the filtering process with minimal human intervention, and aggregate the cultural scores by the calendar year instead of the fiscal year. Our statistics align with LMSY if we use the original version of data.

industries use more ethics-related words in their 10K financial reports than others.[3] A high *integrity* score does not necessarily imply that sin industries uphold high moral standards. Rather, it suggests that managers frequently use ethics-related terms during conference call Q&A sessions. This could highlight a specific risk that draws analysts' attention and warrants thorough discussion. Additionally, managers might deliberately choose culture-related words to engage in window dressing.

The business nature of an industry significantly influences the topics discussed. For instance, the drug industry scores high in *Teamwork*, as managers frequently mention collaboration during earnings calls. The business services and computer industries score high in *Innovation*, aligning with the stereotype of new economy sectors where technology drives competitiveness. The personal service industry ranks highest in *Respect*, highlighting the importance of empowering employees. The computer industry leads in *Quality*, reflecting a strong focus on quality management and delivering high-quality products or services. These observations underscore industry-specific cultural values shaped by the priorities emphasized by managers in different sectors.

To account for these cross-industry patterns in corporate cultural values, we adjust each firm's cultural scores by subtracting its yearly industry average. Thus, a positive cultural score indicates that a firm's manager mentions culture-related words more frequently than its peers. For example, in the sin industries, the gaming sector significantly increases its mentions of

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[3] For the readers' interest, panel C of Table IA1 shows the cultural values of the sin industries. On average, the *integrity* score of the sin industries (2.901) is higher than the mean value reported in Panel A (2.491), especially for tobacco (3.112) and gaming (3.196) stocks. The gaming industry is a subset of the fun industry, which is ranked the top 8 industry in terms of *integrity* (Panel B). These sin stocks place greater emphasis on integrity, i.e., accountability, ethic, and responsibility. This emphasis may serve to address investors' concerns, as they might shy away from such stocks due to prevailing social norms.

ethics-related words in 10Ks during the post-SOX period (Loughran et al., 2009). Despite this, Wynn Resorts Ltd stands out, ranking second among S&P 500 companies for integrity-related mentions in earnings calls (LMSY). This adjustment also enhances comparability across the five cultural dimensions. We then calculate the average of industry-adjusted corporate cultural values across firms within an analyst's research portfolio. A higher average indicates the analyst's stronger cultural preference in a particular cultural dimension.

Our approach to uncovering an analyst's cultural preference assumes that her research portfolio reflects her autonomous selection of firm coverage. However, an analyst may not have complete control over her coverage decisions (Pacelli, 2019). Unreported summary statistics reveal substantial variations in the aggregated cultural values across brokerages, suggesting that brokerage cultural preferences might influence analysts' coverage decisions. To address this issue, we further adjust analysts' industry-adjusted cultural scores by subtracting the brokerage average each year. A positive brokerage-adjusted cultural score indicates that the analyst covers firms with higher industry-adjusted cultural scores than the average analyst in the brokerage. We also explicitly control for brokerage average culture in subsequent tests.

Further scrutinization reveals that the dispersion of cultural values across firms within an analyst's research portfolio varies among analysts. We argue that an analyst's cultural preference is considered more reliable when she covers a range of firms with consistent cultural values in a specific dimension. This logic aligns with Hilary and Hsu (2013), who propose that analysts with lower standard deviations in forecast errors exhibit higher forecast consistency. Therefore, we calculate the dispersion of cultural scores across firms in an analyst's research portfolio and use this dispersion to standardize the mean of industry- and brokerage-adjusted cultural values in her portfolio. In this way, an analyst is considered to have stronger preference if she follows firms with lower dispersions in a particular cultural dimension. For example, if an analyst follows 3 firms, each with a high *Integrity* score of 3, her preference for integrity is deemed reliable. Conversely, if the scores vary widely (e.g., 1, 3, and 5), her preference is considered unreliable, even if the average score is the same.

To summarize, we follow five steps to calculate an analyst's cultural preference. (1) For each firm *i* in year *t*, we adjust its cultural score in dimension *k* by the industry mean for that year. (2) For each analyst *j* in year *t*, we calculate the average of industry-adjusted culture score in dimension *k* (from step 1) based on firms in her coverage portfolio. (3) For each brokerage house in year *t*, we calculate the average of analysts' cultural scores (from step 2) in dimension *k*. We then adjust analysts' cultural scores (from step 2) by subtracting the brokerage average. This industry- and brokerage-adjusted analyst's cultural score is denoted as μ_{jtk} for analyst *j* in dimension *k* in year *t*. (4) For each analyst *j* in year *t*, we calculate the standard deviation of cultural scores of her research portfolios in dimension *k* (from step 3) to get σ_{jtk}. A lower σ_{jtk} suggests more consistent cultural preference. (5) We use the ratio μ_{jtk}/σ_{jtk} as our ultimate measure to capture analyst *j*'s cultural preference in dimension *k* in year *t*.

[Insert Table 2 here]

Our dataset of analysts' cultural preferences comprises 47,562 analyst-year observations, covering 8,693 analysts over a 20-year span from 2002 to 2021. Table 2 shows summary statistics for each cultural dimension. After adjusting for industry and brokerage averages, the magnitudes of the five cultural dimensions are comparable. The negative average values are statistically indistinguishable from zero.

2.3 Validation against national culture

Readers might question whether analysts' coverage decisions are too noisy to accurately reflect their cultural preferences. To address this, we have meticulously removed industry- and brokerage-common components from analysts' research portfolios, aiming to isolate the voluntary aspect of their coverage decisions. In this subsection, we further validate our measure against other cultural metrics to enhance its credibility and ensure it accurately represents analysts' cultural preferences before proceeding with further analyses.

First, we validate our measure against the prior measure based on analysts' inherited national culture (Brochet et al., 2018; Pan et al., 2020; Cao et al., 2024). Hofstede (1983)'s initial national culture measure covers 72 countries in 1973 and is updated twice in 2001 and 2010, covering five dimensions of power distance, uncertainty avoidance, individualism /collectivism, masculinity/femininity, and long-term orientation. The experimental results of Ramamoorthy and Flood (2004) reveal that national culture of individualism/collectivism orientations influence team loyalty and pro-social behavior, which are two aspects of teamwork attitudes. Therefore, we cross-validate analysts' cultural preferences for *Teamwork* against the inherited national culture of *Individualism*. Following Cao et al. (2024), we assign analysts to originating countries by matching their surnames using two dictionaries, Ancestry.com and forebears.io. For example, an analyst with the surname Jones is matched to England.

[Insert Table 3 here]

We first aggregate our analysts' cultural preferences to the country level based on their culture origins and then examine the correlation between our aggregated analysts' culture of *Teamwork* and national culture of *Individualism*. We conduct a Pearson correlation based on 31 countries with available data. Panel A of Table 3 shows confirming evidence that our coverage-based analysts' *Teamwork* culture is negatively correlated with the national culture of *Individualism*. The correlation coefficient is -0.109, statistically insignificant at conventional levels in this small sample. We suspect that aggregating to the country level may obscure valuable within-country variations and potential time-series transformations in national culture.

We proceed by utilizing analyst-year panel data to regress analyst *Teamwork* culture on national *Individualism* culture, while controlling for a range of analyst characteristics including the size of her brokerage house, the size of her research portfolio, her average firm-specific experience, her average forecast frequency in the year, and her general and industry specific experience. To address the overrepresentation of certain countries in our sample (e.g., 45% analysts are from the U.S. and 17% from England), we randomly select at most 20 analysts per country-year for the panel regression, as the median number of analysts per country each year is 20. This results in a total of 2,191 analysts from 31 countries. We repeat the sampling process with replacement 100 times, generating a sample of 546,600 analyst-year observations for the regression.

Panel B of Table 3 presents the results of the analyst-year panel regression. Column (2) shows that when analyst-level *Teamwork* culture is the dependent variable, the national culture of *Individualism* has a significantly negative coefficient. It suggests that analysts originated from countries with high *Individualism* tend to cover firms with low *Teamwork* culture, which validates our measure of analysts' cultural preferences. It is worth noting that analysts' cultural preference is only partially inherited from their origins. In the panel regression, national culture accounts for only 0.2% of the variance in analysts' *Teamwork* culture. The adjusted R-squared increases to 1.6% when we include analyst and brokerage characteristics. These results confirm that analysts' cultural preferences are influenced not only by their inherited national culture but also by the "education and professional training" they receive (LMSY).

The second validation test is motivated by Chen et al. (2017), which provides evidence that firms are more innovative in high *Individualism* or low *Uncertainty-avoidance* countries. In a similar spirit, we validate analyst culture of *Innovation* against national cultures of *Individualism* and *Uncertainty-avoidance*. Panel A of Table 3 presents the country-level correlation results that support our hypotheses. Across 31 countries, analysts' culture of *Innovation* is positively corelated to national culture of *Individualism* and negatively associated with *Uncertainty avoidance*. The magnitudes of both correlation coefficients are higher than 0.3 and statistically significant at the 10% level. We also adopt the sampling methodology to randomly select at most 20 analysts from each country and conduct the analyst-level analysis by controlling for analyst and brokerage characteristics. Panel regression results reported in Panel B show that analysts from countries with higher *Individualism* and lower *Uncertainty avoidance* have a stronger preference for the culture of *Innovation*.

To sum up, we cross-validate our measure of analysts' cultural preferences, derived from the corporate culture of firms under research coverage, with national culture matched by analysts' surnames. We find that analyst culture aligns with national culture in ways predicted by prior literature. These results validate our methodology of recovering analysts' personal cultural preference from their research coverage. More importantly, our analyst-year measure of cultural preference contains richer information than the traditional static country-level national culture measure. Our approach enables more powerful empirical tests on how analysts' cultural preferences influence information discovery in financial intermediation.

Prior studies measure analyst cultural preference based on the culture of analyst's country of origin (Merkley et al., 2020; Cao et al., 2024), which is sticky and lacks time-series variations (Pan et al., 2020). Such a top-down approach implicitly assumes that all individuals from a specific ethnic origin share the same lifelong culture preference. For example, it ignores the diverse cultural preferences among over 1.4 billion Chinese, despite differences in living standards, education, or career backgrounds. In contrast, we propose a new bottom-up approach to measure analysts' cultural preferences by observing the corporate culture of firms they cover. This method allows for analyst-specific and time-varying measures, capturing more extensive and current information than traditional national culture metrics. We will show evidence that our new measure is effective: analysts' cultural preferences, as quantified by our approach, significantly influence the financial market.

3. Analyst cultural preference and forecasting performance

After developing and validating our measure of analysts' cultural preferences based on corporate culture of firms under coverage, we investigate how these diverse cultural preferences influence analysts' forecasting performance.

3.1 Principal component analysis

[Insert Table 4 here]

Graham et al. (2022) describe corporate culture as "a belief system," "a coordination mechanism," and "an invisible hand." In a similar vein, LMSY argue that attributing business outcomes to specific cultural values is challenging. Therefore, we initially plan to include all five cultural dimensions as explanatory variables to examine the joint influence of analyst culture on forecasting performance. However, as documented in LMSY and confirmed by our results in Panel A of Table 4, the five cultural dimensions are highly correlated. Representative words in the culture dictionary (Table 2 of LMSY) also overlaps across dimensions. These high correlations among the five cultural dimensions lead to potential multicollinearity problems. To address this concern, we employ PC analysis to transform five-dimensional cultural values to reduced orthogonal dimensions. Panel B of Table 4 presents the summary statistics for the five *PC*s. We retain the first two *PCs* as their eigenvalues are greater than one. *PC1* explains about 38% of the total variation among the five cultural values, and *PC2* explains an additional 24%.

Panel C of Table 4 presents the loadings of *PC*s on each cultural value. *PC1* has positive loadings for all five cultural dimensions, ranging from 0.23 to 0.54. Previous literature (e.g., LMSY) adopts a simple summation of cultural values across all five dimensions to quantify the overall strength of corporate culture. An unreported correlation test using firm-year panel data reveals that our *PC1* is nearly identical to this summation, with a correlation coefficient of 0.987. We accordingly name *PC1* as "sumculture", with a high *PC1* indicating a strong firm culture. LMSY find that firms with strong cultures exhibit higher operational efficiency, more corporate risk-taking, less use of discretionary accruals, etc., and ultimately higher Tobin's *Q*.

We expect that *PC1* will similarly have a positive impact on analysts' forecasting performance.

Panel C of Table 4 shows that *PC2* has positive loadings for *Innovation* and *Quality* but negative loadings for *Integrity*, *Teamwork*, and *Respect*. This suggest that *PC2* reflects a tendency for firms to prioritize growth and customer satisfaction over moral considerations, which we term the "growth-at-all-costs" factor. We predict that *PC2* has a detrimental impact on analysts' forecasting performance. Our investigations into *PC2* are novel and echo prior literature on analyst aggressiveness or boldness (Clarke and Subramanian, 2006; Altınkılıç et al., 2019; Cao et al., 2024).

After extracting the two *PC*s of corporate culture at firm-year level, we perform industry- and brokerage-adjustment to obtain the two PCs of analysts' cultural preferences at analyst-year level. We also obtain *PC1_broker* and *PC2_broker* to control for brokerage average culture in subsequent tests. We then examine the impact of cultural preference on analysts' forecasting performance from five perspectives: forecast accuracy, recommendation profitability, forecast optimism, forecast boldness, and forecast horizon.

3.2 Forecast accuracy

The first metric of forecasting performance we examine is forecast accuracy, which is crucial to financial analysts' career outcomes and has been extensively investigated in prior literature. Hong and Kubik (2003) document that forecast accuracy help analysts to move up to high-status brokerage houses. We investigate whether and how analysts' cultural preference influences their forecast accuracy. LMSY find that strong culture would improve firms' operation efficiency and increase firms' value (Tobin's *Q*). Besides, Pacelli (2019) shows that analysts from financial institutions with weak corporate culture (evidenced by more "Financial Industry Regulatory Authority" violations) issue less accurate forecasts. Therefore, we hypothesize that analysts with stronger cultural preferences issue more accurate forecasts.

We retain the last quarterly earnings forecast an analyst issues in a particular year, and adopt the approach of Clement and Tse (2005) to define forecast accuracy in a relative way. Specifically, an analyst's forecast *Accuracy* is calculated as the maximum absolute forecast error among all analysts following a firm during the year, minus the analyst's absolute forecast error, and scaled by the range of the absolute forecast errors for that firm-year. In total, we have 399,245 yearly analyst-firm pairings, covering 8,589 analysts and 7,363 firms from 2002 to 2021. We winsorize the variables at the 1st and 99th percentiles to mitigate the impact of outliers.

[Insert Table 5 here]

Panel A of Table 5 reports the summary statistics for *Accuracy*. As a relative accuracy measure, its mean value is 68.85% and median is 81.82%. Panel B of Table 5 report the Pearson correlation tests results. It shows that *PC1* is positively correlated with *Accuracy*, providing preliminary support for our hypothesis that analysts with stronger cultural preference deliver better forecasting performance. Furthermore, *PC2* is positively correlated with *Accuracy*, aligning with prior literature that bold forecasts tend to be more accurate (Clement and Tse, 2005). We proceed with the panel-data regression using our analyst-firm-year observations.

$$Accuracy_{i,j,t} = \alpha + \beta_1 PC1_{i,j,t-1} + \beta_2 PC2_{i,j,t-1} + \gamma Controls + \varepsilon_{i,j,t}, \tag{1}$$

where $Accuracy_{i,j,t}$ refers to the forecast accuracy of analyst *j* covering firm *i* in year *t*. The variables of interest are two PCs representing analysts' cultural preferences, and we expect positive coefficients for these cultural values. We first control for the brokerage culture obtained in Section 2.2, and then control for a battery of analyst characteristics and firm characteristics (Clement and Tse, 2005). Analyst characteristics include the number of forecasts the analyst issues for the firm in a year (*ForecastFreq*), the analyst's firm-specific research experience in years (*FirmExp*), general experience in the industry (*GeneralExp*), the number of analysts affiliated with the brokerage (*BrokerSize*), and the time lag in days between the analyst's forecast date and the fiscal year-end (*Lag*). Firm characteristics include market capitalization (*FirmSize*), market-to-book ratio (*MB*), and institutional ownership (*IO*) in the multivariate regressions. Detailed variable descriptions are provided in Table 1. Finally, we include year, industry, and brokerage fixed effects to account for omitted variable issues and cluster standard errors by firms to account for correlation in residuals.

Panel C of Table 5 presents the results of the multivariate regressions. Column (1) shows that when forecast *Accuracy* is regressed on analysts' cultural preferences, both *PC1* (*sumculture*) and *PC2* (*growth-at-all-cost*) have significantly positive coefficients. The multivariate regression results align with those from univariate correlation results. It lends further support to the expected beneficial roles played by culture: analysts with strong culture issue more accurate forecasts. Furthermore, aggressive analysts, featured with a tendency to prioritize growth and quality over moral considerations, also issue more accurate forecasts.

Regarding the impact of brokerage cultures, we find that the coefficients for the two PCs of brokerage culture have much larger magnitudes than those for analyst culture. This indicates that the cultural preferences of the brokerage house have a greater impact on analysts' forecasting performance than the analysts' own cultural preferences. Interestingly, while brokerages' *PC1* is positively associated with analysts' forecast accuracy, brokerages' *PC2* has a negative association. The evidence suggests that although aggressive analysts may issue accurate forecasts, aggressive brokerage houses do not. When a brokerage has a strong "growth-at-all-cost" culture, it tends to prioritize company growth and customer satisfaction at the expense of ethical considerations, which could negatively affect the forecasting performance of its analysts. These findings are novel, as prior literature rarely examines brokerage houses as a special sample of "firms" and explores the impact of culture on their "operating performance" through the lens of analysts' forecasting performance. Brokerage houses, as crucial information producers in the financial market, are worthy of extensive investigation. Understanding the cultural preferences and operational behaviors of brokerage houses can provide significant insights into their impact on market efficiency and the quality of financial analysis.

With respect to analyst characteristics used as control variables, we find that the analyst's forecast frequency (*ForecastFreq*) has a significantly positive sign. This is consistent with prior literature in that analysts who obtain information more often than their peers would likely issue more frequent forecasts and provide superior forecasts. The coefficient of analysts' firm-specific experience (*FirmExp*) is significantly positive, whereas the general industry experience (*GeneralExp*) is only insignificantly positive. The evidence indicates that firm-specific experience is more valuable in enhancing analysts' forecasting performance. *BrokerSize* has a significantly positive sign, which indicates that analysts employed by larger brokers provide more accurate forecasts. *Lag* is significantly negative, indicating that earlier forecasts are less accurate. Regarding firm characteristics as control variables, the coefficients for *FirmSize* and *IO* are both significantly positive, suggesting that forecasts for bigger firms or firms with higher institutional ownership are more accurate. These findings align with Harford et al. (2019) that analysts strategically allocate efforts to important firms under coverage, which tend to have big market capitalization and high institutional ownership.

The status of analysts' brokerage might moderate the positive contribution of analyst cultural preference to forecasting performance. We conduct further subsample tests along this dimension by dividing our sample into two groups based on the size of brokerage house (Coleman et al., 2023). Column 1 of Table IA2reports that the beneficial impact of *PC1* is concentrated among analysts from large brokerage houses and insignificant among small brokerages. We conjecture that *PC1* enhances analysts' overall capability, and such a healthy and sustainable approach is encouraged only in reputable brokerage houses. In contrast, low-status brokerages are more aggressive and opportunistic. This argument is further supported by the subsample test results related to *PC2*, as the positive impact of *PC2* is stronger in small brokerages and weaker in large brokerages.

3.3 Recommendation profitability

The profitability of analysts' stock recommendations is a critical factor for institutional investors, often outweighing the importance of forecast accuracy (Brown et al., 2016). Analysts' cultural preferences also influence the profitability of their recommendations. Chen et al. (2020) show that analysts from national culture with a long-term orientation produce more profitable stock recommendations. As we show in section 3.2, analysts with strong cultural preference to issue high-quality forecasts. Precise earnings forecasts are crucial inputs to analysts' valuation models, enabling them to make profitable investment recommendations. Therefore, we hypothesize that analysts with strong cultural preferences have the ability to issue profitable stock recommendations.

We measure recommendation profitability (denoted as *RecomProfit*) as the cumulative market-adjusted return from the day before the recommendation date until the 30 days before the recommendation date is revised or reiterated (Ertimur et al., 2007). Panel A of Table 5 reports the summary statistics of *RecomProfit*, showing an average abnormal returns of 2.1% over the 30-day period after analyst recommendations. Panel B of Table 5 shows that the Pearson correlation between *PC1* and *RecomProfit* is statistically significant, while the correlation between *PC2* and *RecomProfit* is statistically indistinguishable from zero.

We proceed with panel regression by regressing recommendation profitability on analysts' cultural preferences, controlling for a series of analyst and firm characteristics (Ertimur et al., 2007). These controls include recommendation frequency (*RecomFreq*), firm-specific experience (*FirmExp*), general experience (*GeneralExp*), *BrokerSize*, the number of firms analysts follow (*Nfirms*), the number of industries analysts follow (*Nindustries*), prior year forecast accuracy (*LagAccuracy*), *FirmSize*, market-to-book ratio (*MB*), stock return over previous 12 months prior to the recommendation (*Momentum*), and institutional ownership (*IO*). Column (2) of Panel C in Table 5 shows that the coefficient of *PC1* is significantly positive, confirming the univariate correlation results that analysts with stronger cultural preferences issue more profitable stock recommendations.

Table IA2 in the Internet Appendix presents additional subsample results. Panel A shows that the beneficial impact of *PC1* is concentrated among analysts from large brokerage houses (Column 3). We conjecture that *PC1* improves analysts' capability to issue profitable recommendations, and its positive impact is amplified for analysts in reputable brokerage houses.

3.4 Forecast optimism, boldness, and horizon

Prior literature has documented that analyst forecasts are upward biased on average. Such optimism is typically attributed to brokerage incentives, such as obtaining investment banking business (Ljungqvist et al., 2009), relationship maintenance with firm management (Francis and Soffer, 1997), and trade generation. Besides, analysts' behavioral biases (Sedor, 2002) and career concerns (Hong and Kubik, 2003) contribute to forecast optimism. More importantly, not all investors can debias analysts' forecast optimism, and such bias distorts stock prices and predicts future returns in a systematic way (Grinblatt et al., 2023). We expect the invisible hand of analyst culture to impose self-discipline and curb analysts' opportunistic behaviors.

We adopt the approach of (Cowen et al., 2006; Malmendier and Shanthikumar, 2014) to define forecast optimism (denoted as *Optimism*). Specifically, we compare the analyst's earnings forecast with the consensus forecast, and then divide the difference by the prior-day share price. Panel A of Table 5 reports the summary statistics of *Optimism*. Its mean is negative while the median is positive. Further analysis reveals that *Optimism* is negatively skewed and a few extremely negative observations pull down the mean. Besides, unreported subperiod analysis shows that forecasts are less optimistic in the recent subperiod, echoing the evidence in Chang et al. (2023) that mandatory corporate disclosures constraint analysts' forecast optimism.

Simple correlation tests (Panel B of Table 5) show that *PC1* is negatively correlated with *Optimism*, while *PC2* is positively correlated with *Optimism*. We proceed to examine the impact of analyst culture on *Optimism* in a multivariate regression model, controlling for a battery of analyst characteristics and firm characteristics. We control for *ForecastFreq*, *FirmExp, GeneralExp, BrokerSize, Nfirms*, *Nindustries*, *Lag*, *FirmSize, MB, Momentum* and *IO* in the multivariate regressions (Cowen et al., 2006). We further control for year-, industry-fixed and brokerage-fixed effects, and cluster standard errors by firms.

We report the multivariate regression results in column (3) of Panel C. The coefficient of *PC1* (*sumculture*) is significantly negative, indicating that analysts with strong cultural preference tend to issue less optimistic forecasts. This finding supports our hypothesis that analyst culture curbs analysts' self-benefiting opportunistic behaviors, although it is difficult to attribute the finding to a particular cultural dimension. The significantly positive coefficient of *PC2* (*growth-at-all-cost*) gives us additional clues. A higher value of *PC2* captures analysts' aggressiveness or opportunism, which is arguably associated with more optimistic forecasts.

Table IA2 reports additional subsample results. Panel A shows that the beneficial impact of *PC1* is concentrated among analysts from large brokerage houses (Column 5), while the detrimental impact pf *PC2* is concentrated among small brokerages (Column 6). We speculate that *PC1* improves analysts' overall capability, and its positive effect is magnified by the synergy within a reputable brokerage house. In comparison, low-status analysts tend to pursue optimistic behaviors, leading to stronger negative impact of *PC2* among small brokerages.

Overall, we document compelling evidence that analysts' cultural preferences have reliable influence on their forecasting optimism after the control of various determinants. Analyst culture seems to be double-edged sword: whereas strong overall culture curbs the forecasting optimism, the culture of growth-at-all-cost exacerbates optimism.

Prior literature suggests analysts with limited experience and poorer prior forecasting performance tend to issue bold forecasts to win the tournaments. We are curious to know whether analyst culture hinders her from deviating from the consensus and from adopting riskier strategies. We assign *Boldness* to 1 if an analyst's forecast deviates from *both* her prior forecast and the consensus forecast, and zero in all other cases (Clement and Tse, 2005). As we require analysts to have prior year data on forecast accuracy, we lose 45% of analyst-firm-year observations. Univariate correlation test shows that both *PC1* and *PC2* are positively correlated with *Boldness*. We control for *ForecastFreq*, *FirmExp*, *GeneralExp*, *BrokerSize*, *Nfirms*, *Nindustries*, *LagAccuracy*, the day elapsed since the last forecast by any analyst following the firm (*DaysElaspsed*), *Lag*, *FirmSize*, *MB*, *Momentum* and *IO*, in the multivariate regressions.

Panel A of Table 5 shows that about 71.3% of the forecasts are classified as bold, which is similar to the level (73%) in Clement and Tse (2005). Column (4) of Panel C shows that the coefficient of *PC1* is marginally negative, which indicates that analysts with strong cultural preferences adhere to norms and do not take risker strategy, and are less likely to issue bold forecasts. The significantly positive coefficient of *PC2* shows that analysts who prefer growth-at-all-cost factor issue bold forecasts. Column (7) and (8) in Table IA2 show additional subsample results. *PC1* can be interpreted as analyst morality. Similarly, the results show that the impact of strong analyst culture (*PC1*) is concentrated among forecasts for analysts in large brokerage houses. The detrimental impact of *PC2* is more pronounced among analysts in large brokerage houses, as these analysts may face greater competition risk and are more likely to issue bold forecasts.

Then, we examine the effect of cultural preference on forecast horizon, the time analysts take to release their forecasts. It's an alternative measure of boldness (Cao et al., 2024). Some analysts tend to delay the release of their earnings forecasts to incorporate private and public information in their revisions, so that they have more time to produce more accurate forecasts (Shroff et al., 2014). We follow the prior study (Janakiraman et al., 2007), and measure forecast timeliness using the first-forecast horizon, which is the number of days between the first forecast date and the firm's annual-end date (denoted as *Horizon*). Large value of *Horizon* refers to a hasty earnings forecast. We then control for *ForecastFreq*, *FirmExp*, *GeneralExp*, *BrokerSize*, *Nfirms*, *Nindustries*, *DaysElaspsed*, *Lag*, *FirmSize*, *MB*, *Momentum* and *IO*, in the multivariate regressions (Cao et al., 2024).

Column (5) of Panel C in Table 5 shows that the coefficient of *PC1* is significantly negative, which indicates that analysts with strong cultural preference are less likely to issue hasty forecasts. Those analysts wait to issue their forecasts so they can have more time to issue accurate forecasts. The significantly positive coefficient of *PC2* shows that analysts who prefer growth-at-all-cost factor would like to issue hasty forecasts. Similarly, the results of Table IA2 show that the impact of strong analyst culture (*PC1*) is concentrated among analysts from large brokerage houses (Column 9).

3.5 Robustness check

Additional robustness checks reveal that our main results are qualitatively unchanged without controlling brokerage effect (results are reported in Table IA3). Besides, the standard deviation of analyst portfolio culture indicates the consistency of analyst cultural preferences. Considering that the number of coverages would mechanically increase the dispersion, we normalize the standard deviation to the average standard deviation of analysts with the same number of coverages. The empirical results related to forecast performance are also robust when using standardized standard deviation in measuring analyst cultural preference (results are reported in Table IA4).

Also, analysts' cultural preferences reflect some firm characteristics to some extent. For instance, analysts with strong cultural preferences tend to cover firms with a high market-to-book ratio. To mitigate these influences, at least partially, we regress analysts cultural preferences against a set of firms characteristics- namely, firm size, firm turnover, institutional ownership, market-to-book ratio and momentum-and use the residuals from these regressions as our proxy for cultural preference. Our results related to forecast performance are robust when we use the residual proxy for cultural preference (results are reported in Table IA5).

In summary, our findings highlight the positive impact of overall analyst culture. We observe that analysts with stronger cultural preferences tend to issue more accurate earnings forecasts and profitable recommendations, and their forecasts are less optimistic and hasty. Conversely, analysts who prioritize growth-at-all-cost factors tend to make overly optimistic, bold, and hasty forecasts.

4. Diversity in analyst culture and firms' information environment

The influence of analysts' cultural preference extends to firms under their research coverage. As important financial intermediaries, analysts play an indispensable role in collecting and producing information regarding the covered firms. Merkley et al. (2020) find that diversity in analysts' national cultural backgrounds leads to higher quality in their group output. This improvement in information processing stems from the diversification effect related to analysts' cultural backgrounds. Their diversity measure is based on the counts of analysts' cultural origin clusters. In this section, we develop a new measure of analysts' cultural diversity and examine its impact on the information environment of firms under analysts' coverage.

4.1 Measure of analyst cultural diversity

As documented by LMSY, the five dimensions of corporate culture collectively create value for the firm. We argue that if a firm has a group of analysts who care about a wide range of cultural dimensions, such cultural diversity in the analyst-base would lead to the discovery of information in various aspects of the firm and create a more transparent information environment. Consistent with this argument, for each firm, we naively count the number of cultural dimensions (*DiversityCount*) that are followed by at least one attentive analyst. To define "attentive" in each year, we sort analysts into quartiles by their industry- and brokerage-adjusted cultural values in each cultural dimension *k*, and only analysts in the top quartile with the highest cultural scores are counted as attentive in this cultural dimension. Our methodology is consistent with the diversity measure used in Merkley et al. (2020), which counts the number of unique cultural clusters based on analysts' country of origin, and Chhaochharia et al. (2023), who calculate percentage of minority analysts within the firm. Our diversity measure is similar in spirit to that of Drake et al. (2024), which classifies analyst forecasts into five types of quant, sundry, contrarian, herder, and independent forecasts, and then finds that the number of unique forecast types increases consensus forecast accuracy.

To address the endogeneity issue, we subtract the cultural score of the focal firm when calculating the analyst's portfolio cultural score. This allows us to test whether changes in analyst cultural diversity, driven by changes in the cultural scores of other firms, impact the information environment of the focal firms. We then introduce a new measure of analyst cultural score to identify attentive analysts and derive a revised measure of analyst cultural diversity. Our findings partially mitigate the endogeneity problem and demonstrate that increased cultural diversity at the analyst level contributes to a more favorable information environment for focal firms.

[Insert Table 6 here]

Panel A of Table 6 reports the descriptive statistics of *DiversityCount*. At the firm-year level, a typical firm is covered by 8.90 analysts, and 3.39 out of 5 cultural dimensions are covered by attentive analysts. This count-based diversity measure shows wide dispersions, with a 25-pencentile of 2 and a 75-percentile of 4. Untabulated results further show that around 5% of firm-year observations have no coverage by attentive analysts, and 10% of observations have all 5 cultural dimensions covered.

As a robustness check, we calculate an alternative measure of diversity based on Herfindahl-Hirschman index (*DiversityHHI*). For each firm year, we calculate the share of attentive analysts in each cultural dimension, and *DiversityHHI* is one minus summed squared share. For example, among 8 analysts covering a particular firm in a particular year, 1 analyst is attentive in *Integrity*, 2 analysts are attentive in *Teamwork*, 3 analysts are attentive in *Innovation*, and no analysts are attentive in *Respect* and *Quality*. In this case, *DiversityCount* is 3, and *DiversityHHI* would be calculated as 1-((1/6)^2+(2/6)^2+(3/6)^2). As we have a total of five cultural dimensions, *DiversityHHI* ranges from 0 to 0.75. Different from the simple count, *HHI* takes into consideration of the percentage of analysts interested in each dimension. Consistent with the count, a higher value of *DiversityHHI* indicates greater diversity in the analyst base across various cultural dimensions. Panel B of Table 6 reveals a high correlation coefficient of 0.89 between *DiversityCount* and *DiversityHHI*. This indicates that the two measures capture similar aspects of analyst diversity based on their cultural preference.

4.2 Consensus forecast accuracy

To examine the impact of analyst cultural diversity on firms under coverage, we adopt the accuracy of consensus forecast (*ConAccuracy*) used in **Merkley et al. (2020)** to measure the quality of firms' information environment. It is defined as the absolute difference between the consensus analyst earnings forecast at the end of the fiscal year and the actual earnings per share, scaled by the stock price at the end of the prior fiscal year, multiplied by -100. A higher value of *ConAccuracy* indicates a more accurate consensus forecast. So, *ConAccuracy* is non-positive values by definition. Panel A of Table 6 shows that the mean (-0.84) of *ConAccuracy* is lower than the median (-0.19). Further analysis reveals that *ConAccuracy* is non-normally distributed but left skewed and a few extremely negative observations pull down the mean. We require at least two analysts to calculate the consensus forecast accuracy.

Panel B of Table 6 shows the correlation among variables. Both *DiversityCount* and *DiversityHHI* have significantly positive correlations with *ConAccuracy*, which is consistent with our prediction that a greater cultural diversity among analysts contributes to more effective price discovery, and therefore, higher accuracy in consensus forecasts. We continue to employ the following regression model based on our panel data of firm-year observations:

$$ConAccuracy_{i,t} = \alpha + \beta Diversity_{i,t-1} + \gamma Controls + \varepsilon_{i,t}, \tag{2}$$

where $ConAccuracy_{i,t}$ refers to the consensus forecast accuracy for firm *i* in year *t*. The variable of interest is the two alternative measures of *Diversity*: *DiversityCount* and *DiversityHHI*. We expect positive coefficients for these diversification measures. We also include a vector of control variables as in Merkley et al. (2020), including the number of analysts following the firm (*Nanalysts*), the logarithm of the market capitalization (*FirmSize*), market-to-book ratio (*MB*), return on assets (*ROA*), the standard deviation of *ROA* over the last five years (*STD_ROA*), the stock return over previous 12 months (*Momentum*), and the standard deviation of daily stock returns over the previous 12 months (*STD_DRet*). To mitigate the omitted variable problems, we control for industry- and year-fixed effects, and cluster standard errors by firms.

Panel C of Table 6 reports the results of multivariate regression using Eq. (2). Column (1) shows the result when *Diversity* is measured by the number of dimensions (*DiversityCount*). The coefficient of *DiversityCount* is 0.038, which is both statistically and economically significant. An average firm has 3.39 out of 5 cultural dimensions covered by attentive analysts with a standard deviation of 1.40. The unconditional mean of scaled absolute forecast error in consensus is 0.84%. One additional cultural dimension covered by attentive analysts would reduce the forecast error to 0.80%. The result is qualitatively similar when *Diversity* is measured by *DiversityHHI*.

The coefficients for the control variables align with the findings of prior studies. Notably, higher analyst coverage suggests a greater likelihood of a diverse following, which we account for in our analysis. We also control several factors, including firm size, performance, and volatility. The number of analysts following a firm is positively and significantly associated with forecast accuracy, consistent with the finding that competition enhances the quality of consensus forecasts (e.g., Hong and Kacperczyk (2010)). Additionally, forecast accuracy is higher for larger firms and those with superior and less volatile performance.

Our findings indicate that firms benefit from an enhanced information environment when their analysts possess diverse cultural backgrounds. Such diversity facilitates the discovery of information pertaining to various aspects of the firm. We conjecture that the results could be driven by the diversification effect. Our results are consistent with those of Merkley et al. (2020), who measure analyst diversity by the cluster of national culture derived from analysts' country of origin. Cultural diversity does not exhibit persistence. Untabulated results show that the average *AR*(1) coefficient of *DiversityCount* is -0.53. The situation for *DiversityHHI* is similar. Therefore, employing the lagged dependent variable could partially help to mitigate the possible endogeneity problem. Our results are also robust if we calculate analyst culture without subtracting the focal firm culture, when measuring cultural diversity in analyst-base (results are reported in Table IA6).

4.3 Consensus forecast dispersion

Analysts with different cultural preferences may provide varying forecasts. Next, we examine how analyst cultural diversity relates to analyst consensus dispersion (*Dispersion*) used in Drake et al. (2024). It is defined as the standard deviation of all analyst forecasts scaled by stock price at the end of the fiscal year, multiplied by 100. A higher value of *Dispersion* indicates a more volatile consensus forecast. Panel A of Table 6 shows that the mean (20.31) of *Dispersion* is higher than the median (7.70), indicating that a few forecasts are highly volatile.

Panel B of Table 6 shows that both *DiversityCount* and *DiversityHHI* have significantly positive correlations with *Dispersion*, which is consistent with our prediction that a greater cultural diversity among analysts is likely to lead to different forecasts.

We present the equation (3) results using *Dispersion* as the dependent variable in column (3) and (4) in panel C. We find significantly positive coefficients for *DiversityCount* and *DiversityHHI*, respectively. These results indicate that greater diversity in analyst culture increases the dispersion of analyst forecasts. Our results are consistent with Drake et al. (2024), who find that a greater diversity of forecast types is associated with increased consensus dispersion.

Overall, the results reflect the diverse cultural backgrounds of various analysts, offering varied forecasts and unique perspectives that enhance the information environment of the firms they cover.

5. Cultural similarity and analyst forecasts

5.1 Measure of cultural similarity

In this section, we examine the impact of cultural similarity on analysts' coverage decisions and forecast quality. This series of tests is motivated by recent literature investigating the economic outcomes of cultural similarity among various parties. For example, Bereskin et al. (2018) find that firms with greater similarity in firms' corporate social responsibility characteristics are more likely to merge, and these mergers have greater synergies. LMSY use their text-based corporate culture measure and confirm the finding that cultural similarity adds to the probability of merger and acquisition, and that the acquirer's culture becomes a mix of two parties involved. Related to financial analysts, Du et al. (2017) find that for Chinese firms listed in the U.S. market, analysts with Chinese ethnic origin issue more accurate forecasts. Closely related to our study, Frijns and Garel (2021) provide evidence that the greater distance in national culture between analyst and firm CEO, matched by their surnames and country of origin, leads to higher forecast errors.

We measure the cultural similarity between analysts and firms based on our new measure of analysts' cultural preferences. Consistent with the method of Frijns and Garel (2021), in each year, for each cultural dimension *k*, we rank analysts' industry- and brokerage-adjusted culture score into percentiles. We do the same for industry-adjusted firm culture score. We calculate the distance in the percentiles for each analyst-firm pair. In each year, analyst-firm pair with shortest cultural distances in the bottom quartile are considered to share similar culture in dimension *k*. For each analyst-firm pair, we then count the number of similar cultural dimensions and define it as *Similarity*. This variable ranges from zero to five. A higher value of *Similarity* indicates more similar cultural initiative shared by the analyst and the firm under coverage.

[Insert Table 7 here]

Panel A of Table 7 shows the summary statistics. In this analysis, we have a total of 307,857 observations in the panel data of firm-analyst pairings and year. On average, analysts and firms share around 1.27 cultural dimensions out of 5. The median number is 1. Unreported statistics show that we have around 33% of firm-analyst pairings without similar culture in any way, and 6% of firm-analyst pairings that are similar in all 5 cultural dimensions.

5.2 Analyst coverage decision

We continue examine whether *Similarity* between corporate culture and analyst culture influences an analyst's decision to initiate, continue, or stop coverage for a firm. We hypothesize that analysts are more likely to initiate the coverage, continue to cover, or less likely to drop firms with a similar corporate culture.

We adopt the method of Liang et al. (2008) to define an ordinal variable, Δ*Coverage*, to quantify analysts' coverage decisions. This discrete variable equals -1 if the analyst stops covering a firm within a year, 0 if coverage continues, and 1 if new coverage is initiated. In the summary statistics in Panel A of Table 7, among 286,664 analyst-firm-year coverage decisions, around 19% are newly-adds, 9% are drops, and 72% are continued coverages. Panel B reports results of a preliminary correlation analysis that coverage decision is positively correlated with the cultural similarity between firm and analyst. We further perform the following ordered probit regression analysis:

$$\Delta Coverage_{i,j,t} = \alpha + \beta * Similarity_{i,j,t\text{-}1} + \gamma Controls + e_{i,j,t-1} \quad (3)$$

where $\Delta Coverage_{i,j,t}$ captures changes in the position of firm *i* in the portfolios covered by analyst *j* in year *t*. A higher $\Delta Coverage_{i,j,t}$ reflects a higher likelihood for analyst *j* to follow firm *i* in year *t*. The variable of interest, $Similarity_{i,j,t-1}$, captures the cultural similarity between firm *i* and analyst *j* in year t-1, and its expected coefficient is positive.

We also control for firm, analyst, and brokerage characteristics that may affect changes in analyst coverage (Liang et al., 2008; Yu, 2008). Firm characteristics include the logarithm of the total annual market capitalization (*FirmSize*), the logarithm of the number of analysts following (*Nanalysts*), the logarithm of the market-to-book ratio (*MB*), return on assets (*ROA*), the growth rate of total assets (*AssetGrowth*), the log of annual trading volume (*TrdVol*), stock return over previous 12 months (*Momentum*), and the percentage of institutional ownership (*IO*). The brokerage characteristic includes the logarithm of the number of analysts employed by the brokerage (*BrokerSize*). Analyst characteristics include the analyst' relative experience for the firm (*RelExp*), calculated as the difference between firm-specific experience of the analyst and the average firm experience for all analysts who provide forecasts for the same firm, the logarithm of the number of years of industry experience for the analyst (*GeneralExp*), and the logarithm of the number of firms an analyst follows (*Nfirms*).

Panel C in Table 7 shows the results of the ordered probit model of Eq. (3). As expected, *Similarity* has a significantly positive coefficient in Column (1). It indicates that an analyst is more likely to cover a firm with a similar culture.

We perform further tests using the logit model to examine whether the change in analyst coverage is attributable to add or drop decisions.

$$Add_{i,j,t} = \alpha + \beta * Similarity_{i,j,t\text{-}1} + \gamma Controls + e_{i,j,t-1}, \tag{4}$$

where *Add is* a dummy variable that equals one if the analyst initiates the coverage of the stock in year t and zero if she drops the stock from her coverage portfolio in year t. Column (2) of Panel C shows the result of the probit model. The coefficient of *Similarity* is significantly positive, which indicates that analysts are more likely to add firms with a similar culture.

5.3 Analyst forecast quality

We then examine how cultural similarity between analysts and covered firms influences the quality of analysts' research output. Cultural closeness could help analysts and covered firms communicate easily, leading to more information sharing. We measure the quality of analysts' research output by analysts' forecast accuracy and recommendation profitability. The regression model is:

$$Quality_{i,j,t} = \alpha + \beta Similarity_{i,j,t} + \gamma Controls + \varepsilon_{i,j,t}, \tag{5}$$

where the dependent variables is the two alternative measures of *Quality*: $Accuracy_{i,j,t}$ and $RecomProfit_{i,j,t}$. $Accuracy_{i,j,t}$ refers to the analyst *j*'s forecast accuracy for firm *i* in year *t*, measured as the maximum absolute forecast error of analysts that follow a firm during the year minus the absolute forecast error of the analyst of interest, scaled by the range of the absolute forecast errors for the firm year. *RecomProfit* refers to the cumulative market-adjusted return from the day before the recommendation date until the earlier 30 days before the recommendation date is revised or reiterated. The variable of interest is *Similarity*, and we expect a positive coefficient.

Panel B of Table 7 shows *Similarity* has a strong correlation with *Accuracy*. Column (3) and (4) of panel C show that the coefficients of *Similarity* are significantly positive. Our results suggest that cultural similarity between firms and analysts could contribute to the formation of an analyst's social network and communication channels for private information. The cultural closeness can also facilitate better communication between analysts and covered firms, reducing information asymmetry and leading to more accurate forecasts and more profitable recommendations.

In summary, this subsection provides evidence supporting our measure of analysts' cultural preferences by examining its impact on analyst coverage changes and forecast quality. The results indicate that analysts tend to add or drop firms with (dis)similar corporate culture, and they issue more accurate forecasts and more profitable recommendations for firms with similar cultural values.

6. Conclusion

Our paper is directly motivated by the availability of dynamic firm-level corporate culture from LMSY, which scores corporate culture from five dimensions of *integrity, teamwork, innovation, respect,* and *quality*. In the same spirit of the recent literature that reveals mutual fund ESG performance from ESG of firms held by the fund (Cao et al., 2023), we propose a novel approach of analysts' cultural preferences based on the cultural values of firms in analysts' research portfolios. Validation tests show that our micro-based measure of analysts' culture shares aspects with prior measures based on national culture yet contains richer information.

In align with the positive role played by corporate culture (LMSY), we document that analyst culture improves the quality of information production and firms' information environment under coverage. In particular, we find that analysts with stronger cultural preferences tend to issue more accurate forecasts and more profitable recommendations, and their forecasts are less optimistic and/or less hasty. Moreover, analysts who prioritize growth over morality are more likely to issue optimistic, bold, and/or hasty forecasts. Finally, we document robust evidence that diversity in analyst culture helps improve covered firms' information environment. The evidence supports the positive role played by culture for financial analysts, who are crucial information producers in the financial market and directly influences the information environment of covered firms and the overall market efficiency.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Copilot in order to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Table 1. Variable definitions

Variables	Definition
Firm cultural value	
Integrity *Teamwork* *Innovation* *Respect* *Quality*	Five dimensions of corporate cultural values measured by counting the frequency of culture-related words and phrases in earnings call transcripts, and culture dictionary is composed using machine learning techniques (LMSY).
Analyst cultural value	
PC1 & PC2	For each of five cultural dimensions, we calculate average of industry- and brokerage-demeaned culture value of stocks in analyst's coverage portfolio to get μ, standard deviation of demeaned culture scores of stock portfolios to get σ, and use μ/σ to measure analyst culture values. We then extract the first and second principal components (PC) of analyst cultural values.
PC1_broker *PC2_broker*	The first and second PC of brokerage culture, which is aggregated from industry-demeaned analyst cultural scores.
Analyst national culture (Table 3)	
Individualism *Uncertainty avoidance*	Two dimensions of Hofstede's national culture index. Analyst's country of origin is identified by surname (Cao et al., 2024).
Analyst performance (Table 5)	
Accuracy	Relative forecast accuracy. Maximum absolute forecast error of all analysts following a firm in the year minus absolute forecast error of the analyst of interest, scaled by range of absolute forecast errors for the firm-year (Clement and Tse, 2005).
RecomProfit	Cumulative market-adjusted return from day before recommendation until the 30 days before the recommendation date is revised or reiterated(Ertimur et al., 2007).
Optimism	Analyst's earnings forecast minus consensus forecast, scaled by prior-day price (Malmendier and Shanthikumar, 2014).
Boldness	Boldness in earnings forecast, which equals one if analyst's current forecast is higher or lower than both consensus forecast and her previous forecast, and zero otherwise (Clement and Tse, 2005).
Horizon	Log days from analyst's first forecast to fiscal year-end (Janakiraman et al., 2007).
Firm information Environment (Table 6)	
DiversityCount	Number of cultural dimensions followed by at least one attentive analyst. Only analysts in the top quartile with the highest cultural scores are considered as attentive (Merkley et al., 2020).
DiveristyHHI	One minus sum of squared percentage of analysts following each cultural dimension (Merkley et al., 2020).
ConAccuracy	Absolute difference between analysts' consensus forecast at fiscal year end and actual earnings, scaled by stock price at prior fiscal year end, multiplied by -100 (Merkley et al., 2020).

Dispersion	Standard deviation of all analysts' forecasts scaled by stock price at fiscal year end (Drake et al., 2024).
Analyst coverage decision (Table 7)	
Similarity	Number of similar cultural dimensions. In each year, analyst-firm pairs with shortest cultural distances in bottom quartile are considered similar in dimension *k* (Liang et al., 2008).
Δ*Coverage*	Change in analyst coverage, which is one for initiated coverage, zero for continued coverage, and minus one for drop (Liang et al., 2008).
Add	One for initiated coverage and zero for drop (Liang et al., 2008).
Analyst/forecast characteristics (Tables 3, 5, & 7)	
ForecastFreq	Log number of forecasts the analyst issues for the firm.
RecomFreq	Log number of recommendations the analyst makes for the firm.
FirmExp	Log of 1+ years of firm-specific experience of the analyst.
GeneralExp	Log of 1+ years of industry experience of the analyst.
BrokerSize	Log number of analysts employed by the brokerage.
Nfirms	Log number of firms the analyst follows.
Nindustries	Log number of industries the analyst follows.
LagAccuracy	Prior year analyst forecast accuracy.
Dayselapsed	Log of days elapsed between the analyst's earnings forecast and most recent preceding forecast by any analyst.
Lag	Log of time lag in days between analyst forecast date to fiscal year-end.
RelFexp	Firm-specific experience of the analyst minus average firm experience for all analysts following the firm.
Firm characteristics (Tables 5, 6, &7)	
FirmSize	Log market capitalization.
MB	Log market-to-book ratio.
Momentum	Stock return over previous 12 months.
IO	Percentage of institutional ownership.
Nanalysts	Log number of analysts following.
ROA	Return on total assets.
Std_ROA	Standard deviation of *ROA* over the last five years.
Std_DRet	Standard deviation of daily stock returns over the previous 12 months.
AssetGrowth	Growth rate of total assets in percentage.
TrdVol	Log annual trading volume.

Table 2. Descriptive statistics of analyst cultural preference

This table provides summary statistics for each dimension of analyst's cultural preference. Procedures are as follows. (1) For firm *i* in year *t*, we adjust its cultural score in dimension *k* by industry mean. (2) For analyst *j* in year *t*, we calculate the average of industry-adjusted culture score in dimension *k* (from step 1) based on firms in her coverage portfolio. (3) For each brokerage house in year *t*, we calculate average of analysts' cultural scores in dimension *k*. We then demean analysts' cultural scores (from step 2) by brokerage. We denote this industry- and brokerage-adjusted cultural score as μ_{jtk} for analyst *j* in year *t* in dimension *k*. (4) For analyst *j* in year *t*, we calculate standard deviation of cultural scores of her stock portfolios in dimension *k* (from step 3) to get σ_{jtk}. A lower σ_{jtk} suggests greater consistency in analysts' cultural preferences. (5) Finally, μ_{jtk}/σ_{jtk} is ultimate measure to capture analyst *j*'s cultural preference in dimension *k* in year *t*.

	N	Mean	Std	P25	P50	P75
Integrity	47,562	-0.109	0.587	-0.387	-0.037	0.242
Teamwork	47,562	-0.116	0.662	-0.419	-0.038	0.269
Innovation	47,562	-0.144	0.712	-0.486	-0.071	0.272
Respect	47,562	-0.151	0.637	-0.447	-0.056	0.238
Quality	47,562	-0.203	0.794	-0.582	-0.116	0.261

Table 3. Validation against national culture

Panel A shows country-level correlations between analysts' cultural preferences (in dimensions of *Teamwork* and *Innovation*) and analysts' national culture (in dimensions of *Individualism* and *Uncertainty avoidance*). Panel B reports panel regression results by regressing analysts' cultural preferences on their national culture, using analyst-year observations. We control for year-fixed effects. The *t*-statistics are in parentheses, and ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Correlation at country-level analysis		
	Teamwork	*Innovation*
Individualism	-0.109	0.336*
Uncertainty avoidance		-0.314*

Panel B: Analyst-year panel regression				
	(1)	(2)	(3)	(4)
	Teamwork		*Innovation*	
Individualism	-0.006	-0.038***	0.118***	0.051***
	(-1.23)	(-7.89)	(22.65)	(9.60)
Uncertainty avoidance			-0.035***	-0.048***
			(-8.54)	(-11.42)
Nfirms		0.060***		0.123***
		(31.87)		(61.67)
Nindustries		0.064***		0.019***
		(43.15)		(11.91)
GeneralExp		-0.004***		-0.007***
		(-2.87)		(-4.45)
FirmExp		-0.058***		0.016***
		(-27.71)		(7.07)
ForecastFreq		-0.053***		0.055***
		(-28.54)		(27.77)
BrokerSize		-0.023***		-0.033***
		(-29.31)		(-39.88)
Constant	-0.122***	-0.045***	-0.215***	-0.412***
	(-37.79)	(-7.87)	(-44.88)	(-60.57)
Observations	546,600	531,615	546,600	531,615
Adj R-squared	0.002	0.016	0.004	0.019

Table 4. Principal component analysis of corporate cultural values

Panel A reports correlations among five corporate cultural dimensions. Panel B reports summary statistics for principal components. Panel C presents loadings of principal components on each cultural dimension. We perform industry- and brokerage-adjustment to obtain the two PCs of analysts' cultural preference at analyst-year level. Panel D shows the summary statistics for these two PCs.

Panel A: Correlations among five corporate cultural dimensions					
	Integrity	*Teamwork*	*Innovation*	*Respect*	*Quality*
Integrity	1				
Teamwork	0.303***	1			
Innovation	0.074***	0.362***	1		
Respect	0.310***	0.315***	0.324***	1	
Quality	-0.064***	0.144***	0.308***	0.005	1

Panel B: Summary statistics for principal components			
	Eigenvalue	Variance explained	Cumulative
PC1	1.904	0.381	0.381
PC2	1.204	0.241	0.622
PC3	0.741	0.148	0.770
PC4	0.638	0.128	0.898
PC5	0.511	0.102	1.000

Panel C: Loadings of principal components on each cultural dimension					
	PC1	*PC2*	*PC3*	*PC4*	*PC5*
Integrity	0.378	-0.539	0.568	0.322	-0.371
Teamwork	0.541	-0.040	0.246	-0.714	0.366
Innovation	0.507	0.378	-0.359	-0.108	-0.677
Respect	0.501	-0.261	-0.538	0.437	0.445
Quality	0.234	0.704	0.443	0.427	0.265

Table 5. Impact of analyst cultural preference on forecasting performance

This table reports impact of analyst cultural preference on forecasting performance. Dependent variables include forecast accuracy, recommendation profitability, forecast optimism, boldness, and horizon. Independent variables of interest include *PC1* as *sumculture* factor and *PC2* as *growth-at-all-costs* factor. Detailed definition of variables is in Table 1. Panel A reports descriptive statistics of forecasting performance measures. Panel B reports correlations between variables. Panel C reports the panel regression results. We control for year-, industry-, and brokerage-fixed effects, and cluster standard errors by firms. Pseudo R-squared is shown separately in Column (4). The t-statistics and *z*-statistics are in parentheses, and ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Descriptive Statistics						
	N	Mean	Std	P25	P50	P75
Accuracy	286,204	68.847	32.867	50	81.818	95.238
RecomProfit	159,497	2.103	12.565	-3.940	1.602	7.669
Optimism	399,245	-0.131	1.58	-0.193	0.011	0.177
Boldness	225,203	0.713	0.452	0	1	1
Horizon	345,536	5.573	0.409	5.533	5.743	5.802

Panel B: Correlations among variables					
	Accuracy	*RecomProfit*	*Optimism*	*Boldness*	*Horizon*
PC1	0.014***	0.009***	-0.005**	0.006***	0.017***
PC2	0.035***	0.003	0.009***	0.020***	0.031***

Panel C: Regressing forecasting performance on analyst cultural preference					
	(1)	(2)	(3)	(4)	(5)
	Accuracy	*RecomProfit*	*Optimism*	*Boldness*	*Horizon*
PC1	0.416**	0.183**	-0.015***	-0.005	-0.003*
	(2.09)	(2.50)	(-3.00)	(-0.38)	(-1.89)
PC2	1.110***	0.046	0.025***	0.050***	0.012***
	(5.61)	(0.64)	(5.37)	(3.77)	(6.85)
PC1_broker	4.162***	-0.454	0.048*	0.049	0.038***
	(5.16)	(-1.19)	(1.65)	(0.79)	(5.09)
PC2_broker	-3.355***	-0.982	0.072	0.072	-0.066***
	(-2.75)	(-1.61)	(1.57)	(0.78)	(-5.67)
ForecastFreq	5.568***		-0.104***	0.133***	0.555***
	(27.51)		(-14.39)	(6.57)	(133.64)
RecomFreq		0.686***			
		(6.20)			
FirmExp	0.478***	-0.113*	0.009**	0.006	0.207***
	(4.59)	(-1.87)	(2.37)	(0.34)	(86.77)
GeneralExp	0.064	0.044	-0.011***	-0.023	-0.003
	(0.71)	(0.83)	(-3.22)	(-1.33)	(-1.56)
BrokerSize	0.500*	-0.178	0.014	-0.203***	-0.062***
	(1.82)	(-1.52)	(1.42)	(-5.70)	(-13.59)

Nfirms		0.181*	0.037***	0.019	0.050***
		(1.86)	(5.69)	(0.91)	(18.24)
Nindustries		-0.095	-0.029***	-0.013	0.003
		(-1.19)	(-5.83)	(-0.68)	(1.06)
LagAccuracy		0.001		0.162***	
		(0.88)		(8.69)	
DaysElapsed				-0.350***	
				(-20.66)	
Lag	-12.361***		-0.021***	0.193***	
	(-53.24)		(-3.93)	(10.10)	
FirmSize	2.474***	-0.605***	0.062***	0.064***	0.031***
	(26.31)	(-18.38)	(35.70)	(10.05)	(35.15)
MB	0.073	0.026**	0.001*	-0.001	-0.001***
	(0.39)	(2.42)	(1.68)	(-0.80)	(-2.75)
Momentum		-2.248***	0.483***	0.068***	-0.021***
		(-14.71)	(70.49)	(3.05)	(-8.03)
IO	4.638***	-1.019***	0.124***	0.235***	0.087***
	(8.09)	(-4.97)	(11.93)	(6.46)	(16.84)
Constant	89.339***	7.218***	-0.583***	-0.368	4.883***
	(50.91)	(12.75)	(-11.57)	(-1.45)	(556.61)
Observations	286,204	159,497	399,245	225,203	345,536
Adj R-squared	0.119	0.022	0.031	0.0163	0.283

Table 6. Impact of diversity in analyst culture on firm information environment

This table reports impact of analyst cultural diversity (*DiversityCount* or *DiversityHHI*) on firms' information environment (*ConAccuracy* or *Dispersion*). Detailed definition of variables is in Table 1.Panel A reports descriptive statistics of variables. Panel B reports correlations between main variables. Panel C reports panel regression results. We control for year- and industry-fixed effects, and cluster standard errors by firms. The *t*-statistics are in parentheses, and ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Descriptive Statistics						
	N	Mean	SD	P25	Median	P75
ConAccuracy	35787	-0.842	2.561	-0.573	-0.191	-0.061
Dispersion	34677	20.307	44.279	3.17	7.704	19.057
DiversityCount	35787	3.395	1.402	2	4	5
DiversityHHI	35787	0.555	0.233	0.5	0.64	0.72

Panel B: Correlations among variables				
	ConAccuracy	*Dispersion*	*DiversityCount*	*DiversityHHI*
ConAccuracy	1			
Dispersion	-0.287***	1		
DiversityCount	0.079***	0.005	1	
DiversityHHI	0.050***	0.008*	0.886***	1

Panel C: Regressing firm information environment on analyst cultural diversity				
	ConAccuracy		*Dispersion*	
	(1)	(2)	(3)	(4)
DiversityCount	0.038***		0.939***	
	(2.72)		(4.10)	
DiversityHHI		0.149*		5.700***
		(1.89)		(4.58)
Nanalysts	0.033***	0.035***	-1.274***	-1.245***
	(9.03)	(9.81)	(-10.29)	(-10.08)
FirmSize	0.011	0.012	8.547***	8.561***
	(0.59)	(0.63)	(14.02)	(14.05)
MB	0.341***	0.342***	-4.166***	-4.180***
	(12.48)	(12.49)	(-7.31)	(-7.33)
ROA	1.001***	1.000***	1.294	1.369
	(5.43)	(5.42)	(0.44)	(0.47)
Std_ROA	-0.756***	-0.753***	12.820***	12.909***
	(-3.02)	(-3.01)	(3.42)	(3.44)
Momentum	9.200***	9.148***	-65.578***	-66.221***
	(14.85)	(14.81)	(-7.17)	(-7.23)
Std_DRet	-43.431***	-43.325***	568.464***	568.479***
	(-13.65)	(-13.61)	(11.58)	(11.6)
Constant	-0.611***	-0.590***	-46.042***	-46.372***
	(-3.68)	(-3.57)	(-10.67)	(-10.62)
Observations	35,787	35,787	34,677	34,677
Adj R-squared	0.142	0.142	0.107	0.107

Table 7. Impact of cultural similarity on analyst coverage and forecasting performance
This table reports impact of cultural *Similarity* on analysts' coverage decisions (Δ*Coverage* and *Add*) and forecasting performance (*Accuracy* and *RecomProfit*). Detailed definition of variables is in Table 1. Panel A reports descriptive statistics. Panel B reports correlations. Panel C reports panel regression results. We control for year- and industry-fixed effects, and cluster standard errors by firms. The *t*-statistics and *z*-statistics are in parentheses, and ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

Panel A: Descriptive Statistics

	N	Mean	Std	P25	Median	P75
Similarity	307,857	1.270	1.189	0	1	2
Δ*Coverage*	286,664	0.100	0.522	0	0	0
Add	80,644	0.677	0.468	0	1	1
Accuracy	307,857	69.032	32.760	50	82	95.349
RecomProfit	294,594	0.021	0.132	-0.043	0.015	0.079

Panel B: Correlations among variables

	Δ*Coverage*	*Add*	*Accuracy*	*RecomProfit*
Similarity	0.033***	0.074***	0.007***	-0.001

Panel C: The impact of cultural similarity on analyst forecasts

	(1) Δ*Coverage*	(2) *Add*	(3) *Accuracy*	(4) *RecomProfit*
Similarity	0.048***	0.107***	0.127**	0.059***
	(20.15)	(21.07)	(2.32)	(2.70)
FirmSize	0.047***	0.101***	0.159	-0.623***
	(17.76)	(18.31)	(1.00)	(-18.54)
Nanalysts	-0.014***	-0.024***	11.733***	-0.112*
	(-33.99)	(-27.10)	(41.79)	(-1.66)
MB	0.045***	0.085***	0.159	0.212***
	(11.79)	(10.65)	(1.00)	(3.95)
IO	0.070***	0.180***	1.169**	-0.464***
	(6.04)	(7.82)	(2.32)	(-3.08)
BrokerSize	-0.018***	-0.009*	-0.015	0.153***
	(-8.15)	(-1.95)	(-0.22)	(7.07)
Nfirms	0.004***	0.016***	1.541***	0.010
	(12.99)	(28.12)	(9.45)	(0.18)
ROA	0.090***	0.243***		
	(3.49)	(4.81)		
AssetGrowth	0.195***	0.319***		
	(21.60)	(17.26)		
TrdVol	0.028***	0.042***		
	(10.22)	(7.34)		
Momentum	0.076***	0.100***		
	(11.62)	(7.59)		
RelFexp	-0.020***	-0.033***		
	(-74.39)	(-58.74)		

Lag			-16.016***	
			(-73.41)	
RecomFreq				0.301***
				(3.79)
FirmExp			0.713***	0.225***
			(7.33)	(6.68)
GeneralExp			0.298***	0.066**
			(3.52)	(2.06)
Constant		-1.062***	102.699***	6.106***
		(-5.96)	(81.01)	(23.81)
Observations	286,035	80,644	307,857	286,664
Adj R-squared	0.0234	0.0751	0.122	0.010

Internet Appendix

Table IA1. Descriptive statistics of corporate cultural values (LMSY)

Panel A: Summary statistics for corporate cultural values

	N	Mean	Std	P25	Median	P75
Integrity	74391	2.491	1.270	1.599	2.234	3.091
Teamwork	74391	2.550	1.742	1.360	2.054	3.191
Innovation	74391	4.425	2.608	2.565	3.786	5.61
Respect	74391	3.019	2.000	1.603	2.502	3.858
Quality	74391	2.355	1.474	1.286	2.004	3.035

Panel B: Top 10 industries in each dimension

Integrity		*Teamwork*		*Innovation*		*Respect*		*Quality*	
Industry	Value	Industry	Value	Industry	Value	Industry	Value	Industry	Value
Insurance	3.781	Drug	5.332	Business Services	6.737	Personal Services	7.370	Computers	3.982
Gold	3.210	Business Services	3.524	Apparel	6.285	Healthcare	5.587	Ships	3.913
Healthcare	3.170	Healthcare	3.263	Computers	6.195	Medical Equip	4.715	Autos	3.820
Tobacco	3.112	Computers	3.086	Books	6.177	Real Estate	4.274	Fabricated Products	3.644
Drug	3.080	Medical Equip	2.972	Toys	6.148	Business Services	4.264	Chips	3.558
Utility	3.064	Communication	2.859	Retail	5.874	Meals	4.005	Aircraft	3.239
Mines	2.830	Candy & Soda	2.798	Beer & Liquor	5.557	Fun	3.641	Machinery	3.227
Fun	2.806	Guns	2.651	Communication	5.499	Books	3.638	Electrical Equip	3.182
Other	2.730	Fun	2.616	Consumer Goods	5.339	Drug	3.582	Lab Equip	3.174
Trading	2.726	Personal Services	2.557	Candy & Soda	5.337	Insurance	3.487	Transportation	3.159

Panel C: Cultural values of sin industries

	N	*Integrity*	*Teamwork*	*Innovation*	*Respect*	*Quality*
All	777	2.901	2.154	4.653	2.508	1.503
Tobacco	132	3.112	1.777	4.263	1.610	1.136
Gaming	374	3.196	2.401	4.203	3.232	1.741
Alcohol	271	2.380	2.000	5.557	1.934	1.339
Gun	124	2.691	2.651	4.447	3.315	2.942

Table IA2. Subsample tests of Table 5

This table reports subsample analysis results for impact of analyst cultural preference on forecasting performance, categorized by brokerage size. Control variables are included but not reported due to space limitations. All variables are defined in the Table 1. We control for year- and industry-fixed effects, and cluster standard errors by firms. The *t*-statistics and *z*-statistics are in parentheses, and ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Accuracy		*RecomProfit*		*Optimism*		*Boldness*		*Horizon*	
	Big	Small	Big	Small	Big	Small	Big	Small	Big	Small
PC1	0.531**	0.301	0.229**	0.153	-0.018*	-0.011	-0.019	0.007	-0.006***	-0.001
	(2.14)	(1.32)	(2.36)	(1.57)	(-1.74)	(-1.16)	(-1.11)	(0.38)	(-2.61)	(-0.44)
PC2	0.942***	1.340***	0.162*	-0.102	0.019**	0.029***	0.059***	0.037**	0.016***	0.015***
	(4.07)	(5.81)	(1.70)	(-1.11)	(2.01)	(2.96)	(3.73)	(2.30)	(6.66)	(6.48)
Observations	150,862	135,301	79,982	79,481	203,158	185,916	119,089	105,992	173,219	160,896
Adj R-squared	0.118	0.124	0.025	0.024	0.032	0.037	0.0156	0.0194	0.115	0.123

Table IA3. Robustness of Table 5 without controlling for brokerage effect

	(1) *Accuracy*	(2) *RecomProfit*	(3) *Optimism*	(4) *Boldness*	(5) *Horizon*
PC1	0.368*	0.002***	-0.025***	-0.017	-0.005***
	(1.82)	(2.97)	(-5.16)	(-1.34)	(-3.10)
PC2	0.931***	-0.000	0.019***	0.038***	0.010***
	(4.78)	(-0.38)	(4.10)	(3.17)	(6.21)
ForecastFreq	6.154***		-0.069***	0.185***	0.401***
	(31.78)		(-9.95)	(10.11)	(131.97)
RecomFreq		0.001			
		(1.44)			
FirmExp	0.563***	-0.001*	0.025***	0.039**	0.259***
	(5.51)	(-1.70)	(7.03)	(2.37)	(100.89)
GeneralExp	0.580***	0.002***	-0.018***	0.007	-0.007***
	(6.58)	(3.32)	(-5.51)	(0.43)	(-4.26)
BrokerSize	-0.062	0.001***	-0.008***	0.001	0.207***
	(-0.84)	(5.05)	(-3.61)	(0.05)	(100.50)
Nfirms		0.001	0.060***	-0.047***	0.035***
		(0.67)	(10.39)	(-2.75)	(17.07)
Nindustries		-0.002**	-0.037***	0.034*	0.002
		(-2.24)	(-8.12)	(1.85)	(0.85)
LagAccuracy		0.000*		0.205***	
		(1.80)		(11.81)	
DaysElapsed				-0.390***	
				(-25.09)	
Horizon	-12.126***		-0.028***	0.200***	
	(-52.47)		(-5.49)	(11.39)	
Mktcap	2.296***	-0.007***	0.059***	0.067***	0.023***
	(21.92)	(-22.66)	(37.96)	(11.99)	(31.99)
MB	0.310*	0.000***	-0.001*	-0.001	-0.000***
	(1.68)	(2.83)	(-1.93)	(-0.41)	(-2.64)
Momentum		-0.022***	0.457***	0.088***	-0.022***
		(-15.72)	(70.53)	(4.25)	(-11.07)
IO	4.886***	-0.009***	0.126***	0.232***	0.070***
	(8.64)	(-4.75)	(12.59)	(6.99)	(16.42)
Constant	89.496***	0.075***	-0.535***	-0.467**	5.071***
	(65.24)	(20.92)	(-15.79)	(-2.44)	(807.23)
Observations	332,368	183,256	473,312	260,136	470,639
Adj R-squared	0.106	0.015	0.023	0.0120	0.210

Table IA4. Robustness of Table 5: Alternative cultural preference measure

This table presents robustness checks of Panel C of Table 5 using an alternative measure of analyst cultural preference. Before calculating $\mu_{jtk}/\ \sigma_{jtk}$, we normalize standard deviation, σ_{jtk}, by dividing average standard deviation of analysts with same number of firm coverages.

	(1) *Accuracy*	(2) *RecomProfit*	(3) *Optimism*	(4) *Boldness*	(5) *Horizon*
PC1	0.486**	0.212**	-0.014**	-0.015	-0.003*
	(2.12)	(2.52)	(-2.56)	(-0.95)	(-1.89)
PC2	1.706***	0.054	0.037***	0.068***	0.012***
	(5.60)	(0.49)	(5.20)	(3.42)	(6.85)
PC1_broker	4.171***	-0.454	0.048*	-0.012	0.038***
	(5.17)	(-1.19)	-1.67	(-0.28)	(5.09)
PC2_broker	-3.350***	-0.974	0.072	-0.086	-0.066***
	(-2.75)	(-1.60)	-1.57	(-1.35)	(-5.67)
ForecastFreq	5.569***		-0.104***	0.178***	0.555***
	(27.52)		(-14.38)	(9.03)	(133.64)
RecomFreq		0.685***			
		(6.20)			
FirmExp	0.478***	-0.114*	0.009**	0.034*	0.207***
	(4.59)	(-1.88)	-2.38	(1.93)	(86.77)
GeneralExp	0.063	0.044	-0.011***	0.007	-0.003
	(0.70)	(0.84)	(-3.21)	(0.45)	(-1.56)
BrokerSize	0.499*	-0.179	0.014	0.002	-0.062***
	(1.82)	(-1.52)	-1.42	(0.12)	(-13.59)
Nfirms		0.181*	0.037***	0.038*	0.050***
		(1.85)	-5.67	(1.92)	(18.24)
Nindustries		-0.096	-0.029***	-0.057***	0.003
		(-1.20)	(-5.82)	(-3.14)	(1.06)
LagAccuracy		0.001		0.198***	
		(0.88)		(10.66)	
DaysElapsed				-0.389***	
				(-22.54)	
Horizon	-12.361***		-0.021***	-0.389***	
	(-53.23)		(-3.93)	(-23.04)	
Mktcap	2.474***	-0.605***	0.062***	0.063***	0.031***
	(26.30)	(-18.38)	(35.70)	(10.56)	(35.15)
MB	0.070	0.026**	0.001*	-0.001	-0.001***
	(0.37)	(2.42)	(1.66)	(-0.72)	(-2.75)
Momentum		-2.247***	0.483***	0.069***	-0.021***
		(-14.70)	(70.50)	(3.12)	(-8.03)
IO	4.638***	-1.019***	0.124***	0.260***	0.087***
	(8.09)	(-4.97)	(11.94)	(7.11)	(16.84)
Constant	89.356***	7.222***	-0.583***	-0.425**	4.883***

	(50.93)	(12.75)	(-11.57)	(-2.19)	(556.61)
Observations	286,204	159,497	399,245	225,367	345,536
Adj R-squared	0.119	0.022	0.031	0.011	0.283

Table IA5. Robustness of Table 5: Residual cultural preference

This table presents robustness checks of Panel C of Table 5 using residuals from regressing analysts' cultural preferences on a set of firms' characteristics including firm size, firm turnover, institutional ownership, market-to-book ratio and momentum.

	(1) *Accuracy*	(2) *RecomProfit*	(3) *Optimism*	(4) *Boldness*	(5) *Horizon*
PC1	0.456**	0.181**	-0.015***	-0.009	-0.005***
	(2.15)	(2.29)	(-2.60)	(-0.65)	(-2.85)
PC2	1.279***	0.015	0.020***	0.049***	0.015***
	(5.91)	(0.20)	(3.69)	(3.58)	(8.06)
PC1_broker	4.784***	-0.558	0.039	-0.023	0.042***
	(5.50)	(-1.39)	(1.20)	(-0.53)	(5.41)
PC2_broker	-3.763***	-0.737	0.014	-0.089	-0.094***
	(-2.83)	(-1.17)	(0.27)	(-1.34)	(-7.72)
ForecastFreq	5.363***		-0.100***	0.178***	0.466***
	(25.04)		(-12.42)	(8.80)	(113.97)
RecomFreq		0.652***			
		(5.77)			
FirmExp	0.468***	-0.135**	0.008**	0.034*	0.166***
	(4.29)	(-2.16)	(2.05)	(1.88)	(69.10)
GeneralExp	-0.012	0.042	-0.017***	0.003	-0.035***
	(-0.12)	(0.75)	(-4.28)	(0.20)	(-16.32)
BrokerSize	0.350	-0.248**	0.004	0.008	-0.009***
	(1.20)	(-2.01)	(0.35)	(0.46)	(-3.19)
Nfirms		0.177*	0.028***	0.034*	-0.004
		(1.70)	(3.60)	(1.67)	(-1.61)
Nindustries		-0.145*	-0.034***	-0.064***	0.002
		(-1.74)	(-6.37)	(-3.43)	(0.85)
LagAccuracy		0.001		0.200***	
		(1.28)		(10.52)	
DaysElapsed				-0.389***	
				(-22.54)	
Horizon	-11.861***		-0.026***	0.200***	
	(-48.82)		(-4.44)	(10.33)	
Mktcap	2.548***	-0.606***	0.061***	0.065***	0.028***
	(27.03)	(-17.85)	(32.85)	(10.83)	(31.99)
MB	0.154	0.027**	0.000	-0.001	-0.000**
	(0.79)	(2.46)	(0.82)	(-0.47)	(-2.28)
Momentum		-2.245***	0.480***	0.075***	-0.022***
		(-14.20)	(63.82)	(3.29)	(-8.07)
IO	4.345***	-1.014***	0.109***	0.236***	0.076***
	(7.09)	(-4.65)	(9.62)	(6.30)	(14.65)
Constant	87.705***	7.580***	-0.462***	-0.298	5.042***
	(47.97)	(12.41)	(-8.06)	(-1.35)	(558.82)
Observations	332,368	150,728	330,764	216,861	289,143
Adj R-squared	0.106	0.022	0.032	0.011	0.232

Table IA6. Robustness of Table 6: Diversity in analyst culture including focal firm
This table reports the robustness check of Table 6 using an alternative measure of analyst cultural diversity (*DiversityCount* and *DiversityHHI*), which are calculated based on corporate culture of all covered firms (including the focal firm).

Panel A: Descriptive Statistics						
	N	Mean	SD	P25	Median	P75
ConAccuracy	49,164	-1.050	3.118	-0.653	-0.211	-0.065
Dispersion	42,500	20.837	46.497	3.055	7.592	19.092
DiversityCount	49,164	2.780	1.533	2	3	4
DiversityHHI	49,164	0.467	0.281	0.319	0.571	0.693

Panel B: Correlations among variables				
	ConAccuracy	*Dispersion*	*DiversityCount*	*DiversityHHI*
ConAccuracy	1			
Dispersion	-0.300***	1		
DiversityCount	0.069***	0.015***	1	
DiversityHHI	0.051***	0.008*	0.908***	1

Panel C: Regressing firm information environment on analyst cultural diversity				
	ConAccuracy		*Dispersion*	
	(1)	(2)	(3)	(4)
DiversityCount	0.039***		0.733***	
	(3.28)		(3.29)	
DiversityHHI		0.197***		2.571**
		(3.20)		(2.46)
Nanalysts	0.034***	0.036***	-1.435***	-1.402***
	(9.64)	(10.16)	(-11.80)	(-11.52)
FirmSize	0.029	0.029	8.853***	8.862***
	(1.62)	(1.63)	(15.82)	(15.83)
MB	0.351***	0.352***	-3.905***	-3.867***
	(12.51)	(12.54)	(-6.77)	(-6.72)
ROA	1.143***	1.140***	-2.912	-3.057
	(6.68)	(6.67)	(-1.06)	(-1.12)
Std_ROA	-0.864***	-0.864***	10.864***	10.906***
	(-3.49)	(-3.49)	(3.00)	(3.01)
Momentum	10.623***	10.598***	-63.707***	-64.692***
	(17.67)	(17.64)	(-7.56)	(-7.71)
Std_DRet	-47.786***	-47.718***	538.122***	541.506***
	(-16.06)	(-16.05)	(12.51)	(12.58)
Constant	-0.683***	-0.678***	-44.157***	-43.743***
	(-4.49)	(-4.46)	(-11.82)	(-11.73)
Observations	44,791	44,791	42,500	42,500
Adj R-squared	0.147	0.147	0.112	0.112