Cultural Diversity on Wall Street: Evidence from Sell-Side Analysts' Forecasts

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December 2017

Abstract: We study cultural diversity on Wall Street using information about sell side analysts' cultural backgrounds. We find evidence consistent with higher levels of cultural diversity improving the accuracy of analysts' consensus forecasts, and reducing optimism bias and dispersion. The positive effects of diversity on consensus forecast accuracy are more pronounced when firms have more opaque information environments, but also exhibit declining returns to scale. These results are robust to controlling for other dimensions of diversity (i.e., gender and educational diversity). Further, using exogenous shocks to analyst coverage resulting from brokerage house mergers, we find that drops in analyst coverage that reduce cultural diversity have a more significant impact on forecast accuracy. In additional analyses, we explore conference calls as one plausible mechanism for diversity to improve information flows, and find that cultural diversity is associated with more interaction on conference calls (as evidenced by analysts raising more questions on calls). Overall, our findings offer important insights on the effects of diversity between competitive agents.

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1. Introduction

> *"For us to be successful, our men and women must reflect the diversity of the communities and cultures in which we operate. That means we must attract, retain and motivate people from many backgrounds and perspectives. Being diverse is not optional; it is what we must be."*
> – Lloyd Blankfein (CEO of Goldman Sachs)

On January 27, 2017, President Donald J. Trump announced that, effective immediately, the United States was closing its borders and banning travel from seven Muslim-majority countries. In the days that followed, many corporations joined together to formally protest the travel ban, as executives espoused diversity as a key driver of firm value.[1] Top executives from Wall Street firms represented some of the more vocal critics of the travel ban. For example, Bank of America CEO Brian Moynihan stated that the firm was "dependent on diverse sources of talent." Morgan Stanley distributed a letter to its employees indicating that diversity was critical in the firm's "success in serving its clients." Similarly, Wells Fargo posted a statement on its employee website expressing its "commitment to fostering a culture of diversity."[2] The response from Wall Street firms surrounding the travel ban raises more general and fundamental questions regarding the importance of diversity in the financial services industry.

In this study, we seek to provide empirical evidence on how cultural diversity impacts behavior among one key component of Wall Street's labor force: sell-side equity analysts. Sell-side equity analysts provide a useful setting for examining the effects of cultural diversity on Wall Street for several important reasons. First, sell-side equity analysts represent a vital component of the labor force on Wall Street and are important information intermediaries in capital markets. The information that analysts produce (e.g., research reports and earnings forecasts) helps improve the information flow and efficiency of capital markets (Brennan et al., 1993; Womack 1996; Gleason and Lee, 2003; Clement and Tse, 2003) and can also have important economic implications for managers' real decisions and reporting behavior (Yu, 2008; Derrien and Kecskés, 2013; Balakrishnan et al., 2014). The consensus earnings forecast, in particular, represents one of the most important and widely publicized economic benchmarks for publicly traded firms (Graham et al., 2005), as it sets market earnings expectations for managers and investors.

[1] "Deeply concerned: Corporate America responds to Trump's travel ban." Washington Post, January 30, 2017.
[2] "Wall Street Reassures Employees, Without Wholly Rejecting Travel Ban." New York Times, January 30, 2017.

Second, analysts' reporting activities present a unique opportunity to examine the role of diversity in a non-cooperative environment (e.g., analysts from different banks competing against each other), whereas prior studies examine the role of cultural diversity in cooperative environments (e.g., Brochet et al., 2016; Gompers et al., 2016; Giannetti and Zhao, 2017). Non-cooperative settings are common on Wall Street (e.g., brokers often compete to provide better services, underwriters compete for investment banking mandates, etc.) and generate very different incentives from those present in cooperative settings. In cooperative settings (e.g., board of directors), there are strong incentives for individuals to arrive at a consensus and incorporate peers' beliefs as their incentives are based, in part, on the group outcome (e.g., firm performance). In contrast, non-cooperative settings remove many group decision-making issues as individuals independently choose and act on the information that is most relevant to their own performance. Sell-side equity analysts in particular face strong economic incentives to compete to outperform their rivals in industry rankings, and thus are naturally inclined to scrutinize and challenge their rivals' views (Hong and Kacperzyk, 2010; Merkley et al., 2017).

Finally, from a practical perspective, the sell-side equity analyst industry provides us with a rich setting for examining the effects of cultural diversity, as there is plentiful micro data available to measure their output with precision (unlike, for example, the specific contribution of a board member to the output of a firm). Furthermore, these data also allow us to identify analysts' surnames and assign employee ethnicity using new techniques imported from the public health and population genetics literature, and recently employed in economics-based studies (e.g., Kerr and Lincoln, 2010; Bengtsson and Hsu, 2015; Hedge and Tumlinson, 2014; Brochet et al., 2016; Gompers et al., 2016; Liu, 2016). This unique combination – the ability to calculate both input (cultural diversity) and output (performance) in a precise manner – coupled together with a plausibly exogenous shock to diversity provide a rich laboratory for examining the effect of diversity on the quality of analysts' output. Moreover, this setting also allows for the investigation of the potential mechanisms underlying the role of diversity.

We examine whether cultural diversity across competing analysts influences the overall quality (e.g., accuracy) of consensus forecasts derived from their individual reports. We test this question by employing a variety of empirical strategies designed to alleviate endogeneity concerns, including fixed effects and a quasi-natural experiment involving brokerage house mergers and closures. While by no mean the only mechanism, we also explore how diversity impacts analysts' interactions on conference calls to better identify an important mechanism whereby diversity can facilitate information sharing among analysts. Ultimately, our goal is to shed light on how cultural diversity influences the quality of information analysts jointly provide to market participants.

Ex ante, the relationship between diversity and forecast accuracy is unclear. On the one hand, diversity leads to increased heterogeneity in the perspectives, priors, and practices of individuals because different cultures emphasize different ways of thinking and communicating (Page, 2007; Hong and Page, 2001; Chang et al., 2015; Lin and Liu, 2017). Prior studies suggest that such heterogeneity can improve group productivity as a collection of "cognitively diverse" problem solvers offer unique perspectives, allowing them to better solve difficult problems and interpret information (Alesina et al., 2000; Alesina and La Ferrara, 2000; Hong and Page, 2001; Alesina and La Ferrara, 2005). In the context of financial markets, recent evidence indicates that heterogeneity among traders or investors can improve market outcomes as investors are more likely to scrutinize others' decisions, challenge each other's beliefs, and identify important issues (Levine et al., 2014; Ishi and Xuan 2014; Gompers et al., 2016). Thus, higher levels of cultural diversity could lead to more accurate consensus forecasts if analysts from different cultural heritages incorporate their perspectives into their forecasts, and their rivals learn about these perspectives and update their forecasts accordingly.

On the other hand, any benefits associated with increased heterogeneity will not be realized if cultural diversity limits the flow of information. Indeed, prior studies suggest that diversity often reduces communication effectiveness and increases the costs of gathering information (Rogers and Bhowmik, 1970; Giannetti and Yafeh, 2012). If divergence in perspectives and ideas is too pronounced, analysts may even choose to gather and disseminate information in ways that are independent of their rivals. This line of reasoning is consistent with prior studies indicating that market imperfections make it optimal for individuals to transact only with those of similar ethnicity (Greif, 1993; La Ferrara, 2003; Hedge and Tumlinson, 2014). Diversity can also be associated with a lack of trust and conflicts of preferences (Alesina and La Ferrara, 2005; Giannti and Yahfeh, 2012), which mute the effects of diversity on accuracy. Overall, whether and to what extent cultural diversity improves output quality, the quality of analysts' consensus forecasts in our investigation, remains an unresolved empirical question.

To examine the effects of cultural diversity, we first construct a unique dataset that identifies the cultural origins of sell-side equity analysts based on their surname. We obtain surnames from I/B/E/S for approximately 15,000 analysts employed between 1994 and 2014. We then use three separate name dictionaries to identify the most likely country of origin for each surname and map each country of origin to a cultural cluster following classification schemes from the organizational behavior literature (e.g., House et al., 2002). Using this dataset, we classify analysts into ten distinct cultural backgrounds and construct measures of analyst cultural diversity based on the number of unique cultural clusters contributing to the consensus forecast. Our main analyses examine how the accuracy of a firm's consensus earnings forecast varies with the number of unique cultural clusters contributing to the consensus forecast.

Our initial findings suggest that increased cultural diversity is positively associated with increased accuracy of the consensus forecast. Specifically, we document positive and significant associations between the number of cultural clusters contributing to the consensus and the accuracy of the consensus forecast. Our results suggest that a one-unit change in the number of cultural clusters is associated with an 11% increase in forecast accuracy relative to the unconditional sample mean. To assess whether any net benefits or costs of cultural diversity on forecast accuracy have declining returns to scale, we also examine the relationship between forecast accuracy and the square of the number of cultural clusters of the analysts contributing to the consensus. These analyses indicate that the benefits of cultural diversity are lower at higher levels of diversity, suggesting a nuanced view of diversity in that net benefits decline at higher levels of diversity.

We obtain similar results when we examine alternative measures of cultural diversity based on the concentration of different cultural clusters and the average distances between cultural clusters contributing to the consensus. Our results also persist after we augment our analyses with individual analyst fixed effects or with cultural cluster fixed effects, suggesting that the diversity does not simply capture variation in analyst talent or the presence of specific cultural backgrounds. Finally, the relation between cultural diversity and forecast accuracy is more pronounced when firms have greater information uncertainty (i.e., smaller firms, firms with less analyst following, firms with higher stock volatility), consistent with diversity mattering most in situations when information is complex or less available.

Our baseline analyses are subject to potential endogeneity concerns if the degree of cultural diversity in a firm's analyst coverage is driven by factors that also impact the consensus forecast accuracy. These factors must correlate with analysts' coverage decisions in a way that not only leads to greater coverage, but also leads to more diverse coverage (e.g., asymmetric incentives across analysts of different cultural origins). To help alleviate such concerns, we control for time-invariant firm heterogeneity through both the inclusion of firm fixed effects and also re-estimate our regression models using a first differences changes specification. We also re-examine our analyses using entropy-matching based on firm characteristics that prior studies suggest explain the level of analyst following. Across all of these tests, our inferences are unchanged, suggesting that time-invariant firm heterogeneity does not explain the association between cultural diversity and consensus forecast accuracy.

We also utilize a natural experiment based on plausibly exogenous variation in analyst cultural diversity to further reduce endogeneity concerns. The exogenous variation in diversity is an outcome of brokerage house mergers and closures that result in drops in analyst coverage (Hong and Kacperzyk, 2010; Merkley et al., 2017). We identify firm-years that contain an exogenous drop in analyst coverage and classify them into drops that decrease analyst cultural diversity and those that do not. We then regress forecast errors on the interaction of changes in analyst cultural diversity and the pre-drop level of cultural diversity. Our results indicate that exogenous drops in analyst cultural diversity reduce forecast accuracy. However, this effect is muted at higher levels of diversity, suggesting that reductions in analyst cultural diversity are less consequential to market participants when the firm has higher levels of diversity.

Another concern for our analysis is that cultural diversity may somehow be correlated with other forms of diversity. To examine this possibility, we obtain data from an online business networking service for a subsample of analysts with available profiles. With this data, we partition our sample based on gender diversity and educational diversity to determine how much other types of diversity influence our findings. Our results continue to indicate that cultural diversity is associated with higher levels of forecast accuracy, regardless of the level of gender or educational diversity, suggesting that other forms of diversity do not explain the effect of cultural diversity on consensus forecast accuracy. Overall, our findings thus far paint a consistent picture regarding the effects of cultural diversity on analysts' consensus forecast accuracy as they suggest that diversity is associated with more accurate forecasts and these benefits decline at higher levels of diversity.

Our results raise important questions regarding the mechanisms by which the benefits of diversity emerge and how, in our investigation, diversity impacts how analysts produce and process information. For example, what setting or forum enables a group of analysts from different investment banks to jointly hear alternative perspectives and arrive at a higher quality consensus forecast? It is possible that some information is transmitted simply by reading rival analysts' reports and learning their opinions or concerns. Another, not mutually exclusive, channel is through discussions during conference calls. We thus explore how cultural diversity affects analysts' behavior on conference calls, as they provide us a unique setting to examine how a diverse set of analysts interact, learn and potentially benefit from their rivals' views. Specifically, we examine the relationship between cultural diversity and the number of questions raised and length of question and answer discussions on conference calls (after controlling for industry and time fixed effects as well as other variables known to affect conference call discussions). Our findings indicate that cultural diversity is associated with a greater number of questions and lengthier analyst discussion on conference calls, suggesting that diversity results in more information being discussed on conference calls. These results suggest that conference calls provide one plausible mechanism for the effect of cultural diversity on analysts' consensus forecasts.

Our final analyses examine how cultural diversity relates to analyst bias and dispersion. Recent experimental evidence suggests that investors are more likely to question their peers and discipline price bubbles when they have different ethnic backgrounds (Levine et al., 2014), suggesting that cultural diversity may help to discipline forecast optimism (i.e., positive bias) that is maybe more prevalent in homogenous groups. Diversity may also lead to a weaker tendency to herd which in turn reduces bias. Furthermore, if analysts incorporate their rivals' views into their forecasts throughout the fiscal period, greater cultural diversity, which increases information production, should also reduce forecast dispersion. Our results indicate negative associations between cultural diversity and forecast optimism-bias and forecast dispersion. Moreover, these associations are less pronounced at higher levels of diversity. Taken together, this evidence indicates that cultural diversity improves the consensus forecast across multiple dimensions (accuracy, bias, and dispersion), but with declining returns to scale.

Our study contributes to the literature along several dimensions. First, we contribute to a recent and growing literature examining how cultural differences between economic agents relate to economic outcomes. Prior studies in this area examine the effects of culture and cultural diversity in a variety of cooperative settings, including corporate board behavior, debt syndication, venture capitalist project selection, and management conference calls (Giannetti and Yafeh, 2012; Chang et al., 2014; Brochet et al., 2016; Giannetti and Zhao, 2017; Gompers et al., 2016; Liu, 2016). Our findings contribute to this literature by demonstrating the importance of cultural diversity in a competitive setting (i.e., sell-side equity analysts' forecasting behavior) that influences the quality of information available to other market participants. Our results also relate to a recent experimental study which suggests that increased diversity improves the aggregation of information in prices (Levine et al., 2014). We contribute to these findings using a setting where output quality (i.e., analysts' forecast accuracy) can be measured precisely and in a broader sample encompassing a large population of U.S. equity analysts who are tasked with gathering and producing information for investors.

Second, we contribute to the literature examining analyst following (e.g., Bhushan, 1989; Hong and Kacperzyk, 2010; Merkley et al., 2017). While prior studies generally document benefits associated with greater analyst following, they do not shed light on how the cultural composition of analyst following can impact forecast properties. We extend this literature by examining how cultural diversity, one important and controversial issue related to Wall Street's labor force, can influence the consensus forecasts produced by equity analysts and ultimately market expectations and stock prices. In this light, our findings suggest that diversity makes competition more intense.

More broadly, our study has implications for practitioners and regulators. Since the financial crisis there have been increasing concerns regarding a purported lack of diversity in the financial services industry.[3] Recent political events once again call into question the value of diversity in labor markets. While our setting is limited to the impact of diversity on analysts output, the finding of the positive effect of diversity on output likely goes beyond just analysts and applies more generally, suggesting the concept of diversity goes beyond fairness but also positively affects efficiency.

2. Sample Selection and Measuring Cultural Diversity

We measure analyst cultural diversity by mapping analyst surnames to geographic regions that are likely to represent an analyst's country of ancestry. We begin our sample construction using the I/B/E/S detailed analyst recommendation file as it provides the most accurate data on analysts' surnames. We use the recommendation file, as opposed to the earnings forecasts file, since I/B/E/S has stopped providing a table that can be used to link analyst names to individual

[3] For example, see "Wall Street's Young Bankers Are Still Mostly White and Male, Report Says." Wall Street Journal, September 30, 2014.

earnings forecasts. We select all analysts in the recommendation file with valid last names and first initials. This excludes anonymous analysts as well as those with missing names. We also exclude names that do not appear to be valid (e.g., instances in which the name of an industry appears instead of the name of an analyst) as well as hyphenated names, and reports that identify more than one analyst. To be included in our sample, we require each analyst to provide at least five recommendations in the dataset and cover at least five distinct firms. This initial sample results in the selection of 17,202 unique analyst surnames.

We identify the country of origin associated with an analyst's surname using recently developed technology that is described as an epidemiological approach for categorizing ancestry (e.g., Fernández, 2011; Liu, 2016). Prior research suggests that ancestry has a persistent cultural effect that lasts for several generations or more (Guiso et al., 2006). We use dictionaries from three different sources to assign each analyst's surname to a specific country of origin. The first dictionary, and our primary source for name classification, is the Oxford Dictionary of American Family Names. This dictionary is the result of a ten-year research project based on the work of thirty linguistic consultants led by Editor-in-Chief Patrick Hanks. The dictionary contains more than 70,000 of the most common surnames in the United States and provides information on their linguistic and historical backgrounds, as well as genealogical notes.[4] The second dictionary is based on data about family names and origins collected by Ancestry.com from immigration passenger lists from 1820-1957.[5] This dictionary is historical in nature in that country origins are assigned based on immigration patterns. The third dictionary is created from data on surname origins provided by Forebears, a genealogical website that has collected data on more than 11 million surnames. This dictionary is based on information regarding the country where people with particular surnames currently reside.

Using each of these dictionaries, we first independently map analyst surnames to their country of origin. In the case of multiple origins, we map surnames to the most likely country based on the relative frequency of the name and country combinations. We then map the country of origin to a cultural cluster following the methodology used in the Global Leadership & Organizational Behavior Effectiveness (GLOBE) Study (i.e., House et al., 2002)).[6] These cultural

[4] An online version of the dictionary is available at http://www.oxfordreference.com/view/10.1093/acref/9780195081374.001.0001/acref-9780195081374.
[5] http://www.ancestry.com/learn/facts/
[6] http://www.inspireimagineinnovate.com/pdf/globesummary-by-michael-h-hoppe.pdf.

clusters are as follows: Anglo, Nordic Europe, Latin America, Southern Asia, Confucian Asia, Middle East, Eastern Europe, Sub-Sahara Africa, Latin Europe, and Germanic Europe. Our classification system allows us to match cultural origin information from at least one of the three dictionaries to about 90% of the unique names we identified from I/B/E/S. In about 74% of these cases there is complete agreement with the available dictionaries regarding the cultural identification. When there is disagreement across dictionaries, we use the classification from what we deem to be the most reliable source. We rank the dictionaries, giving priority to the Oxford Dictionary of American Names, followed by Ancestry.com, and finally Forebears. We rank in this manner based on our understanding of the relative accuracy of each dataset. The Oxford Dictionary of American Names is scholarly work, so we consider it the most reliable, whereas Ancestry.com and Forbears are based on surveys of historical and current data respectively. Overall, this approach allows us to assign a cultural classification to 15,383 unique names.

We next link analyst identities to earnings forecasts using the analyst identifier code in the recommendations file (AMASKCD). We keep forecasts that are outstanding in the three months prior to the fiscal year end and require data from Compustat and CRSP for the prior year. We also require data on actual earnings from I/B/E/S and stock prices at the end of the prior fiscal year to be at least $5. We limit our sample to data for fiscal years after 1994 because analyst data on recommendations is not widely available on I/B/E/S prior to this time and end our sample at the end of 2013. We aggregate these forecasts at the firm and year level, which yields a sample of 55,117 firm-year observations.

Our main measure of cultural diversity is the number of unique cultural clusters represented by analysts contributing to the consensus earnings forecast (*DiverseNum*). This measure is simple in construction and easy to interpret with respect to the findings of prior studies that consider the effect of changes in the number of analysts covering a firm on the quality of analyst reports (e.g., Hong and Kacperczyk, 2010; Merkley et al., 2017). In additional analyses, we also explore other measures of cultural diversity that capture concentration and cultural distance.

Panel A of Table 1 reports descriptive statistics on *DiverseNum* by year. These data are also illustrated in Figure 1. In both cases, we observe a steady increase in the average number of cultural clusters represented by firms' analysts. Panel B of Table 1 reports descriptive statistics on the average number of cultural clusters from select industries (those with 500+ observations) based on two digit SIC codes. These data suggest that there is significant variation in analyst cultural diversity across industries. Panel B of Table 1 reports descriptive statistics on the average number of cultural clusters from select industries (those with 500+ observations) based on two digit SIC codes. These data suggest that there is significant variation in analyst cultural diversity across industries. For example, the oil industry, which has a large global footprint has large levels of diversity, with around four unique cultural clusters. In all of our analyses, we include either industry or firm fixed effects to ensure that any relationship between cultural diversity and forecast accuracy is not explained by time-invariant differences in industry characteristics.

3. Analyst Cultural Diversity and Consensus Forecast Accuracy

3.1 Baseline Model

Our primary research question is whether cultural diversity relates to the accuracy of analyst reports through increasing the amount of information analysts incorporate in their reports. To test this question, we first employ the following regression models:

$$Accuracy = \alpha_0 + \alpha_1 DiverseNum + \sum\beta_i Controls + \varepsilon \quad (1),$$

$$Accuracy = \alpha_0 + \alpha_1 DiverseNum + \alpha_2 DiverseNum\ X\ DiverseNum + \sum\beta_i Controls + \varepsilon \quad (2),$$

where $Accuracy$ is calculated as the absolute difference between the consensus analyst earnings forecast and the actual earnings per share scaled by stock price at the end of the prior fiscal year multiplied by negative one. We also include a vector of control variables based on previously established determinants of analysts' forecast properties, including: *AnalystNum*, the number of analysts included in the consensus forecast; *LNSIZE*, the natural log of the equity market value of the firm; *LNBM*, the natural log of the ratio of market value of equity to book value of equity; *ROA*, the ratio of income before extraordinary items to total assets; *STD_ROA*, the standard deviation of ROA over the last five years; *RETVOL*, the standard deviation of daily stock returns over the last 12 months; *RET*, the average monthly return over the last 12 months; *Foreign_Sales*, an indicator for whether the firm reports foreign sales activity. Control variables are lagged such that they are calculated based on the prior fiscal year relative to the period for which analysts are forecasting. All tests include year and industry (two digit SIC) fixed effects, except for tests that include firm fixed effects in place of industry fixed effects. The difference between equations (1) and (2) is the inclusion of a square term for *DiverseNum* in equation 2 to test whether and to what extent the relation between diversity and forecast accuracy is nonlinear.

3.2 Descriptive Statistics

Table 2 reports the descriptive statistics for the sample of firm-year observations. The mean (median) value of *DiverseNum* is 2.833 (3.000), indicating that, on average, the consensus forecast is composed of analysts representing approximately three unique cultural clusters. The mean (median) number of analysts covering a firm is 6.252 (4.000) and the median firm has a market value of $853 million and book-to-market ratio of 0.458. The mean (median) *ROA* and *STD_ROA* are 0.032 (0.038) and 0.072 (0.027), respectively. The mean (median) *RET* and *RETVOL* are 0.018 (0.015) and 0.028 (0.025), respectively. About 56% of sample observations conduct foreign sales activity (*Foreign_Sales*). Given that we require that our firms have analyst coverage to be able to measure analyst cultural diversity, our sample firms are larger and more profitable on average than those in the general Compustat universe.

Table 3 reports Pearson correlations for the variables employed in the analysis. The table indicates several interesting correlations. First, consistent with prior studies (e.g., Merkley et al., 2017), higher levels of analyst coverage are associated with more accurate consensus forecasts as evidenced by the positive association between *Forecast Accuracy* and *Num_Analysts* ($\rho = 0.121$). Second, the table also suggests that there is a positive relationship between cultural diversity and forecast accuracy, as evidenced by the positive association between *DiverseNum* and *Forecast Accuracy* ($\rho = 0.118$). Not surprisingly, the table also indicates a strong positive association between *Num_Analysts* and *DiverseNum*, highlighting the importance of controlling for the level of analyst following in our analyses as having more analysts increases the likelihood of having more cultural diversity.

3.3 Results

Table 4 reports the results of estimating the baseline models (i.e., equations (1) and (2)) and variations of these models. Column (1) reports the results from estimating equation (1) which includes time varying controls and industry and year fixed effects. The results indicate a positive and significant relationship between *DiverseNum* and *Accuracy* ($p < 0.01$), suggesting that higher levels of diversity improve the quality of the consensus forecast. Our results also appear to be economically meaningful. The coefficient on *DiverseNum* is 0.0011, which implies that a one-unit change in the number of cultural clusters is associated with an 11% increase in forecast accuracy relative to the unconditional sample mean of -0.0100.[7] The coefficients on the control variables are consistent with the findings of prior studies in that accuracy is higher for larger firms, and for firms with better and less volatile performance. Notably, the level of analyst following is positively and significantly associated with forecast accuracy, consistent with competition improving the quality of the consensus forecast (e.g., Hong and Kacperzyk, 2010; Merkley et al., 2017). However, we also note that comparatively, the coefficient on *Num_Analysts* is significantly smaller than that on *DiverseNum*, highlighting the relative importance of cultural diversity.

In Column (2) we further explore whether the relationship between diversity and forecast accuracy is non-linear. Accordingly, we augment the model with squared terms for diversity, as specified in equation (2). The results indicate several interesting trends. First, consistent with the above findings, the coefficient on *DiverseNum* continues to load positively and significantly ($p < 0.01$), suggesting that the consensus forecast is more accurate for firms with higher levels of analyst cultural diversity. Moreover, the results also indicate that the squared diversity term loads negatively and significantly, suggesting that the benefits of diversity decline at higher levels of diversity. Taken together, the results in Columns (1) and (2) suggest that effects of diversity on forecast accuracy are nuanced. Diversity appears to be associated with a higher quality consensus forecasts, but the benefits decline as diversity reaches higher levels. These findings support the contention of Wall Street banks that cultural diversity is helpful to their businesses, but also support the views of detractors in that the effects of cultural diversity diminish and, in the extreme, may even reverse.

These baseline analyses are subject to potential endogeneity concerns if cultural diversity is driven by another omitted (and perhaps unobservable) factors that also impacts the consensus forecast accuracy. It is important to note that the most obvious confound to our analyses is the number of analysts following a firm, as higher analyst coverage naturally implies a greater possibility for a diverse following. Therefore, all of our analyses control for this important factor. We recognize that our empirical models may still be insufficient if some other omitted factor also correlates with analysts' coverage decisions in a way that not only leads to higher levels of

[7] Note that our measure of consensus forecast accuracy contains values ranging from negative infinity to zero as it is computed as the absolute forecast error multiplied by negative one. Thus, increases in accuracy correspond to changes that make the value less negative.

coverage, but also to more diverse coverage. To help alleviate these concerns, we consider a battery of additional tests that help strengthen our inferences.

First, we re-estimate equations (1) and (2) using both firm fixed effects and first-difference regressions. Doing so controls for time-invariant firm heterogeneity (e.g., unobserved factors of the covered firm that attract more diverse coverage and are also associated with a higher quality information environment). These types of tests can be very restrictive given that properties of the consensus forecast tend to be quite persistent.

Columns (3) and (4) of Table 4 provide the results when equation (1) and (2) are re-estimated with firm fixed effects, and Columns (5) and (6) provide the results when all variables of interest are first-differenced while still including year fixed effects. These results provide similar inferences to those generated in the baseline models reported in Columns (1) and (2). For example, the coefficient on *DiverseNum* loads positively and significantly in the firm fixed effects models, while the coefficient on the squared diversity term loads negatively and significantly. Admittedly, while the first difference models (i.e., Columns (5) and (6)) generate similar inferences, the results exhibit weaker economic significance, potentially due to limited variation. Overall, these analyses continue to indicate that cultural diversity results in higher levels of consensus forecast accuracy, but also that this relation exhibits declining returns to scale.

To further control for unobservable differences among firms that might be correlated with diversity we also estimate the relation between consensus forecast accuracy and diversity using an entropy-matching estimator. In this approach, we match firms with high levels of cultural diversity to peers with lower levels of cultural diversity, but that are otherwise similar across observable characteristics. Recent studies (e.g., Hainmueller, 2012) indicate that entropy matching is generally more effective than simple matching or propensity score matching because it obtains a high degree of covariate balance across multiple moments of the covariate distribution, relies on less restrictive assumptions (i.e., lower model dependency), and retains more information by allowing weights to vary smoothly across observations in a more flexible manner.

Table 5 reports the results from the entropy-matching procedure. Firms are matched on the first two moments (i.e., mean and variance) of the control variables (e.g., Num_Analysts, LNSIZE, LNBM, ROA, STD_ROA, RETVOL, RET, and Foreign_Sales) following Hainmueller and Xu (2013). The variable *HighDiv* is an indicator variable that takes the value of one if a firm has high levels of cultural diversity (i.e., above median or top quartile of *DiverseNum*), and zero otherwise.

Column (1) provides the results when *HighDiv* is measured based on the median and Column (2) provides the results when it is measured based on the top quartile. The results indicate a positive and significant association between *HighDiv* and *Accuracy*, which provides additional support for our findings that cultural diversity improves the consensus forecast accuracy. The coefficients in Columns (1) and (2) suggest an increase of 14% and 9% in forecast accuracy, respectively for firms with high levels of cultural diversity compared to the unconditional sample mean. It is important to note that, while this analysis helps sharpen our inferences, it is limited in that it cannot accommodate the squared diversity term and test for non-linearities as it matches on a discrete (i.e., non-continuous) treatment measure.

Another concern for our analyses is that diversity is simply capturing analyst talent or superior the forecasting abilities of a given cultural cluster. To consider this alternative explanation, we re-estimate our analyses with the inclusion of either cultural cluster fixed effects or analyst fixed effects. Table 6 provides the results of this analysis. In Column (1) we augment our model with fixed effects for each of the ten cultural clusters to control for heterogeneity across different ethnicities. In Column (2) we control for analyst fixed effects to account for any omitted time-invariant analyst heterogeneity that is not absorbed by cultural origins (e.g., innate ability). Our results persist in both settings, suggesting that the unique combination of different cultural groups generates effects that are distinct from those of any particular analyst or cultural group and that are results are not likely to be driven by a relation between diversity and analyst talent.

Finally, we further consider the potentially confounding effects of other types of diversity, such as gender diversity or education diversity, on our findings. To help address this issue, we obtain data on analyst gender and education from an online business networking service. One limitation of this analysis is that we do not have data for all analysts in our sample since many do not have a presence on the online business networking service we use and data was not available for earlier years in our sample. In addition, we are not able to find profiles for all of the analysts covering a given firm. To address this limitation, we assume that the analysts with available profiles are representative of the general group of analysts covering a firm. We then re-estimate the regression model in equation (2) for different subsets of firms. Table 7 reports the results of this analysis.

Column (1) of Table 7 reports results for the subsample of firms in which none of the analysts with profiles are female (i.e., no gender diversity) and Column (2) reports results for those with at least one identified female (i.e., some gender diversity). In both columns, the coefficient on *DiverseNum* loads positive and significant and the coefficient on *DiverseNum X DiverseNum* loads negative, consistent with the results in Table 4. The coefficients appear to be of similar size for these variables in both columns. We report similar results in Columns (3) and (4) using partitions based on education diversity. Column (3) reports results where we are unable to identify any analyst as having received an MBA degree (i.e., no educational diversity) and Column (4) reports results for firm-years in which we identify at least one analyst with an MBA (i.e., some educational diversity). These results suggest that our results hold in subsamples with no gender diversity as well as in samples with some such diversity, consistent with cultural diversity having distinct effects from gender and education diversity. These findings help support the notion that the form of diversity we examine is associated analyst forecast quality in ways that are distinct from other forms of diversity.

Overall, our analyses thus far paint a consistent set of results regarding the effects of cultural diversity on consensus forecast accuracy. The results continue to indicate that higher levels of diversity are associated with more accurate consensus forecasts. Importantly, the benefits associated with diversity also appear to decline at higher levels of diversity.

3.4 Evidence from a Quasi-Natural Experiment

The results thus far provide evidence of cultural diversity influencing analysts' forecast accuracy. To mitigate possible identifications issues, we control for industry and firm fixed effects, and also employ an entropy matching procedure that allow us to control for non-linearities and possible omitted variables. While neither method can be considered as random assignment of firms to different levels of cultural diversity, both methods take significant and orthogonal strides towards strengthening the associations we document. A natural challenge with this line of research is that it is difficult to generate an exogenous shock to diversity in a non-laboratory setting. Prior studies examining diversity in other contexts, such as a classroom setting, can conduct an experiment that randomly assigns students based on their ethnicity and examine the effects of diversity on class outcomes (e.g., Hattie, 2002). However, randomly assigning analysts across a large set of firms is obviously not feasible. It is also unlikely that any economic shock (e.g., change in regulation or policy) directly impacts the cultural diversity of such a group at the firm level while not influencing other related forces.

Nevertheless, we attempt to strengthen our inferences by using a quasi-natural experiment connected to brokerage house mergers and closures. Prior studies use brokerage house mergers and closures to test how changes in analyst following impact firms' information environments (e.g., Hong and Kacperczyk, 2010; Merkley et al., 2017). These studies assume these changes are exogenous and compare firms with analyst drops to those without such drops. We adopt this approach in our setting by examining variation in cultural diversity within firms that experience these shocks. When some analysts stop covering a firm, they change not only the firm's analyst following but also the extent of its analyst cultural diversity. Thus, we consider whether variation in changes in analysts' cultural diversity across firms experiencing an exogenous drop in analyst coverage is associated with the consensus forecast accuracy. This experiment operates under the assumption that it is unlikely that individual broker's decisions to terminate an analyst correlates with the broker's consideration of the level of diversity across the stocks the analyst follows.

We identify analyst drops following prior studies. Within this subsample, we create an indicator variable *Decrease* which is set to one if an analyst drop is associated with a decrease in the number of cultural clusters in the analysts following a firm in a given year, and zero otherwise. We also create a count variable *Change* which captures the number of clusters that where dropped in connection with the analyst drop as the signed change in the number of clusters. We remove from our analysis analyst drops where the firm in question only had one cultural cluster prior to the drop because such observations could not be affected by the drop. Given the nonlinearity in the relation between analyst quality and cultural clusters reported in Table 4, we also include an interaction between our measures of cultural cluster changes and the number of cultural clusters following the firm prior to the analyst drop shock (*Lag_DiverseNum*). Similar to our results in Table 4, we expect decreases in cultural clusters to be negatively associated with analyst forecast accuracy, but at a declining rate such that the coefficient on interaction between drops in cultural clusters and *Lag_DiverseNum* is positive.

Table 8 reports the results of this analysis based on the reduced sample of analyst drops. Column (1) reports results using the *Decrease* indicator variable. We find that coefficient on *Decrease* is negative and significant and the coefficient on *Decrease X Lag_DiverseNum* is positive and significant. These results support the findings reported in Table 4, but do so using changes in cultural clusters that are exogenous to the firm. We find that a drop in cultural diversity from two to one clusters results in a 16% decrease in analyst accuracy relative to the unconditional sample mean, whereas a drop from three to two cluster results in a 6% decrease. Column (2) reports similar results using the variable *Change*, which captures the count of the number of cultural clusters that were lost in connection with the analyst drop shock. While these results comprise a less general subset of firms than our previous results (i.e., less external validity), they provide stronger internal validity regarding the relation between analyst cultural diversity and analyst report quality.

3.5 Different Measures of Diversity

The results thus far employ a relatively straightforward measure of cultural diversity in that we simply count the number of cultural clusters contributing to the forecast. This methodology lends itself well to some of our analyses, especially the natural experiment involving brokerage house mergers and closures. In this section, we also consider alternative measures that potentially reflect different aspects of cultural diversity.

Specifically, we explore two alternative measures. First, we examine cultural concentration, measured as the percentage of analysts in different cultural clusters. Doing so allows us to assess whether the benefits of diversity depend on the mere presence of at least one diverse perspective or a concentrated and focused presence from a diverse group of individuals. It also allows us to address concerns about noise in the *DiverseNum* measure created by a small number of analysts in one cultural cluster having too much weight in the overall measure. We construct a concentration measure similar to the Herfindahl index as follows:

$$DiverseHHI = 1 - \sum \left(\frac{Coverage_{ijt}}{Coverage_{jt}}\right)^2$$

where $Coverage_{ijt}$ is the number of analysts representing cultural cluster *i* covering firm *j* in year *t* and $Coverage_{jt}$ is the number of analysts covering firm *j* in year *t*.

Second, we examine cultural concentration based on the extent of differences between cultures. Prior studies indicate that certain cultures have greater distances from each other in terms of their norms and values, and that these distances can impact how individuals interact and learn from each other. Accordingly, we create a measure of cultural diversity that takes into account the cultural distances between analysts' cultures comprising the consensus to assess whether the benefits of diversity vary based on differences in cultural identity. We compute a distance measure by averaging of the pair-wise distances between the cultural clusters represented in a given consensus earnings forecast (*DiverseScore*). The distance for these cultural clusters is computed using the methodology from the GLOBE study conducted by House et al. (2002), and is measured as the number of nodes away from a given cultural cluster between any given analyst pair. For example, the distance between Southern Asia and Germanic Europe would be coded as 4 nodes away, and the distance between Latin America and Germanic Europe clusters would be 3 nodes away. We average all the distances for all analysts covering a firm. This measure takes into account the notion that some cultures are more similar or different to other cultures.

Table 9 reports the results of our analyses considering alternative diversity measures. Column (1) reports our previous findings using *DiverseNum* for comparison purposes. Columns (2) and (3) reports our results based on *DiverseHHI* and *DiverseScore*, respectively. Similar to the results in Column (1), we find that the coefficients on *DiverseHHI* and *DiverseScore* are positive and significant and the coefficients on their square terms are negative and significant. These results indicate that the association between analyst cultural diversity and forecast quality extends beyond just the level of cultural diversity, but also relates to cultural concentration and distance.

3.6 Cross-Sectional Analyses

We next explore cross-sectional variation in the relation between cultural diversity and consensus forecast accuracy. As previously explained the results in Table 4 indicate that the positive association between analyst cultural diversity and forecast accuracy declines as a function of the level of cultural diversity (i.e., decreasing returns to scale). Similarly, we also predict that the positive association should be weaker for firms with better information environments because there is a lower marginal benefit for diversity for these firms. If cultural diversity helps analysts incorporate a broader set of ideas into their reports, cultural diversity is likely to produce less new information in settings where there is already a high level of public disclosure and incorporation of information.

To test this conjecture, we examine subsamples of firm-years where we expect there to be higher quality information environments. Specifically, we expect the information environments to be of better quality for firms with greater analyst following, higher market capitalization, and lower stock price volatility. Accordingly, we interact *DiverseNum* with *Num_Analysts, LNSIZE,* and *RETVOL* and re-examine equation (2).

Table 10 reports the results of this analysis. For each cross-section, we re-estimate equation (1) and (2) to control for non-linearities in the relationship between cultural diversity and forecast accuracy. Columns (1) and (2) report the results based on the interaction of *DiverseNum* with

Num_Analysts. As expected the coefficient on the interaction term *DiverseNum X Num_Analysts* is negative and significant. We find similar results in Columns (3) and (4) based on interactions of *DiverseNum* with *LNSIZE*. These results suggest that cultural diversity plays a less significant role for firms with better information environments, consistent with our predictions. Column (5) and (6) reports the results for *RETVOL*. The coefficient on the interaction term *DiverseNum X RETVOL* is positive and significant, suggesting that cultural diversity plays a more significant role for firms with worse information environments as measured by stock return volatility. Taken together, the results reported in Table 10 suggest the relation between cultural diversity and forecast quality varies in ways consistent with the notion of analyst cultural diversity facilitating the incorporation of new information into analysts' reports.

4. Mechanism: Analyst Cultural Diversity and Analyst Conference Call Behavior

The results thus far raise an important question regarding the mechanism by which diversity facilitates better information sharing and production among sell-side analysts. In particular, what setting or forum enables a group of analysts from different investment banks to jointly hear alternative perspective and arrive at a higher quality consensus forecast? Of course, many of these opportunities might be subtle and unobservable, such as simply reading peer analyst reports and discussions in industry conferences. In this section, we attempt to explore one potential forum through which diversity can facilitate information sharing.

We examine how cultural diversity relates to analyst conference call behavior. In particular, we examine two important attributes of conference calls: the number of questions and total word length of questions that analysts ask on conference calls. If cultural diversity increases the information used by analysts in their reports, then one possible source of this information is increased information flow on conference calls. That is, if communication through conference calls is a mechanism for the impact of cultural diversity, then analysts will ask more questions and longer questions on calls when the covered firm has greater analyst cultural diversity because the pool of analysts is more likely to have unique questions and views.

To test this prediction, we obtain a sample of 74,135 conference call transcripts for 2,662 firms from the Thomson Reuters StreetEvents database spanning from 2000 to 2015. We focus on the discussions made by analysts in the question and answer session of each call. We remove short conversations containing less than 35 characters as these typically involve confirming comments and acknowledgements (e.g., thank you, good afternoon, etc.). We extract the number of distinct analyst questions as well the total number of words in all of the analysts' questions. We examine conference calls that occur in the 11 months prior to the fiscal year end of the consensus analyst forecast. We then estimate the models in equations (1) and (2) by replacing the dependent variable with these measures. As conference calls are generally a quarterly phenomenon, they can occur multiple times during the fiscal year. As such, we cluster our standard errors in these analyses by the combination of firm and year.

Table 11 reports the results. Column (1) reports that the coefficient on *DiverseNum* is positive and significant, consistent with analysts asking more questions when cultural diversity is higher. Specifically, this result suggest that a one-unit change in the number of cultural clusters is associated with a 4.6 % increase in analyst conference call questions. Column (2) reports that this association is declining in scale as the square term for *DiverseNum* is negative and significant. Columns (3) and (4) report similar results based on the total number of analyst words in conference call questions. Overall, these results provide support for one possible mechanism, analyst conference call questions, through which analyst cultural diversity could help analysts incorporate more information into their reports.

5. Analyst Cultural Diversity and Analyst Forecast Bias and Dispersion

Our results thus far indicate an important role for cultural diversity in impacting the accuracy of analysts' forecasts. It is important to note, however, that accuracy represents just one attribute of the consensus forecast. Indeed, it is also possible that cultural diversity may relate to other aspects of analysts' consensus forecasts such as the extent to which the consensus forecasts are biased or their level of dispersion. While we argue that the connection between accuracy and diversity relates to diversity improving the information set available to analysts, the conceptual channels for bias and dispersion are less clear.

One hypothesis is that having a more diverse analyst group disciplines analyst forecast optimism, such that bias is lower. Prior studies indicate that analysts have a natural tendency to issue optimistically biased research due to economic incentives or psychological biases (e.g., Kahneman and Lovallo, 1993; Michaely and Womack, 1999). Thus, increased diversity might introduce new perspectives that lead analysts to question these "rosy" expectations. On the other hand, higher levels of cultural diversity might have no effect on analyst consensus bias if analysts do not put sufficient weight on the views expressed by analysts from other cultures (e.g., Greif, 1993; La Ferrara, 2003).

A priori, the conceptual link between dispersion and diversity is also ambiguous. For example, higher levels of diversity can increase dispersion if the number of unique views increases. It may also reduce dispersion, if analysts are able to converge and aggregate these views into a unified perspective before the earnings announcement date. Ultimately, cultural diversity can have a number of interesting implications for analysts' forecast bias and dispersion. However, given the finding that diversity increases accuracy, we should expect a similar directional impact on bias and possibly dispersion.

We explore the associations between cultural diversity and forecast bias and dispersion by re-estimating equations (1) and (2), with measures of forecast bias and dispersion. We calculate forecast bias as the difference between the consensus analyst earnings forecast and the actual earnings per share scaled by stock price at the end of the prior fiscal year. We calculate analyst forecast dispersion at the firm-year level as the standard deviation of analyst forecasts scaled by stock price.

Table 12 reports the results from our bias and dispersion tests. Columns (1) and (2) provide the results for *Bias*. In Column (1), the coefficient on *DiverseNum* is negative and significant, suggesting that the consensus forecast is less upwardly biased when cultural diversity is higher. The coefficient of -0.0006 suggests that a one-unit change in *DiverseNum* is associated with a 20% decrease in optimism bias relative to the unconditional sample mean of 0.003. Similar to our previous results, we continue to find evidence of declining returns to scale in this relation as the coefficient on the square term in Column (2) is positive and significant. These findings are consistent with diversity reducing analysts' tendency to issue optimistic forecasts. Similar to our results for accuracy, we also find that the coefficient on *DiverseNum* is significantly higher than that on *Num_Analysts*, consistent with *DiverseNum* having a relatively important effect on consensus forecast bias.

Columns (3) and (4) of Table 12 report the results for *Dispersion*. In Column (3), the coefficient on *DiverseNum* is negative, but not statistically significant, suggesting no relation between analyst cultural diversity and forecast dispersion. However, this coefficient becomes negative and significant in Column (4) once we take into the account the possible nonlinearity in this relation by including a square term. This result suggests that diversity reduces forecast dispersion, potentially due to analysts aggregating each other's' views prior to the forecast announcement date, but this association attenuates as diversity increases. Overall, while the implications are more nuanced, the bias and dispersion results provide further support for our conjecture that analyst cultural diversity has the potential to provide capital market benefits at some levels, but at higher levels these benefits are declining and have the potential to create costs.

6. Conclusion

The objective of this study is to examine the effect of corporations' cultural diversity on output of their labor force. To this end, we examine one of the most visible Wall Street outputs, sell-side analysts' consensus earnings forecasts. Not only is this an important and visible output, but also one of the only instances where we can identify the cultural backgrounds of employees, and have a measurable and precise output of labor force. We construct measures of cultural diversity by tracing back analysts' cultural origins based on their surname.

Our findings indicate that higher levels of cultural diversity result in higher quality consensus forecasts (i.e., more accurate, less optimistically biased, and less dispersion). Our findings are not easily explained by other types of diversity (such as education and gender diversity), indicating that cultural diversity has distinct effects on analysts' behavior. In other words, the results suggest that cultural diversity, at least in the context of sell-side analysts, appears to add to social welfare by improving the market's consensus forecast. In addition, we also demonstrate that conference calls provide an important mechanism for diversity to impact analysts' forecasting behavior.

The effects of cultural diversity on analysts' forecasts are nuanced, though. Our evidence suggests that the net benefits of cultural diversity appear to exhibit declining returns to scale. This finding suggests that there may be an optimal level of diversity. Initiatives on Wall Street that focus on just increasing diversity without considering its costs (e.g., information frictions) may have unintended, negative consequences for market participants.

Our study provides one of the first examinations of cultural diversity in a competitive (as opposed to cooperative) setting. Moreover, our study sheds light on recent political debates regarding the value of an ethnically diverse workforce for Wall Street. These findings should be of interest to regulators and investors as we provide evidence that higher analyst cultural diversity is associated with a higher quality consensus earnings forecasts, a significant factor in setting market expectations.

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Variable Appendix

Variable	**Definition**
Forecast Accuracy	The absolute difference between the analyst earnings forecast and the actual earnings per share scaled by stock price at the end of the prior fiscal year multiplied by negative one.
Forecast Bias	The difference between the analyst earnings forecast and the actual earnings per share scaled by stock price at the end of the prior fiscal year.
Forecast Dispersion	The standard deviation of analyst forecasts scaled by stock price.
DiverseNum	the number of unique cultural clusters represented by analysts contributing to the consensus earnings forecast
DiverseHH1	A concentration measure similar to the Herfindahl index and is constructed as follows: $$DiverseHHI = 1 - \sum \left(\frac{Coverage_{ijt}}{Coverage_{jt}} \right)^2$$ where $Coverage_{ijt}$ is the number of analysts representing cultural cluster *i* covering firm *j* in year *t* and $Coverage_{jt}$ is the number of analysts covering firm *j* in year *t*.
DiverseScore	The average of pair-wise distances between the cultural clusters represented in a given consensus earnings forecast (*DiverseScore*). The distance for these cultural clusters is computed using the figure from House et al. (2002). The distance is measured as the number of nodes away from a given cultural cluster for any given analyst pair.
Num_Analysts	The number of analysts included in the consensus forecast.
LNSIZE	The natural log of the equity market value of the firm.
LNBM	the natural log of the ratio of market value of equity to book value of equity.
ROA	The ratio of income before extraordinary items to total assets.
STD_ROA	The standard deviation of ROA over the last five years.
RETVOL	The standard deviation of daily stock returns over the last 12 months.
RET	The average monthly return over the last 12 months.
Foreign_Sales	An indicator variable set to one if the firm reports non-missing and non-zero values of any of the following: foreign sales from the Compustat Segment file, foreign pretax income, foreign taxes, or foreign currency translation.

Figure 1 - Analyst Cultural Diversity Over Time

This figure depicts the number of cultural clusters represented in the sample each year. Cultural clusters are measured following House et al. (2002).

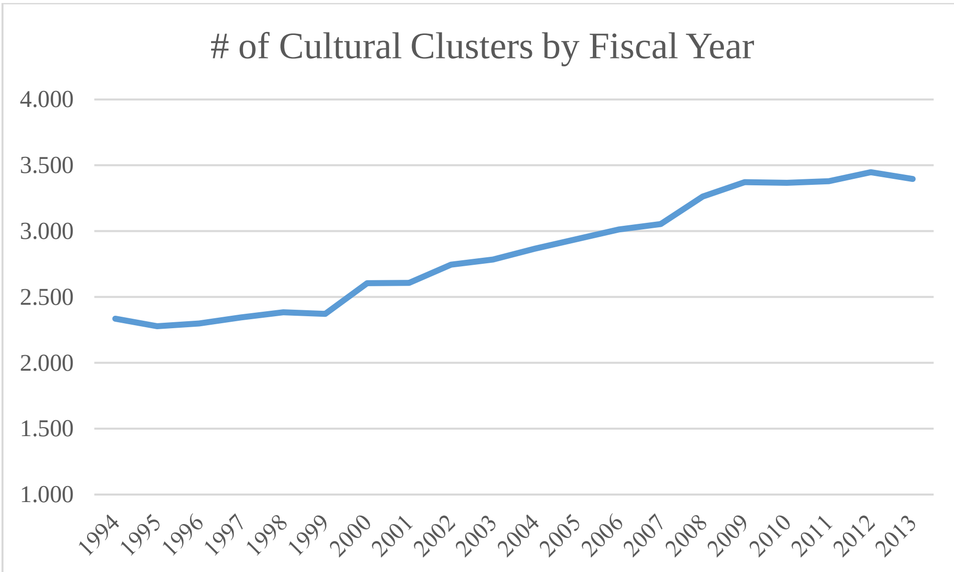

Table 1 - Analyst Cultural Diversity

This table presents the frequency of cultural clusters in the sample. Panel A presents the frequency by year. Panel B presents the frequency by SIC 2-digit industry codes for industries with at least 500 observations.

Panel A. Analyst Cultural Diversity by Year

Year	Obs.	# of Clusters
1994	2,552	2.335
1995	2,884	2.278
1996	3,024	2.299
1997	3,029	2.344
1998	2,831	2.384
1999	2,523	2.373
2000	2,574	2.604
2001	2,719	2.609
2002	2,551	2.746
2003	2,945	2.784
2004	3,014	2.868
2005	3,031	2.939
2006	3,008	3.012
2007	2,925	3.054
2008	2,437	3.262
2009	2,563	3.373
2010	2,631	3.367
2011	2,562	3.379
2012	2,579	3.448
2013	2,735	3.396

Panel B: Analyst Cultural Diversity by Select Industry

Industry	**SIC2**	**N. Obs**	**Mean # of Clusters**
Depository Institutions	60	5,748	2.33
Business Services	73	5,388	3.00
Chemical & Allied Products	28	4,019	3.04
Electronic & Other Electric Equipment	36	3,699	3.12
Industrial Machinery & Equipment	35	2,986	3.09
Instruments & Related Products	38	2,877	2.74
Electric, Gas, & Sanitary Services	49	2,428	2.79
Insurance Carriers	63	2,111	3.05
Holding & Other Investment Offices	67	1,863	2.03
Oil & Gas Extraction	13	1,855	4.08
Communications	48	1,675	2.61
Transportation Equipment	37	1,200	2.84
Food & Kindred Products	20	1,083	3.00
Wholesale Trade - Durable Goods	50	939	2.44
Miscellaneous Retail	59	908	2.73
Primary Metal Industries	33	806	2.75
Engineering & Management Services	87	797	2.53
Security & Commodity Brokers	62	782	3.10
Health Services	80	745	2.70
Apparel & Accessory Stores	56	688	3.47
Eating & Drinking Places	58	679	2.82
Wholesale Trade - Nondurable Goods	51	552	2.66
Paper & Allied Products	26	526	2.81
Fabricated Metal Products	34	519	2.48
Nondepository Institutions	61	512	2.88

Table 2 - Descriptive Statistics

This table reports descriptive statistics for the variables used in the baseline analyses. All variable definitions are provided in the Appendix.

Variable	N	Mean	SD	Q1	Median	Q3
Forecast Accuracy	55,117	-0.010	0.026	-0.007	-0.003	-0.001
DiverseNum	55,117	2.833	1.544	2.000	3.000	4.000
Num_Analysts	55,117	6.252	5.574	2.000	4.000	9.000
LNSIZE	55,117	6.909	1.720	5.660	6.749	8.001
LNBM	55,117	-0.870	0.719	-1.280	-0.781	-0.371
ROA	55,117	0.032	0.102	0.009	0.038	0.078
STD_ROA	55,117	0.072	0.621	0.011	0.027	0.063
RETVOL	55,117	0.028	0.014	0.018	0.025	0.035
RET	55,117	0.018	0.039	-0.004	0.015	0.036
Foreign_Sales	55,117	0.563	0.496	0.000	1.000	1.000

Table 3 - Pearson Correlations

This table reports Pearson correlation statistics for the variables used in the main analyses. Correlations in **bold** are significant at the 0.05 level or higher. All variable definitions are provided in the Appendix.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Forecast Accuracy	1									
(2) DiverseNum	**0.118**	1								
(3) Num_Analysts	**0.121**	**0.826**	1							
(4) LNSIZE	**0.150**	**0.519**	**0.594**	1						
(5) LNBM	**-0.133**	**-0.161**	**-0.167**	**-0.248**	1					
(6) ROA	**0.208**	**0.077**	**0.110**	**0.200**	**-0.061**	1				
(7) STD_ROA	**-0.028**	**-0.012**	**-0.018**	**-0.038**	**-0.068**	**-0.098**	1			
(8) RETVOL	**-0.163**	**-0.077**	**-0.100**	**-0.345**	**-0.087**	**-0.280**	**0.090**	1		
(9) RET	**0.098**	-0.005	**-0.022**	**0.016**	**-0.371**	**0.041**	**0.039**	**0.148**	1	
(10) Foreign_Sales	**0.038**	**0.186**	**0.188**	**0.280**	**-0.134**	**0.112**	0.003	**0.058**	0.003	1

Table 4 - Analyst Cultural Diversity and Forecast Accuracy

This table examines the relationship between the consensus forecast accuracy (*Forecast Accuracy*) and the number of cultural clusters (*Diverse_Num*). Columns 1 and 2 include year and industry fixed effects (two digit SIC). Columns 3 and 4 include firm and year fixed effects. Columns 5 and 6 reports results using a first differences specification and includes year fixed effects. All variables are defined in the Appendix. t-statistics reported in parentheses are based on standard errors clustered by firm. ***, **, and * denote 1%, 5% and 10% level of significance, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
DiverseNum	0.0011***	0.0038***	0.0004***	0.0012***	0.0002*	0.0005
	(8.41)	(11.00)	(2.72)	(3.56)	(1.80)	(1.34)
DiverseNum x DiverseNum		-0.0004***		-0.0001***		-0.0000
		(-9.76)		(-3.19)		(-0.85)
Num_Analysts	0.0001***	0.0002***	0.0000	0.0000	0.0001**	0.0001**
	(2.98)	(4.91)	(0.20)	(0.62)	(2.22)	(2.24)
LNSIZE	0.0004**	0.0003**	0.0021***	0.0021***	0.0036***	0.0036***
	(2.43)	(2.06)	(5.95)	(5.89)	(6.11)	(6.10)
LNBM	-0.0031***	-0.0030***	-0.0032***	-0.0032***	-0.0037***	-0.0037***
	(-10.32)	(-10.08)	(-7.94)	(-7.85)	(-5.46)	(-5.45)
ROA	0.0373***	0.0376***	0.0207***	0.0207***	0.0082***	0.0082***
	(15.58)	(15.71)	(8.60)	(8.61)	(3.35)	(3.34)
STD_ROA	-0.0002	-0.0002	0.0003	0.0004	0.0010	0.0010
	(-0.68)	(-0.66)	(0.80)	(0.81)	(1.25)	(1.25)
RETVOL	-0.3468***	-0.3441***	-0.2007***	-0.2008***	-0.0019	-0.0019
	(-19.60)	(-19.47)	(-9.22)	(-9.22)	(-0.09)	(-0.09)
RET	0.0579***	0.0581***	0.0445***	0.0446***	0.0253***	0.0254***
	(13.59)	(13.63)	(10.60)	(10.62)	(5.68)	(5.68)
Foreign_Sales	-0.0007*	-0.0007	-0.0009	-0.0009	-0.0001	-0.0001
	(-1.71)	(-1.60)	(-1.56)	(-1.56)	(-0.18)	(-0.18)
Observations	55,117	55,117	55,117	55,117	48,965	48,965
R-squared	0.115	0.117	0.541	0.542	0.039	0.039

Table 5 - Analyst Cultural Diversity and Forecast Accuracy: Entropy Matching

This table examines the relationship between the consensus forecast accuracy (*Forecast Accuracy*) and higher levels of the number of cultural clusters (*HighDiv*). In Column 1, *High Div* equals 1 if the firm has a number of cultural clusters that is at the sample median level or higher of *DiverseNum*. In Column 2, *High Div* equals 1 if the firm has a number of cultural clusters that is at the top sample quartile level or higher. Regressions employ entropy matching based on the control variables for both the mean and variance of the distributions following Hainmueller (2012) and Hainmueller and Xu (2013). Year and industry fixed effects (two digit SIC) are included in the regressions. All variables are defined in the Appendix. t-statistics reported in parentheses are based on standard errors clustered by firm. ***, **, and * denote 1%, 5% and 10% level of significance, respectively.

VARIABLES	(1)	(2)
HighDiv	0.0014**	0.0009*
	(2.23)	(1.76)
Num_Analysts	0.0003***	0.0001***
	(5.03)	(3.21)
LNSIZE	0.0004	0.0003
	(1.38)	(1.12)
LNBM	-0.0015**	-0.0026***
	(-2.40)	(-5.56)
ROA	0.0265***	0.0171***
	(7.94)	(5.84)
STD_ROA	-0.0046**	-0.0010
	(-2.26)	(-0.60)
RETVOL	-0.2579***	-0.3187***
	(-8.02)	(-5.09)
RET	0.0678***	0.0547***
	(8.14)	(10.01)
Foreign_Sales	-0.0004	0.0000
	(-0.73)	(0.02)
Observations	55,115	55,113
R-squared	0.120	0.128

Table 6 – Analyst Cultural Diversity and Forecast Accuracy:
Culture and Analyst Fixed Effects

This table examines the relationship between the consensus forecast accuracy (*Forecast Accuracy*) and the number of cultural clusters (*Diverse_Num*) after controlling for culture and analyst fixed effects. Column 1 reports the results after including culture fixed effects and column 2 reports results after including fixed effects for all of the individual analysts included in the consensuses forecasts. Both regressions include year and industry fixed effects (two digit SIC). All variables are defined in the Appendix. t-statistics reported in parentheses are based on standard errors clustered by firm. ***, **, and * denote 1%, 5% and 10% level of significance, respectively.

VARIABLES	(1)	(2)
DiverseNum	0.0020**	0.0031***
	(2.22)	(7.14)
DiverseNum x DiverseNum	-0.0004***	-0.0003***
	(-7.05)	(-5.53)
Num_Analysts	0.0002***	0.0000
	(4.61)	(0.39)
LNSIZE	0.0003**	0.0013***
	(2.19)	(6.55)
LNBM	-0.0030***	-0.0024***
	(-10.04)	(-6.72)
ROA	0.0375***	0.0373***
	(15.64)	(14.08)
STD_ROA	-0.0002	-0.0000
	(-0.65)	(-0.08)
RETVOL	-0.3433***	-0.3309***
	(-19.42)	(-15.86)
RET	0.0581***	0.0553***
	(13.66)	(11.72)
Foreign_Sales	-0.0007	-0.001
	(-1.57)	(-1.62)
Observations	55,117	55,117
R-squared	0.117	0.276

Table 7 - Analyst Cultural Diversity and Forecast Accuracy: Alternative Forms of Diversity

This table provides the results of regressions of analyst forecast accuracy on cultural diversity forecast accuracy for subsamples of firm-years with varying degrees of gender and education diversity. *Female* is and indicator set to one if at least one analyst contributing to the consensus forecast is identified on LinkedIn as female. *MBA* is and indicator set to one if at least one analyst contributing to the consensus forecast is identified on LinkedIn as having received an MBA degree. Regressions include year and industry fixed effects (two digit SIC). All variables are defined in the Appendix. t-statistics reported in parentheses are based on standard errors clustered by firm. ***, **, and * denote 1%, 5% and 10% level of significance, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	Female = 0	Female > 0	MBA = 0	MBA > 0
DiverseNum	0.0023***	0.0028***	0.0021**	0.0024***
	(4.65)	(2.69)	(2.30)	(4.67)
DiverseNum X DiverseNum	-0.0002***	-0.0003***	-0.0003**	-0.0003***
	(-4.09)	(-2.96)	(-2.29)	(-4.43)
Num_Analysts	0.0001***	0.0002**	0.0003***	0.0001**
	(2.95)	(2.37)	(3.25)	(2.08)
LNSIZE	0.0004*	0.0012***	0.0004	0.0005***
	(1.90)	(3.78)	(1.33)	(2.66)
LNBM	-0.0029***	-0.0012**	-0.0036***	-0.0022***
	(-8.04)	(-2.14)	(-6.45)	(-6.16)
ROA	0.0302***	0.0202***	0.0360***	0.0236***
	(10.54)	(4.83)	(7.86)	(8.74)
STD_ROA	-0.0031*	0.0013	-0.0010	-0.0044*
	(-1.94)	(0.44)	(-0.76)	(-1.77)
RETVOL	-0.2878***	-0.2544***	-0.3028***	-0.2729***
	(-11.62)	(-5.52)	(-7.52)	(-11.04)
RET	0.0546***	0.0769***	0.0539***	0.0616***
	(9.18)	(7.19)	(5.61)	(9.58)
Foreign_Sales	-0.0002	-0.0011	0.0001	-0.0008
	(-0.31)	(-1.43)	(0.14)	(-1.62)
Observations	25,658	6,734	9,657	22,735
R-squared	0.112	0.149	0.128	0.111

Table 8 - Analyst Coverage Drops, Cultural Diversity, and Forecast Accuracy

This table reports results regarding the association of analyst cultural diversity and forecast accuracy for a subsample of firms that received a drop in analyst coverage from a brokerage house merger or closure. *Decrease* is set to one if the drop resulted in a decline in the number of cultural clusters represented by a firm's analysts. *Change* is the number of cultural clusters that were lost in connection with the drop. Regressions include year and industry fixed effects (two digit SIC). All variables are defined in the Appendix. t-statistics reported in parentheses are based on standard errors clustered by firm. ***, **, and * denote 1%, 5% and 10% level of significance, respectively.

	Forecast Accuracy	
VARIABLES	(1)	(2)
Decrease	-0.0041*	
	(-1.81)	
Decrease X lagDiverseNum	0.0012***	
	(2.84)	
Change		0.0035*
		(1.66)
Change X lagDiverseNum		-0.0010**
		(-2.53)
lagDiverseNum	-0.0002	-0.0001
	(-0.42)	(-0.29)
Num_Analysts	0.0004***	0.0004***
	(3.21)	(3.22)
LNSIZE	0.0001	0.0001
	(0.13)	(0.13)
LNBM	-0.0019*	-0.0019*
	(-1.70)	(-1.70)
ROA	0.0273***	0.0274***
	(3.84)	(3.84)
STD_ROA	-0.0035	-0.0035
	(-1.02)	(-1.02)
RETVOL	-0.2536***	-0.2540***
	(-2.73)	(-2.74)
RET	0.0793***	0.0791***
	(3.14)	(3.14)
Foreign_Sales	-0.0011	-0.0011
	(-0.82)	(-0.83)
Observations	3,262	3,262
R-squared	0.150	0.150

Table 9 - Analyst Cultural Diversity and Forecast Accuracy: Alternative Measures

This table provides the results of regressions of analyst forecast accuracy on cultural diversity forecast accuracy using additional measures of cultural diversity. *DiverseHHI* takes into account the percentage of analysts in each cluster and *DiverseScore* takes into account the cultural distance between cultures. Regressions include year and industry fixed effects (two digit SIC). All variables are defined in the Appendix. t-statistics reported in parentheses are based on standard errors clustered by firm. ***, **, and * denote 1%, 5% and 10% level of significance, respectively.

	Forecast Accuracy		
VARIABLES	(1)	(2)	(3)
DiverseNum	0.0038***		
	(11.00)		
DiverseNum X DiverseNum	-0.0004***		
	(-9.76)		
DiverseHHI		0.0111***	
		(6.40)	
DiverseHHI X DiverseHHI		-0.0082***	
		(-3.61)	
DiverseScore			0.0077***
			(8.69)
DiverseScore X DiverseScore			-0.0039***
			(-7.41)
Num_Analysts	0.0002***	0.0002***	0.0002***
	(4.91)	(6.90)	(6.73)
LNSIZE	0.0003**	0.0003**	0.0004**
	(2.06)	(2.17)	(2.26)
LNBM	-0.0030***	-0.0031***	-0.0031***
	(-10.08)	(-10.18)	(-10.21)
ROA	0.0376***	0.0374***	0.0373***
	(15.71)	(15.62)	(15.61)
STD_ROA	-0.0002	-0.0002	-0.0002
	(-0.66)	(-0.69)	(-0.70)
RETVOL	-0.3441***	-0.3454***	-0.3454***
	(-19.47)	(-19.56)	(-19.54)
RET	0.0581***	0.0579***	0.0580***
	(13.63)	(13.60)	(13.60)
Foreign_Sales	-0.0007	-0.0007	-0.0007*
	(-1.60)	(-1.58)	(-1.66)
Observations	55,117	55,117	55,117
R-squared	0.117	0.116	0.116

Table 10 – Cross-Sectional Variation in Firms' Information Environments

This table reports results regarding the association of analyst cultural diversity and forecast accuracy for cross-sections of firms based on the number of analysts (*Num_Analysts*), firm size (*LNSIZE*), and return volatility (*RETVOL*). Control variables are included in the regression but suppressed from the output. Regressions include year and industry fixed effects (two digit SIC). All variables are defined in the Appendix. t-statistics reported in parentheses are based on standard errors clustered by firm. ***, **, and * denote 1%, 5% and 10% level of significance, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
DiverseNum	0.0018***	0.0019***	0.0037***	0.0045***	-0.0006***	0.0019***
	(11.06)	(4.10)	(9.16)	(10.62)	(-3.06)	(5.37)
DiverseNum X DiverseNum		-0.0000		-0.0003***		-0.0004***
		(-0.34)		(-6.25)		(-9.25)
Diverse X Num_Analysts	-0.0001***	-0.0001***				
	(-10.95)	(-5.65)				
DiverseNum X LNSIZE			-0.0004***	-0.0002***		
			(-7.44)	(-3.25)		
DiverseNum X RETVOL					0.0607***	0.0577***
					(8.46)	(8.12)
Observations	55,117	55,117	55,117	55,117	55,117	55,117
R-squared	0.117	0.117	0.116	0.117	0.117	0.119

Table 11 – Cultural Diversity & Conference Call Behavior

This table results regarding the association of analyst cultural diversity and analyst conference call behavior based on number of questions analysts asked in the call (Log(# of Questions)) and the total number of words in the statements containing questions (Log(# of words)). All variables are defined in the Appendix. Regressions include year and industry fixed effects (two digit SIC). t-statistics reported in parentheses are based on standard errors clustered by the combination of firm and year. ***, **, and * denote 1%, 5% and 10% level of significance, respectively.

	Log (# of Questions)		Log (# of Words)	
VARIABLES	(1)	(2)	(3)	(4)
DiverseNum	0.0462***	0.1711***	0.0462***	0.1904***
	(14.79)	(20.91)	(14.57)	(22.84)
DiverseNum X DiverseNum		-0.0179***		-0.0206***
		(-16.67)		(-19.04)
Num_Analysts	0.0111***	0.0129***	0.0148***	0.0168***
	(12.33)	(14.23)	(16.13)	(18.35)
LNSIZE	0.0373***	0.0391***	0.0713***	0.0733***
	(12.34)	(12.98)	(22.97)	(23.67)
LNBM	-0.0206***	-0.0167***	-0.0198***	-0.0154***
	(-4.36)	(-3.56)	(-4.12)	(-3.22)
ROA	0.2092***	0.2240***	0.1110***	0.1280***
	(6.45)	(7.00)	(3.39)	(3.98)
STD_ROA	-0.0103	-0.0083	-0.0086	-0.0063
	(-0.50)	(-0.42)	(-0.60)	(-0.47)
RETVOL	2.4033***	2.5576***	2.6323***	2.8104***
	(8.61)	(9.24)	(9.37)	(10.12)
RET	-0.4077***	-0.3748***	-0.3708***	-0.3328***
	(-4.67)	(-4.31)	(-4.16)	(-3.76)
Foreign_Sales	-0.0026	-0.0010	0.0166**	0.0184**
	(-0.33)	(-0.13)	(2.11)	(2.37)
Observations	74,135	74,135	74,135	74,135
R-squared	0.158	0.166	0.227	0.237

Table 12 – Cultural Diversity, Forecast Bias, and Dispersion

This table results regarding the association of analyst cultural diversity and forecast bias and dispersion. All variables are defined in the Appendix. Regressions include year and industry fixed effects (two digit SIC). t-statistics reported in parentheses are based on standard errors clustered by firm. ***, **, and * denote 1%, 5% and 10% level of significance, respectively.

	Bias		Dispersion	
VARIABLES	(1)	(2)	(3)	(4)
DiverseNum	-0.0006***	-0.0019***	-0.0001	-0.0005***
	(-5.62)	(-7.26)	(-1.47)	(-3.01)
DiverseNum X DiverseNum		0.0002***		0.0001***
		(6.44)		(2.80)
Num_Analysts	-0.0000	-0.0001**	-0.0001***	-0.0001***
	(-0.88)	(-2.30)	(-3.12)	(-3.56)
LNSIZE	-0.0003**	-0.0002**	0.0001	0.0001
	(-2.35)	(-2.09)	(0.78)	(0.83)
LNBM	0.0008***	0.0008***	0.0013***	0.0013***
	(3.79)	(3.62)	(9.77)	(9.71)
ROA	-0.0098***	-0.0099***	-0.0164***	-0.0164***
	(-6.08)	(-6.17)	(-17.01)	(-17.04)
STD_ROA	-0.0000	-0.0000	0.0001	0.0001
	(-0.04)	(-0.07)	(0.50)	(0.49)
RETVOL	0.1349***	0.1335***	0.1444***	0.1440***
	(9.94)	(9.84)	(17.54)	(17.47)
RET	-0.0291***	-0.0292***	-0.0228***	-0.0228***
	(-7.85)	(-7.87)	(-12.78)	(-12.79)
Foreign_Sales	0.0004	0.0004	-0.0001	-0.0001
	(1.39)	(1.31)	(-0.45)	(-0.46)
Observations	55,117	55,117	45,664	45,664
R-squared	0.030	0.031	0.128	0.128