Diversity, Information Choice, and Market Efficiency

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Abstract

This study examines whether diversity among market participants is associated with diverse information environments and better aggregation of information. Using measures of diversity among sell-side equity analysts, we demonstrate that although minority analyst forecasts are less accurate, their forecasts are more consistent and they employ richer information sets. At the aggregate-level, earnings are more predictable when the consensus is based on a larger proportion of minority forecasts. Predictive ability of minority analysts is stronger when corporate boards are more diverse and market uncertainty is high. Further, stock market reaction following earnings announcement is stronger when the consensus uses inputs from more diverse analysts. Collectively, these results suggest that greater diversity among market participants is associated with better information environments and more efficient stock prices.

Keywords: Equity analysts, diversity, information heterogeneity, earnings predictability, market uncertainty.

JEL Codes: G14, G24.

1. Introduction

Information plays a central role in models of portfolio choice and asset pricing. Different types of market participants are likely to use different information signals, and they may exhibit differences in interpreting these signals. For example, some market participants may focus more on cash flow related information signals while other individuals may pay more attention to macro-economic signals and discount rate news. Further, certain individuals may be more influenced by the aggregate market sentiment. This heterogeneity in information choices and informational sensitivity would affect how quickly and efficiently the market aggregates those information signals.

In this paper, we examine whether racial/ethnic diversity among market participants influences their information gathering and information interpretation strategies.[1] We also examine whether heterogeneity in the information sets at the micro-level has an impact on the information aggregation process at the aggregate market-level. Specifically, we examine whether aggregate consensus forecasts based on more diverse information signals have a stronger ability to predict earnings and the stock market reaction following earnings announcements.

We focus on the information-gathering activities of sell-side equity analysts as they are one of the most important information intermediaries in financial markets. Their decisions are known to influence other market participants (e.g., retail and institutional investors). In addition, their collective opinions, as reflected in the consensus earnings forecast, influence market prices, at least in the short run.

[1] Other forms of diversity are likely to affect information choices of market participants. For example, gender-based diversity or cultural diversity (e.g., Merkley, Michaely, and Pacelli (2020)) could affect informational diversity. In this paper, we focus on race/ethnicity for manageability as different forms of diversity could affect information choices differently. In ongoing research, we examine the relation between gender diversity, information choice, and the aggregate market behavior.

Our main conjecture is that different analyst groups would have different information sets, as they focus on different issues and choose different information gathering or information interpretation strategies. As a result, diversity among sell-side equity analysts would manifest itself in diversity in informational environments. Further, this racial/ethnic diversity among equity analysts could affect market prices.

Although it is easier to see a potential link between agent-level diversity and heterogeneity in their information signals, ex-ante, it is not obvious whether this is beneficial to the agents and the aggregate market. On the one hand, diverse opinions from ethnically different groups of analysts might contribute to better interpretation of information as a more diverse group may pay attention to more pieces of relevant information. This increased attention span might improve the quality of consensus forecasts, thereby making earnings and stock returns more predictable.

Further, diverse groups of analysts might learn from each other or pay more attention to information collected by other analysts, which could further make the consensus more informative (e.g., Alesina and la Ferrara (2005), Hong and Page (2001)). The model in Alesina, Spolaore, and Wacziarg (2000) where 'variety in intermediate inputs' can be treated as variety in individual skills leads to higher output. This idea would be consistent with informational diversity among analysts creating more efficient consensus forecasts. Linking this to evidence from board diversity and its effect on price informativeness, Gul, Srinidhi, and Ng (2011) suggest that presence of women on the board leads to improvement in public disclosure of firms.

On the other hand, competition or lack of trust or language barriers within groups of diverse analysts might prompt them to ignore information collected by rival analysts, and diversity-induced biases such as the in-group bias (e.g., Lazear (1999), Lazear (1999), Giannetti and Yafeh

(2012), Jannati et al. (2021)) might slow down the assimilation of relevant information into earnings and returns.

To test these conjectures, we begin by estimating a series of earnings predictability regressions. Our goal is to determine whether ethnic diversity improves informational efficiency at the aggregate-level. To that end, we interact the percentage of minority analysts within a firm with the consensus earnings forecast and regress it on next quarter firm earnings. We find that minority analysts make the consensus more informative as they have stronger ability to predict next quarter earnings. We additionally find that the minority analyst makes earnings surprises more informative about short-term earnings around earnings announcements. Taken together, these results suggest that minority analysts make the consensus forecast more informative about future earnings and prices, which improve the overall informational efficiency in the market.

We next examine why minority analysts improve informational efficiency. Our results indicate that although minority analysts are less accurate than White analysts, they are more consistent in their forecasts. We also find that minority analysts are likely to have different information sets. Principal components derived from the consensus forecasts based on minority analysts are considerably different from the principal components derived from the consensus forecasts of White analysts. While the first principal components derived from the two groups of forecasts are strongly correlated, the second to fifth principal components are weakly correlated. This evidence suggests that while the forecasting behavior of minority and White analysts exhibit similarities, they also differ along multiple dimensions.

On the face of it, the fact that minority analysts make the consensus more informative and make consistent forecasts and are yet less accurate might seem contradictory. Can lower analyst accuracy at the individual-level generate a consensus with higher predictability at the aggregate-level? Interestingly, this is plausible because accuracy and predictability capture different aspects of analyst behavior. The aggregate-level consensus reflects the consensus-earnings *correlation,* while accuracy depends upon the *distance* between the forecast and the actual earnings. Analysts can exhibit low accuracy, i.e., at the individual-level, analysts can be systematically optimistic or pessimistic and issue forecasts that are systematically either below or above actual earnings. However, at the aggregate-level, the "noise" in individual forecasts can cancel out and generate a stronger correlation between the consensus and earnings. The consensus can move in a more correlated manner with future earnings, which would be associated with stronger earnings predictability.

While our results suggest that minority analysts improve the informational efficiency of the consensus, a reasonable question is: What are the channels through which this happens? It is difficult to observe analyst-level information sets, but we can indirectly establish that different groups of analysts operate in different information environments. For example, one possibility is that analysts are able to extract information better when they share familiarity with the board of the company. Cultural or ethnic ties might allow minority analysts to extract relevant information or interpret signals better.[2] Further, these differences may be more prevalent during periods of high economic uncertainty as Loh and Stulz (2018) suggest that analyst information might be more relevant during bad times.

We find that the predictive ability of minority analysts is stronger when corporate boards are more diverse. In addition, using Baker, Bloom, and Davis (2016) measure of economic uncertainty, we demonstrate that minority analysts improve the predictability of the consensus during times of

[2] Guiso, Sapienza, and Zingales (2009) show that efficiency of economic transactions improve with cultural connections. Cornell and Welch (1996) develop a model to show that cultural proximity can reduce information asymmetry. Consistent with their predictions, Fisman, Paravisini, and Vig (2017) show that borrowers who share their cultural identities with loan officers are more likely to get loans.

high uncertainty. Examining the joint effects of minority board members and uncertainty, we find that minority analysts have greater predictive power when board has minority members and economic uncertainty is high.

The rest of the paper is organized as follows. We describe the data sources and present summary statistics in Section 2. We present our main empirical findings in Sections 3-5. We conclude in Section 6 with a brief summary.

2. Data and Summary Statistics

In this section, we discuss our main data sources and present the summary statistics for our sample.

2.1 Data Sources

Our main data source is the quarterly earnings announcements and forecasts from the Institutional Brokers' Estimate System (I/B/E/S) Detail History file. Actual earnings and earnings announcement dates are from the I/B/E/S Actuals file. Stock price and other financial statement information are obtained from the Center for Research in Security Prices (CRSP) and Compustat, respectively. Historical location data for firms is obtained from the 10K filings[3]. Our sample covers the March 31, 1995 to March 31, 2021 period.[4]

We exclude firm-quarters for which the earnings announcement date is more than 90 days after the fiscal quarter-end. Additionally, we require that the earnings announcement dates are available for quarters t and $t+1$ for each firm-quarter observation. To avoid extreme illiquid stocks, we eliminate observations with the fiscal-quarter-end stock price below \$5. Forecasts with missing analyst and brokerage identifiers are deleted. For each firm quarter, we require at least two analysts

[3] Firm Historical Headquarter State from SEC 10K/Q Filings - Mingze Gao (mingze-gao.com)

[4] As of October 18, 2018, Thomson-Reuters changed the identifiers of a large number of brokers and analysts in I/B/E/S. It is likely that 13.8% of all broker IDs (ESTIMATOR) and 30.7% of all analyst IDs (ANALYS) have been reassigned. (https://wrds-www.wharton.upenn.edu/pages/about/data-vendors/vendor-partner-ibes/.)

to issue forecasts. Our original sample has 2,601,153 firm-quarter-analyst observations, which include initial and revised forecasts by analysts after the quarter t's earnings announcement. Our stock-level analyses exclude utilities (SIC codes 4900 to 4949) and financial firms (SIC codes 6000 to 6999), and firms with a market value below $5 million. In addition to analyst and stock level data, we collect information on all board members from Boardex. This data starts from 1999.

For our study, we require data on analyst race/ethnicity. These are not available from I/B/E/S, but we identify ethnicity based on the analyst's name in the database. I/B/E/S provides the last name and the first initial of each analyst, and we augment this information with hand-collected name information from Kumar (2010). To create a proxy of analyst racial and ethnic backgrounds, we match their last names to the 2010 U.S. Census database[5]. Similar to Liu (2016), we create a dummy variable to capture the racial/ethnic identity of each analyst.

The distribution of ethnic identity based on the last name of each analyst can be White, which is the majority cluster, and the rest are labeled as minorities. Within the minority group, analysts can be further sub-grouped as Asian, Hispanic, African American, Hispanic, Non-Hispanic American Indian, Alaska Native Alone, and Non-Hispanic Two or More Races.[6] When we merge analyst data with racial and ethnic information, the sample size drops to 2,176,588 observations.

Although Census gives a probability-based measure of ethnic identity, we convert this into a dummy variable based on a cutoff. Specifically, if the percentage of White is greater than 50%, the analyst is classified as White, else the analyst is identified as a minority. Then, within all minorities, the race is based on the highest percentage among Asian, African-American, and

[5] The data are available at http://www.census.gov/topics/population/genealogy/data/2010_surnames.html.
[6] For the sake of simplicity, we only keep White, Asian, African American, and Hispanic ethnicities in our tests. The percentage of Non-Hispanic Two or More Races is 0 in our sample. Non-Hispanic American Indian and Alaska Native Alone is 0.01% in our sample.

Hispanic ethnic categories. We employ a similar methodology to identify the ethnicity of members of corporate boards.

We also collect information on whether the analyst is an All-Star analyst from the *Institutional Investor* magazine, which is an indicator variable that identifies whether the analyst has been selected into the All-America Research Team for the coming year. Lastly, we collect analyst location data from BrokerCheck.[7]

2.2 Analyst Diversity Estimates

For each firm, we measure diversity as the percentage of analysts within the firm that fall into the minority category. This diversity measure can be created for each firm for every year and quarter. The measure has the same flavor as Merkley, Michaely, and Pacelli (2020), where they develop a measure of cultural identity associated with analyst coverage.

Table 1, Panel A reports summary statistics for firm-level minority analyst measures. We find that the average percentage of minority (*PMINO*), which is our stock level metric, is 11.9%. This estimate suggests that 11.9% of analysts covering a firm are minorities and matches with the total number of minority analysts in our sample. About 11.7% of the stock-analyst observations in our sample are from minorities.

We also create a second measure of the ethnic identity of a firm based on the number of forecasts made by minority analysts *(PMINOF*). Similar to our stock-based measure of ethnic diversity, 11.9% of forecasts are being made by minority analysts.[8]

Appendix Table A.2 shows the breakdown of analysts by racial/ethnic type. Similar to Liu (2016), we find that of the 16.56% (1,514) unique analysts in our sample whose ethnicity we can

[7] See https://brokercheck.finra.org/.

[8] We present results using both stock-based and forecast-based measures of racial/ethnic diversity.

identify, about 83.44% (7,631) are White. Among the remaining analysts, about 12.31% (1,126) are Asian, and the rest are Hispanic and African American (approximately 4.24%).

Examining the racial/ethnic composition of corporate boards, we find that about 6% of board members in our sample belong to minority groups.

2.3 Summary Statistics

Table 1 presents the summary statistics for our sample. Panel A presents firm-level summary statistics. Panel B and C of Table 1 report the summary statistics for analyst level characteristics as well as sample averages for White and minority analysts. We report the estimates for a number of analyst characteristics, including forecast errors, timeliness, thoroughness (Driskill, Kirk, and Tucker (2020)), and consistency (Hilary and Hsu (2013)).

On average, we find that the typical White analyst makes lower forecast errors (*PMAFE* = -0.012) compared to a minority analyst (*PMAFE* = -0.002). In terms of the other forecast characteristics, White analysts make more timely and thorough forecasts. Interestingly, minority analysts, on average, make more (= 0.367) downward-biased forecasts (*Lowball*) as compared to White analysts (= 0.365). Lowball or downward-biased forecasts tend to be more consistent.

3. Empirical Results

3.1 Analyst Diversity and Earnings Predictability

We begin our empirical analysis by examining whether minority analysts make the consensus more informative. We conjecture that diverse analysts will focus on different information sets or interpret information differently, thereby making the consensus more informative. We test this conjecture using the following predictive regression:

$$Earnings_{it+1} = \alpha_i + \beta_1 Earnings_{it} + \beta_2 PMINO_{it} Consensus_{it} + \beta_3 X_{it} + \delta_i + \varepsilon_{it} \quad (1)$$

At the end of each quarter, we regress firm *i's* earnings in quarter *t+1* on an intercept, lagged earnings in quarter *t*, percentage of minority analysts interacted with the earnings consensus, and a vector of control variables (*X*), which include firm-specific characteristics in quarter *t*. Additionally, all regressions include firm and year-quarter fixed effects.

Following Richardson et al. (2005), we define earnings as operating income after depreciation divided by lagged total assets. We include lagged earnings due to the persistence of firms' earnings. Our main variable of interest is the percentage of minority analysts interacted with the consensus forecasts *(PMINO*Consensus*). The consensus is measured as the median of all forecasts within the 90-day window leading up to the earnings announcement. If an analyst makes multiple forecasts during that period, we take her most recent forecast.

If racial/ethnic diversity improves the information environment, minority analysts would make the consensus more informative. Therefore, the *PMINO*Consensus* term will be able to predict future earnings in quarter *t+1* beyond the predictive ability of firm-specific lagged earnings in quarter *t*. A positive coefficient estimate would indicate that the minority analysts make the consensus more informative about future earnings.

X is a vector of control variables, which includes the following firm attributes: (1) Firm Size, (2) Market-to-Book, (3) Leverage, (4) Income Volatility, (5) Turnover, (6) Loss, (7) Dividend-Price, (8) Dividend Yield, (9) No Dividend indicator, (10) Dividend-price ratio, (11) Institutional ownership, and (12) Number of Analysts. *Leverage* is the sum of short-term and long-term debts scaled by assets. *Loss* and *No-Dividend* are indicator variables that take a value one when operating income and dividend are negative or zero. *Dividend Yield* is defined as dividends scaled by shareholders' equity. These variables together account for differences in size, growth opportunities, and profitability that might account for earnings differences across firms. Additionally, our regression specification includes firm and year-quarter fixed effects, which account for non-time varying firm characteristics. Standard errors are clustered at the firm level.

Table 2 presents the results from the earnings predictability regressions. Consistent with prior evidence, we find that firm's earnings are persistent, as the coefficient on lagged *Earnings* is positive and statistically significant (coefficient = 0.446, t-statistic = 39.18). These effects are similar to those documented in Dichev and Tang (2009) and Frankel and Litov (2009). In column (1) of Table 2 we present the baseline specification without the minority analyst measure. As expected the consensus predicts earnings with a coefficient estimate of 0.0237 and a t-statistic of 27.32. In economic terms, one unit increase in the consensus improves earnings predictability by 0.1%, which represents about 10% of mean earnings.

Further, consistent with our conjecture, we find that the coefficient estimate on *PMINO*Consensus* is positive and statistically significant (Column (2) of Table 2), suggesting that minority analysts make the consensus more informative about earnings in the next quarter. The coefficient estimate on *PMINO*Consensus* is 0.0059, with a *t*-statistic of 2.39.

To interpret the magnitude of this effect, we consider a change in the *PMINO* measure from 0 to 0.2 (75^{th} percentile) or 0.5 (95^{th} percentile) and examine the increment in earnings predictability of the consensus.[9] Since the median number of minority analysts in our sample is zero, we evaluate the significance of the presence of minority analyst when we move from the 50^{th} percentile to the 95^{th} percentile.

We find that when the *PMINO* in a firm increases from 0 the 0.2, the predictability of the consensus improves from 2.3% to 2.4%. And when the *PMINO* moves to the 95% percentile, the predictability of the consensus improves from 2.3% to 2.6%, which is significant at the 5% level.

[9] Both *PMINO* and the *Consensus* are continuous variables.

These results suggest that the presence of minority analysts increases the correlation between earning and the consensus, making it more predictable.

For robustness, we consider an alternative measure of firm-level diversity based on the number of minority forecasts instead of number of minority analysts. We define *PMINOF* measure as the number of forecasts made by minority analysts. In Table 2 Column (3), we present the estimates with *PMINOF* without adjusting for the number of analysts in the industry. We find that similar to our earlier results, the interaction coefficient estimate is 0.0050 and statistically significant at the 5% level (t-statistic = 2.14). In economic terms, this is comparable to the earnings predictability of *PMINO* and suggests that minority analysts improve the earnings predictability of the consensus forecast.

In another robustness test, in Columns (4) and (5), we focus on firms where there is at least one minority analyst.[10] Again, we find that *PMINO*Consensus* strongly predicts earnings. The coefficient estimate is 0.021, which is statistically significant at the 1% level (*t*-statistic = 5.16). In economic terms, this evidence suggests an improvement in earnings predictability of the consensus from 2.1% to 2.6% when the number of minority analysts increases from the 25th percentile (14%) to the 75th percentile (33%). Results using *PMINOF* also suggest a similar effect.

These results suggest that there is an increase in the correlation between the consensus forecast and future earnings in the presence of minority analysts. Consequently, minority analysts make the consensus more informative about future earnings.

[10]The distribution of minority analyst is highly skewed where the median number of minority analysts is 0. This is to be expected, given the nature of representation of minorities in the financial services industry.

3.2 Analyst Diversity and Market Reaction

Next, we investigate whether improvement in earnings predictability also translates into greater predictability for stock returns. Specifically, we examine the effect of analyst diversity on short-term return predictability.

Previous studies (e.g., Howe, Unlu, and Yan (2009), Jegadeesh et al. (2004), Womack (1996)) establish a strong relation between analyst recommendations and future stock returns. Motivated by this evidence, we examine whether minority analysts add to the informativeness of analyst recommendations. Specifically, we run regressions of *PMINO* interacted with the *Earnings Surprise* on cumulative abnormal returns (*CAR's*). *CAR[0,1]* measures the abnormal return around the announcement date, while *CAR[2,61]* captures the post-announcement cumulative abnormal return. The regression specification is similar to that of Hirshleifer, Lim, and Teoh (2009). Specifically, we estimate:

$$CAR[0,1]/[2,61] = \alpha_i + \beta_1 Surprise_{it} + \beta_2 PMINO_{it} \times Surprise_{it} + \beta_3 X_{it} + \delta_i + \varepsilon_{it} \tag{2}$$

At the end of each quarter, we regress the CARs on *Earnings Surprise* measured as actual earnings less the consensus, and *PMINO* interacts with the *Earnings Surprise*. We hypothesize that the presence of minority analysts makes the earnings surprise more predictive of returns, just like earnings. Diversity in analysts either add new information or different perspectives, which then make the earnings surprise more informative about future returns.

Our regression specification includes a number of firm-level control variables very similar to our earnings regression, including (1) Firm Size, (2) Market-to-Book ratio, (3) Leverage, (4) Income Volatility, (5) Turnover, (6) Loss, (7) Dividend Yield, (8) No Dividend indicator, (9) Institutional Ownership, and (10) Analyst Coverage. All variables are defined in detail in

Appendix Table A.1. Year-quarter fixed effects are included to account for any time trends in returns. Finally, standard errors are clustered at the firm-level.

Table 3 reports the results from these regressions. In Column (1), we present the results from our baseline specification where we regress the *CAR[0,1]* on *Earnings Surprise* alone. As expected, the *Earnings Surprise* predicts earnings with a coefficient estimate of 0.223 and *t*-statistic of 16.30. Similar to Hirshleifer, Lim, and Teoh (2009), we also predict post-announcement returns (*CAR[2, 61]*) in Column (2) and find that *Earnings Surprise* is positively associated with post-announcement return.

In Column (3) of Table 3, we include *PMINO*Earnings Surprise* as an additional regressor in the baseline specification. We find that minority analysts significantly improve the informativeness of the *Earnings Surprise* measure. The coefficient on the interaction term is 0.189 and it is statistically significant at the 1% level (*t*-statistic = 2.86). In economic terms, the return predictability of the earnings surprise is improved by the incremental increases in the percentage of minority analysts within the firm. Specifically, an increase in the *PMINO* analyst from 0 to 0.2 (75th percentile) increases the earnings surprise predictability of returns from 20% to 24%. A further increase in the number of minority analysts to 0.5 (95^{th} percentile) increases the predictability of returns to 30%. With an average *CAR[0,1]* of 0.001%, this effect is sizable. Together, these results suggest that minority analysts make returns more predictable.

We also examine whether minority analysts make the earnings surprise more informative about post-announcement return prices. Again, we find a similar but somewhat stronger pattern where presence of minority analysts is associated with stronger post-announcement returns, given the same degree of earnings surprise (Column (4) of Table 3). An increase in the number of minority analysts within a firm increases return predictability of the earnings surprise from 1.4%

to 6.6% and 14.3% when the *PMINO* increases from 0 to 0.2 (75th percentile) and 0.5 (95th percentile), respectively. With the average post-announcement cumulative abnormal return (*CAR [2, 61]*) of -0.963%, this is a sizable effect.[11]

In Columns (5) and (6), we check the robustness of our results using *PMINOF*Consensus* and find similar effects. Following Hirshleifer, Lim, and Teoh (2009), we also interact all firm-level control variables with *Earnings Surprise* and include them as additional control variables in predictability regressions. Our results are qualitatively similar to the results reported in Table 3.

Interestingly, these results are not driven by Asian analysts alone who constitute a large proportion of minority analysts. Appendix Table A.3 presents the earnings and return predictability regressions where we recreate *PMINO* after deleting Asian analysts. Our results are qualitatively similar to those reported in Tables 2 and 3, suggesting that all minority analysts influence the informational efficiency of the consensus and earnings surprise.

3.3 Analyst Diversity and Forecast Accuracy

A reasonable question to ask at this point is how exactly do minority analysts make the consensus and surprise more informative about earnings and returns? It is possible that minority analyst forecast poses certain characteristics that make them more informative? To this end, in this section, we shift our focus to analyst-level characteristics to understand why minority analysts make the consensus and earnings surprise more informative.

First and foremost, we turn to the most common analyst characteristic: forecast error. We conjecture that minority analyst forecasts might be more accurate, thereby improving the

[11] In unreported regressions, we examine the return predictability for 3, 4, 5 and 6 months ahead and do not find significant results.

informational content of the consensus and earnings surprise. Therefore, as the first step, following Clement (1999), we define forecast error as:

$$PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - \widehat{AFE_{j,t}}}{\widehat{AFE_{jt}}}, \tag{3}$$

where AFE_{ijt} is the individual analyst's absolute forecast error. If an analyst made multiple forecasts during that period, we take her most recent forecast. $\widehat{AFE_{j,t}}$ is the median of all absolute forecast errors for a firm j in a quarter t. Larger values of $PMAFE_{i,j,t}$ imply greater forecast errors by the analyst.

Table 4 presents analyst-level panel regressions of minority status on forecast errors. Following the literature on analyst forecast accuracy, our regression specification includes a number of firm controls, including (1) lagged PMAFE, (2) Forecast Horizon, (3) Brokerage Size, (4) Forecast Frequency, (5) Firm Experience, (6) General Experience, (7) Firm Coverage, and (8) Industry Coverage. All variables are defined in detail in Appendix Table A.1. Additionally, we include firm and year-quarter fixed effects, and standard errors are clustered at the firm-level.

The estimates reported in Column (1) of Table 4 suggest that minority analysts make higher forecast errors as compared to White analysts. In fact, White analysts have 0.0131 lower forecast error relative to minority analysts. Given that the average forecast error in our sample is -0.011, White analysts make significantly lower forecast errors compared to minority analysts.

In Columns (2) and (3), we break down these results by All-star analysts and non-All-Star analysts. Stickel (1992) suggests that All-star analysts provide more frequent forecasts and are likely to be more accurate. We, therefore, separately analyze forecast errors for minority and White analysts who are All-Stars and non-All-Stars. Our results in Column (2) of Table 3 suggest that there is no difference between White and minority analysts within the All-Star category. However, for non-All-Star analysts (see Column (3)), there is a significant difference between White and minority analysts. Specifically, White analysts make 0.0147 lower forecast error as compared to minority analysts. This effect is statistically significant at the 1% level. Taken together, these results suggest that racial/ethnic status is not relevant for All-Star analysts. However, within the set of non-All-Star analysts, minority analysts are more likely to make forecast errors relative to White analysts.

Next, in Columns (4) and (5) of Table 4, we break up analysts as local and non-local. Local analysts are identified from a match between the historical headquarter of the firm and the analyst location. This analysis is motivated by the evidence in Bae, Stulz, and Tan (2008), which suggests that local analysts have an information advantage. If local analysts have an informational advantage, irrespective of ethnic status, both minority and White analysts would have access to this information.

We confirm this hypothesis in Column (4) of Table 4, where there are no difference in the forecast errors of White and minority analysts when they are local to the firm (coefficient = 0.0103, *t*-statistic = 1.15). However, when we examine the subset of non-local analysts, there are significant differences between the forecast errors of White and minority analysts (see Column (5) of Table 4). Again, similar to our baseline specification, White analysts have lower forecast errors relative to minority analysts. Collectively, forecast error regression estimates suggest that stronger evidence of earnings predictability in the presence of minority analysts is not induced by the higher accuracy of minority analysts.

3.4 Analyst Diversity and Other Forecast Characteristics

Our next set of tests are motivated by the evidence in recent studies such as Driskill, Kirk, and Tucker (2020) and Du (2020), which focus on alternative characteristics of analysts that capture the "attentiveness" of the forecasts made by the analyst. We create similar variables to capture the timeliness and thoroughness of analysts' forecasts and turn our focus to other features of analyst forecasts other than forecast errors.

It is possible that minority analysts make more timely and thorough forecasts that enable them to improve the predictive ability of the consensus and earnings surprise. To this end, we construct three measures of timeliness, namely *Timely EPS*, *Forecast Lag,* and *Timely Recommendation,* based on the analyst's initial forecast of each firm in each forecast period. Both *Timely EPS* and *Timely Recommendation* variables measure whether an analyst makes his or her earnings forecasts or recommendation in a timely manner on the day of or the day after the announcement date. *Forecast Lag* measures the number of days after the earnings announcement date that the analyst makes his recommendation. All of these variables capture the promptness in analyst forecasts. If minority analysts make timely forecasts, this might be a channel through which their forecasts become more informative about future earnings and prices.

Table 5 presents our analyst-level timeliness regression estimates. In these regressions, we consider the following firm-level controls: (1) Number of Concurrent Forecasts, (2) Broker Size, (3) Firm Experience, (4) General Experience, and (5) Number of Firms Covered. The choice of these controls is motivated by Driskill, Kirk, and Tucker (2020). Additionally, all regressions include firm and year-quarter fixed effects, and standard errors are clustered by firm.

Column (1) of Table 5 shows that minority analysts are less likely to issue timely forecasts. Specifically, minority analysts are 0.0091 less likely to issue *Timely EPS,* and this effect is statistically significant (*t*-statistic = 3.90). Compared to the mean likelihood of issuing a timely forecast (= 0.638), the timeliness of White analysts is 1.43% higher. Results using other measures of timeliness (*Forecast Lag* and *Timely Recommendation*), as reported in Columns (2) and (3) of

Table 5, also exhibit the same pattern. These findings suggest that timeliness in issuing forecasts is not contributing to the predictive ability of minority analysts.

Driskill, Kirk, and Tucker (2020) also create alternative measures of thoroughness based on the timing of earnings forecasts. They define "timely window" as the day of the earnings announcement or one day later, and all thoroughness metrics are computed within this window. This set includes *NEPS Horizon, NEPS Components,* and *NTotal Forecasts. NEPS Horizon* is defined as the number of forecasts that the analysts issues for various horizons like t+1, t+2, etc. *NEPS Components* measure the different types of earnings or earning's component forecast's that the analyst issues. For example, if an analyst issues forecasts for cash flows, revenues, and gross margins in addition to earnings forecast, it would be considered to be a thorough forecast. *NTotal Forecasts* counts all forecasts (for any horizon and any incidences of earnings or earnings components) issued by an analyst. Our regression specification is identical to that of Table 5.

Columns (1)-(3) of Table 6 present the results with these additional thoroughness measures. We find that minority analysts have 0.0187 lower *NEPS Horizon* and this effect is statistically significant (*t*-statistic = -6.55). Compared with the average value of the dependent variable (= ln(1+5.852) = 2.767), this is a 0.68% lower. For our other measures of thoroughness, as shown in Columns (2) and (3), we again find a similar pattern where minority analysts do not issue more thorough forecasts. The effects are statistically significant and economically meaningful. Based on these findings, we conclude that ability to issue more thorough forecasts does not contribute to the informativeness of minority analyst forecasts.

3.5 Analyst Diversity and Consistency

Hilary and Hsu (2013) conjecture that the usefulness of analyst forecasts should be judged not on the basis of forecast accuracy but rather on the informativeness of their forecasts.

Specifically, forecast usefulness should be based on the extent to which an analyst delivers consistent forecast errors, as captured by the volatility of unexpected errors. Hilary and Hsu (2013) construct a measure of analyst consistency based on the standard deviation of forecast errors for a sample firm over the previous 8 quarters. If forecast consistency is more important than forecast accuracy, analysts may strategically trade off accuracy and consistency by delivering downward-biased forecasts with greater consistency.

In this section, we examine whether minority analysts are more consistent and deliver downward-biased forecasts. The forecasts of minority analysts may be more predictable if they are consistently more pessimistic. This, in turn, could create the stronger correlation we observe between the consensus and future earnings when the concentration of minority analysts is higher.

Similar to Hilary and Hsu (2013), we define *Lowball* as the number of positive forecast errors (Actual EPS – EPS Forecast) less the number of negative forecast errors, scaled by the total number of forecast errors over the previous 8 quarters. *Consistency* is measured as the standard deviation of analyst forecast errors for a firm over the previous 8 quarters, and *Accuracy* is defined as the average forecast error over the previous 8 quarters.

Figure 1 shows our main result. On the X-axis we plot the marginal effect of *Lowball* from the 1^{st} percentile to the 99^{th} percentile. On the vertical axis, we plot the consistency and accuracy of the minority and White analysts separately. We see a positive trend (red line) in the relation between consistency and lowballing among minority analysts, whereas the relation is flat and somewhat negative for White analysts. As expected, in the second panel, when we plot accuracy against lowballing, there is a clear negative downward trend for minority analysts in comparison to White analysts.

Overall, the evidence in Figure 1 suggests that minority analyst might be contributing to market efficiency through the consistent lowball forecasts. They are more likely to engage in lowballing, which in turn makes their forecasts more consistent and more useful in predicting earnings and returns.

We next examine this in a regression setting where we include additional control variables and fixed effects. Table 7 presents these results. Our regression specification includes the following controls used in Hilary and Hsu (2013): (1) Forecast Horizon, (2) Bold, (3) Brokerage Size, (4) Firm Experience, (5) Firm Coverage, and (6) Analyst Coverage. All control variables are created using 8 quarters of observations to be aligned with the consistency measure. In addition, we include firm and year-quarter fixed effects and standard errors are clustered at the firm-level.

In Column (1) of Table 7, we find that the interaction between *Minority* and *Lowball* is positive and statistically significant at the 5% level (coefficient = 0.0256, *t*-statistic = 2.89). This evidence indicates that minority analysts who issue lowball forecasts or make downward biased forecasts are more likely to be consistent in their forecasts. In economic terms, one standard deviation increase in lowballing (= 0.272) is associated with 0.00696 (= 0.0256*0.272) more consistent forecasts among minority analysts. Relative to the average consistency of 0.635, minority analysts are 1.10% more consistent.

Consistent with the intuition that local analysts might have an information advantage we break up the analysts into local and non-local analysts and find that there is no difference among White and minority local analysts in terms of their ability to issue lowball or consistent forecasts (Column (2) of Table 7). Among non-local analysts (Column (3) of Table 7), however, we find that minority analysts are more likely to *Lowball* and have more consistent forecasts.

In columns (4) to (6) of Table 7 we examine the *Accuracy* of the minority analyst who *Lowball*, which is defined as the average error (i.e., Actual EPS – EPS Forecast) over the last 8 quarters. We find that *Minority* analysts that *Lowball* are less accurate, as shown by the coefficient in Column (4) of Table 7. Specifically, the interaction between *Minority* and *Lowball* is -0.0201 and is statistically significant at the 1% level.

Overall, our forecast consistency results suggest that minority analysts are more consistent in their forecasts. This consistency contributes directly to their ability to issue more informative earnings forecasts. Intuitively, this might seem contradictory as we know that minority analysts are less accurate. Lower forecast accuracy implies that there is higher variance in the forecasts, while consistency suggests that their forecasts are more predictable, either because they consistently over predict or under predict. This consistency then can generate increased correlation between minority analyst forecasts and future earnings.

4. Analyst Diversity and Diversity in Information Environments

Thus far, our evidence suggests that racial diversity is associated with higher predictability of earnings and returns. Additionally, we find that minority analysts issue consistent forecasts, thereby increasing the correlation between firm-level analyst diversity and future earnings. In this section, we attempt to identify the source of their informational advantage. We conjecture that different types of analysts focus on different information sets and may have different sets of beliefs. When aggregated, these diverse forecasts can generate more accurate consensus.

While it is impossible to observe the information environments of different analyst groups, we provide multiple pieces of evidence that are consistent with the notion that information environments vary significantly cross analyst groups. We present three pieces of evidence that suggest that different types of analysts might collect different information and focus on different information signals.

To begin, we present results from principal components analysis of White and minority consensus forecasts separately. Next, we collect data on the number of words and questions asked in conference calls as an indicator of differences in information sources of minority analysts. Last, following Kandel and Pearson (1995), we conjecture that heterogeneous agents have different beliefs when exposed to the same earnings shocks. This will be reflected in greater flips and divergences among pairs of analysts following the same firm.

4.1 Evidence using Principal Components Analysis

To get a first peak at potential differences in the information environments of minority and White analysts, we use principal components analysis (PCA) to identify potential similarities in the underlying information signals driving the forecasting behaviour of these two groups of analysts. If both groups of analysts operate in very similar informational environments, the firm-level consensus forecasts for the two groups would be strongly correlated. Consequently, the principal components (PCs) of the consensus time-series computed separately for the two groups computed across the entire set of firms will be strongly correlated. In contrast, if there are less commonalities in their information signals, the principal components would exhibit low correlations.

For each firm, we create two consensus forecasts. The first consensus is computed using only minority analyst forecasts and the second consensus measure uses all other analyst forecasts. We perform the PCA on the two sets of consensus forecasts separately and compare the two sets of PCs. We find that the first PCs of the two analyst groups are strongly correlated. The correlation is 0.96, which suggests that both groups use some common information signals. However, the correlations between the other pairs of PCs are considerably lower and below 0.5. This evidence suggests that there is significant heterogeneity in the information sets of minority and White analysts.

Further, we find that the first two PCs for minority analysts explain 68.32% and 14.60% of the total variance in the consensus series, while these estimates for White analysts are 74.39%

and 9.55%, respectively. If the PCs reflect the effects of different information sources, this evidence suggests that the second informational source for minority analysts is more informative. In contrast, White analysts rely more on their first source of information. Together, PCA results suggest that although minority and White analysts use common sources of information, there is also considerable heterogeneity in their information sources. Their degree of reliance on these information sources also differs.

4.2 Evidence using Conference Calls Transcripts

Following Merkley, Michaely, and Pacelli (2020) and Matsumoto, Pronk, and Roelofsen (2011), we use the Q&A section of the earnings conference calls to quantify the different information that might be collected by different types of analysts. A larger number of questions or words might imply an increase in the information set collected to assess the prospects of the firm. Similar to Merkley, Michaely, and Pacelli (2020), we expect that racially/ethnically diverse analysts will use a richer set of information, which will result in more detailed questions. Consequently, our measures of diversity would be positively correlated with the number of questions and number of words in those questions.

To test this conjecture, we collect proxies for information set from Capital IQ. Specifically, based on the Q&A session of each call, we collect the number of questions asked by the analysts following a firm and the number of words in the questions. The data starts in 2008 and transcripts before 2008 are backfilled several years later from the event data.[12]

We estimate two regressions where we regress our measure of diversity *PMINO* on the natural log of the number of questions and number of words. These results are shown in Table 8, Columns (1) and (2), respectively. We find that *PMINO* is positively significantly correlated with

[12] See https://wrds-www.wharton.upenn.edu/pages/grid-items/capital-iq-transcripts/.

the number of words and questions asked in conference calls. Specially, a 1% increase in *PMINO* is associated with a 7% increase in the number of questions (*NQuestions*) and a 16% increase in the number of words (*NWords*). These results are consistent with the conjecture that minority analysts use richer information sets.

4.3 Differential Interpretation of Information

In firms with higher racial/ethnic diversity, we also expect higher diversity in beliefs, which in turn would be reflected in their forecasts. To examine this possibility, we follow Kandel and Pearson (1995) to define two measures of differential interpretation of information. If analysts have the same beliefs or likelihood functions, we expect to see no flips or divergences in the forecasts. Differential interpretations are more likely to generate inconsistencies in their forecasts.

For each earnings announcement event, we define pre- and post-announcement period windows as the time period between consecutive earnings announcement dates. In our sample, the average time from the start of the pre-announcement period to the end of the post announcement window is about 55 days.[13] For each analyst, we examine the last forecast in the pre-announcement window and the first forecast in the post-announcement window. If the analyst did not make a new forecast during the post announcement window, we assume that earnings shock gave the analyst no reason to update the forecast, and we use the last forecast prior to the earnings announcement as the post announcement forecast. Comparing the forecasts in pre- and post-announcement period windows, we can check for each pair of analysts whether their forecasts have flipped or diverged.

Using the notation from Kandel and Pearson (1995), if two analysts make forecasts of X_i and Y_i in the pre-announcement window and X_j and Y_j in the post announcement window, then:

[13] The average number of days from the start of the pre-annoucement date to the earnings announcement is 45 days and from the earnings announcement to the end of post announcement period is 10 days. This is larger than in the original Kandel and Pearson (1995), which has a much smaller sample from 1983-1985.

$$\text{Flip} = \text{Sign}(Y_i - X_i) \neq \text{Sign}(Y_j - X_j) \text{ and } (X_i > X_j) \text{ and } (Y_i < Y_j);$$

$$\text{Divergence} = \text{Sign}(Y_i - X_i) \neq \text{Sign}(Y_j - X_j) \text{ and } |Y_j - Y_i| > |X_j - X_i|.$$

A flip identifies situations when one analyst increases the forecast and the other decreases it, while divergence measures whether the gap in the forecasts widen. Any flips and divergences are a signal of inconsistencies in perception of the same signal.

Similar to Kandel and Pearson (1995), for each pair of analysts following a firm, we create three measures that account for diversion in beliefs: the number of flips, number of divergences, and the sum of flips and divergences. As reported in Table 1, the average number of flips and divergences in 4.122 and 8.068 respectively across all firms.

To examine whether firms with more diverse analysts are more likely to have flips and divergences, we regress our measure of analyst-level racial/ethnic diversity *PMINO* on the number of flips, divergences, and inconsistencies (i.e., flips + divergences) in forecasts. We use a regression specification similar to Table 2 where we control for various firm characteristics. One potential concern with our measures of divergences in beliefs is that mechanically firms with more analysts or larger firms would have more flips and divergences. To account for this possibility, all regressions include an analyst coverage control and firm fixed effects.

Table 8 reports the results. As reported in Column (3), *PMINO* is positively and significantly associated with *NFlips*.[14] Specifically, a 1% increase in the number of minority analysts in the firm increases the number of flips by 11%. We find a similar results with divergence (*NDivergence*) and inconsistency measures (see Columns (4) and (5)). These results suggest that minority analysts are likely to have different beliefs that generate more divergent forecasts.

[14] Our test differs from the original Kandel and Pearson (1995) study as we do not scale the number of flips, divergences and inconsistencies with the number of analyst pairs. We instead use a regression framework and use analyst coverage and firm fixed effects to control for the number of analysts.

Loh and Stulz (2018) suggest that the role of analysts as a financial intermediary increases in importance during bad times as investors rely more on them in these times. Using this idea we examine whether minority analysts are more likely to add information or provide a diverse perspective during bad times. Following Loh and Stulz (2018) we measure uncertainty using the policy uncertainty index from Baker, Bloom, and Davis (2016).[15] Periods of high uncertainty are marked by a dummy variable that equals one when the U.S. historical uncertainty index is in the top tercile of available values.

Table 9 reports regressions of information collection and beliefs of minority analysts during times of high and low uncertainty. In Columns (1) and (2), we regress the number of questions asked in conference calls on the number of minority analysts in a firm and find that PMINO is significantly positively associated with the number of questions, especially during periods of high uncertainty. In economic terms, a 1% increase in the number of minority analysts following the firm increase the number of questions by 10% during more uncertain times. The results are similar with the number of words (Columns (3) and (4)).

Examining differences in analyst beliefs, we find that the association between PMINO and flips and divergences is significantly positive during uncertain periods. Column (6) of Table 9 shows that a 1% increase in the number of minority analysts in a firm increases the number of flips and divergences in beliefs by 26%. Together, the results in Table 9 indicate that, as Loh and Stulz (2018) predicted, analysts work harder during uncertain times, and this is especially true for minority analysts.

[15] Uncertainty index is from www.policyuncertainty.com

5. Conditional Effectiveness of Minority Analysts

Our results with divergence and conference call measures suggest that minority analysts might have different information sets or interpret the same public signals differently. If minority analysts have the ability to improve the information content of consensus forecasts, are there settings where they are able to extract information more effectively? In the last set of tests, we examine whether cultural similarity with board members affect the effectiveness of minority analysts.

5.1 Board Diversity and Forecasting Behavior of Minority Analysts

The earnings predictability regression results with an extended specification are presented in Table 10. In Columns (1) and (2) of Table 10, we interact *PMINO* with measures of board diversity. We use two measures of board diversity: (1) Percentage Minority Board (*% Minority Board*) and (2) an indicator variable that takes a value one if the percentage of minority board members is more than 15%, which corresponds with the 75th percentile in the distribution of minority board members.[16]

We find that minority analysts are more accurate when there are minority members on the board of the firm. Specifically, the interaction between *% Minority Board* and *PMINO* has a coefficient estimate of -0.048 and it is statistically significant at the 10% level. In economic terms, this evidence implies that minority analysts become 4.8% more accurate when there are minority members on the board. When we use the indicator variable, we find similar but statistically more significant results (see Column (2)). Additionally, we find that minority analysts are more likely to issue timely and thorough forecasts in the presence of minority board members (see Columns (3) to (6)).

[16] The distribution of minority members on the board suggest that 50% of the boards have 0 minority members. The 75th percentile is around 12%. Therefore the 15% cutoff is close to the 75th percentile.

These results suggest that ethnic ties might allow the minority analyst to extract relevant information from board members, which make the consensus more informative. It is also possible that minority analysts follow firms with minority board members more closely and, consequently, they have better overall information about future earnings.

5.2 Board Diversity, Economic Uncertainty, and Predictive Power of Minority Analysts

Rounding back to our first set of results, where the presence of minority analysts make the consensus more informative about earnings, we next examine the same when there are minority board members and economic uncertainty is high. The results are reported in Tables 11 and 12.

Column (1) of Table 11 presents our baseline results, which show that presence of minority analysts increase the informativeness of the consensus. In Columns (2) and (3) of Table 11, we break down the sample into firms with and without minority board members. We find that the predictability of the consensus is stronger when there is a larger concentration of minority analysts and there are minority board members. Specifically, the coefficient on *PMINO* interacted with the consensus is 0.0162 (*t*-statistic = 2.89), as compared to the coefficient estimate of 0.0064 (*t*-statistic = 2.10) when there are no minority board members. Last, we find that earnings predictive ability of minority analysts is stronger when economic uncertainty is high (see Column (5) of Table 11). These results suggest that minority analysts increases the correlation between the consensus and future earnings when minority board members exist and also when economic uncertainty is high.

In Table 12, we investigate the joint effects of presence of minority board members and high uncertainty. Similar to our previous analysis, we divide the sample into periods of high and low uncertainty. Columns (1) and (2) repeat the baseline results from Table 11 (last two columns). In Columns (3) and (4), we include a triple interaction term between *PMINO*, consensus, and board minority along with two interaction terms: *PMINO*Consensus* and *Board Minority*Consensus*.

We find that the triple interaction term is significant during periods of high uncertainty. Specifically, the coefficient on the triple interaction of *PMINO, Board Minority,* and *Consensus* has a coefficient of 0.0519 and is statistically significant (*t*-statistic=2.10). In contrast, during low uncertainty period, the triple interaction term has a coefficient estimate of -0.0020 and it is not significant. These estimates are similar when we use a dummy variable to quantify the presence of minority board members (see Columns (5) and (6)).

6. Summary and Conclusions

An emerging literature in finance and accounting has emphasized the importance of diversity (e.g., board diversity). Most of these studies have focused on the potential link between diversity and social biases such as discrimination, in-group bias, etc. In this study, we extend this literature and examine whether individual-level diversity manifests itself in the diversity of information sets at the aggregate level. Specifically, we examine whether greater racial/ethnic diversity among market participants (sell-side equity analysts) is associated with diversity in information sets, information interpretation strategies, and superior aggregate information.

Using measures of diversity among sell-side equity analysts, we find that minority analyst forecasts are more informative: Their forecasts have lower quality as well as lower accuracy, but exhibit greater consistency. Aggregating analyst forecasts at the stock level, we find that earnings are more predictable when consensus forecasts are based on the forecasts of a larger proportion of minority analysts. Further, the market reaction following earnings announcement is stronger when aggregate consensus forecasts are based on more diverse information signals. Collectively, these results suggest that market diversity is associated with better information environments and, consequently, stock prices incorporate new information faster.

In future work, it may be useful to examine whether diversity among other groups of market participants such as institutional investors also influences the information aggregation process. It would also be interesting to examine whether it is possible to aggregate the diverse informational signals optimally to further improve the quality of consensus forecasts and their predictive ability. Lastly, while our study has focused on the informational heterogeneity associated with racial/ethnic diversity, it is likely that diversity along other dimensions, such as wealth, geographical location, gender, etc., also influence firm-level informational environments and stock market efficiency.

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Figure 1: Consistency in Forecasts of Minority Analysts

The graph shows consistency and accuracy (Hilary and Hsu(2012)) of analyst forecasts for White and minority analysts. The X-axis plots lowball that ranges from p1 to p99. The Y-axis plots consistency and accuracy. Consistency is the standard deviation of the analyst forecast errors for the sample firm over the previous 8 quarters. Accuracy is the average forecast error over the previous 8 quarters. Lowball is the number of positive forecast errors (Actual EPS – EPS Forecast) minus the number of negative forecast errors (unclassified zero errors), scaled by the total number of forecast errors over the previous 8 quarters. Dotted lines represent 95% confidence intervals.

Table 1: Summary Statistics

This table presents summary statistics for the firm (Panel A), analyst (Panel B), and consistency (Panel C) variables used in our study. Our core sample period is from March 31, 1995, to March 31, 2021. BoardEx data starts in 1999 (PMBoard and High PMBoard measures) and CIQ conference call data are from 2008 (Nquestions and Nwords variables). Flip, Divergence and FD require number of analysts >=5 to have enough pairs. CAR[0, 1] and [2, 61] are in percentage points. All variables are winsorized at 0.5th and 99.5th percentile levels. Appendix Table A.1 presents the definitions for all variables.

Panel A: Stock-level Statistics

	N	Mean	SD	Median
PMINO	177,909	0.119	0.180	0.000
PMINOF	177,909	0.119	0.183	0.000
Earnings	177,909	0.012	0.053	0.021
CAR[0, 1]	177,909	0.001	0.086	0.021
CAR[2, 61]	177,909	-0.963	0.234	-0.801
Consensus	177,909	0.328	0.583	0.240
Surprise	177,909	0.005	0.034	0.001
Size	177,909	6.876	1.770	6.793
M/B	177,909	3.504	7.248	2.442
Leverage	177,909	0.237	0.217	0.209
Income Vol.	177,909	0.023	0.023	0.015
Turnover	177,909	0.218	0.189	0.165
Loss	177,909	0.149	0.356	0.000
Dividend Yield	177,909	0.000	0.002	0.000
No Dividend	177,909	0.627	0.484	1.000
D/P Ratio	177,909	0.012	0.034	0.000
IOR	177,909	0.686	0.253	0.743
Analyst Coverage	177,909	7.763	5.861	6.000
Uncertainty Index	177,909	114.948	42.308	104.561
PMBoard	131,667	0.061	0.094	0.000
High PMBoard	131,667	0.133	0.339	0.000
NQuestions	94,180	16.651	12.979	15.000
NWords	94,180	1,177.339	988.095	995.000
Flip	84,241	4.122	8.428	1.000
Divergence	84,241	8.068	16.882	2.000
Flips & Divergences	84,241	10.379	20.996	3.000

Panel B: Analyst-level Statistics

	All			White	Minority
	Mean	SD	Median	Mean	Mean
Minority	0.117	0.321	0.000		
PMAFE	-0.011	0.716	-0.042	-0.012	-0.002
Timely EPS	0.638	0.481	1.000	0.632	0.689
Forecast Lag	10.748	21.492	1.000	10.963	9.127
Timely Recommend	0.030	0.171	0.000	0.030	0.029
NConcurrent	1.099	2.442	0.000	1.114	0.986
NEPS Horizon	5.852	2.851	6.000	5.799	6.256
NEPS Component	1.872	1.033	2.000	1.858	1.973
NTotal Forecasts	10.573	8.142	8.000	10.434	11.620
Forecast Horizon	62.439	33.992	76.000	62.195	64.275
Brokerage Size	40.031	27.676	35.000	40.009	40.196
Forecast Frequency	1.394	0.655	1.000	1.395	1.387
Firm Experience	3.560	4.123	2.000	3.654	2.857
General Experience	9.204	6.974	8.000	9.433	7.474
Firm Coverage	12.592	6.059	12.000	12.693	11.831
Industry Coverage	3.104	2.047	3.000	3.154	2.727
N	1,411,350			1,246,135	165,215

Panel C: Consistency

	All			White	Minority
	Mean	SD	Median	Mean	Mean
Lowball	0.366	0.272	0.333	0.365	0.367
Consistency	0.635	0.287	0.667	0.636	0.628
Accuracy	0.475	0.240	0.511	0.476	0.471
Boldness	0.510	0.321	0.500	0.510	0.515
N	788,203			703,683	84,520

Table 2: Earnings Predictability Regression Estimates

This table presents earnings predictability regressions of minority analysts on future earnings. The dependent variable is the earnings in the next quarter (t+1). Minority analysts (PMINO) are measured at the stock level as the percentage of analysts following a firm that has minority status. Minority analysts forecast (PMINOF) measures the percentage of forecasts that are issued by minority analysts. The minority subsample includes firms which have at least 1 minority analyst. Control variables include Earnings, Size, M/B, Leverage, Income Volatility, Turnover, Loss, Dividend Yield, No Dividend, D/P Ratio, Institutional Ownership (IOR), and Analyst Coverage. Appendix Table A.1 includes the definitions for all variables included in the regressions. All regressions include firm and year-quarter-fixed effects. Robust *t*-statistics are in parentheses below the coefficient and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Baseline	Full Sample		Minority Subsample	
	(1)	(2)	(3)	(4)	(5)
PMINO		-0.0012		-0.0036	
		[-1.37]		[-2.30]**	
PMINO × Consensus		0.0059		0.0211	
		[2.39]**		[5.16]***	
PMINOF			-0.0009		-0.0031
			[-1.05]		[-2.11]**
PMINOF × Consensus			0.0050		0.0182
			[2.14]**		[5.06]***
Consensus	0.0237	0.0230	0.0231	0.0195	0.0201
	[27.32]***	[26.22]***	[26.24]***	[15.31]***	[16.09]***
Earnings	0.4463	0.4458	0.4459	0.4194	0.4197
	[39.18]***	[39.10]***	[39.11]***	[26.56]***	[26.57]***
Size	-0.0031	-0.0032	-0.0031	-0.0024	-0.0024
	[-7.39]***	[-7.42]***	[-7.41]***	[-3.58]***	[-3.55]***
M/B	0.0001	0.0001	0.0001	0.0001	0.0001
	[2.63]***	[2.62]***	[2.62]***	[2.65]***	[2.65]***
Leverage	0.0033	0.0033	0.0033	0.0016	0.0016
	[2.26]**	[2.24]**	[2.24]**	[0.70]	[0.68]
Income Vol.	0.0150	0.0146	0.0146	0.0072	0.0074
	[0.93]	[0.91]	[0.91]	[0.31]	[0.32]
Turnover	0.0043	0.0042	0.0042	0.0031	0.0032
	[4.42]***	[4.40]***	[4.40]***	[2.29]**	[2.34]**
Loss	-0.0004	-0.0004	-0.0004	-0.0011	-0.0011
	[-0.57]	[-0.58]	[-0.58]	[-1.11]	[-1.16]
Dividend Yield	0.2217	0.2281	0.2272	-0.0979	-0.1015
	[2.27]**	[2.34]**	[2.33]**	[-0.52]	[-0.54]
No Dividend	0.0013	0.0013	0.0013	0.0029	0.0029
	[2.90]***	[2.95]***	[2.95]***	[3.63]***	[3.63]***
D/P Ratio	-0.0095	-0.0097	-0.0096	0.0040	0.0043
	[-1.86]*	[-1.89]*	[-1.88]*	[0.40]	[0.43]
IOR	0.0112	0.0113	0.0113	0.0134	0.0134
	[12.62]***	[12.70]***	[12.69]***	[9.78]***	[9.79]***
Ln(Analyst Coverage)	-0.0014	-0.0013	-0.0013	-0.0013	-0.0014
	[-5.33]***	[-5.28]***	[-5.31]***	[-2.28]**	[-2.40]**
Observations	177,909	177,909	177,909	79,695	79,695
R-squared	0.792	0.792	0.792	0.801	0.801
Firm FEs	Yes	Yes	Yes	Yes	Yes
Year-Qtr FEs	Yes	Yes	Yes	Yes	Yes

Table 3: Market Reaction Regression Estimates

The dependent variables of OLS regressions are the cumulative abnormal returns over days [0, 1] and [2, 61] after the earnings announcement. In Columns (1), (2), (5), and (6), the stock-level minority analysts, PMINO, and analysts' forecast, PMINOF, are in raw value. Minority analysts (PMINO) are measured at the stock level as the percentage of analysts following a firm that has minority status. Minority analysts forecast (PMINOF) measures the percentage of forecasts that are issued by minority analysts. Control variables include Size, M/B, Leverage, Income Vol., Turnover, Loss, Dividend Yield, No Dividend, D/P Ratio, Institutional Ownership (IOR), and Analyst Coverage. Appendix Table A.1 includes the definitions for all variables included in the regressions. All regressions include firm and year-quarter-fixed effects. Robust *t*-statistics are in parentheses below the coefficient and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Baseline					
	CAR[0, 1]	CAR[2, 61]	CAR[0, 1]	CAR[2, 61]	CAR[0, 1]	CAR[2, 61]
	(1)	(2)	(3)	(4)	(5)	(6)
PMINO			-0.0025	-0.0054		
			[-1.48]	[-1.22]		
PMINO × Surprise			0.1891	0.2586		
			[2.86]***	[2.08]**		
PMINOF					-0.0021	-0.0062
					[-1.30]	[-1.44]
PMINOF × Surprise					0.1596	0.1953
					[2.56]**	[1.60]
Surprise	0.2235	0.0387	0.2054	0.0140	0.2082	0.0200
	[16.30]***	[1.98]**	[14.94]***	[0.65]	[15.20]***	[0.92]
Observations	177,909	177,909	177,909	177,909	177,909	177,909
R-squared	0.059	0.060	0.059	0.060	0.059	0.060
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Forecast Error Regression Estimates

This table presents the relation between the minority status of the analyst and the earning forecast error. The dependent variable of the OLS regression is the proportional mean absolute forecast error (PMAFE). Minority is an indicator variable that identifies minority analysts. Lagged PMAFE, Forecast Horizon, Brokerage Size, Forecast Frequency, Firm Experience, General Experience, FirmsCoverage, and Industry Coverage are included as control variables. Appendix Table A.1 includes the definitions for all variables included in the regressions. Column (1) shows the result of the full sample. In Columns (2) and (3), we break down the analysts by All-Star and others. In Columns (4) and (5), analysts are subsampled into local or non-local analysts based on the historical location of the firm. All regressions include firm and year-quarter-fixed effects. Robust *t*-statistics are in parentheses below the coefficient and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Full (1)	AllStar (2)	Non-All-Star (3)	Local (4)	Non-local (5)
Minority	0.0130	-0.0052	0.0147	0.0107	0.0137
	[5.02]***	[-0.64]	[4.94]***	[1.18]	[4.46]***
Lag(PMAFE)	0.0648	0.0416	0.0609	0.0308	0.0620
	[29.52]***	[11.05]***	[25.85]***	[6.58]***	[26.75]***
Forecast Horizon	0.0010	0.0010	0.0011	0.0012	0.0010
	[21.96]***	[11.17]***	[20.67]***	[11.25]***	[20.38]***
Brokerage Size	-0.0001	0.0001	-0.0001	-0.0002	-0.0001
	[-3.70]***	[1.00]	[-2.72]***	[-1.57]	[-3.59]***
Forecast Frequency	-0.0266	-0.0155	-0.0288	-0.0230	-0.0270
	[-16.78]***	[-4.36]***	[-15.68]***	[-4.85]***	[-15.05]***
Firm Experience	-0.0010	0.0002	-0.0012	-0.0027	-0.0010
	[-4.42]***	[0.33]	[-4.01]***	[-3.19]***	[-3.39]***
General Experience	0.0004	-0.0011	0.0007	0.0019	0.0005
	[2.83]***	[-2.48]**	[4.01]***	[2.99]***	[2.93]***
Firm Coverage	-0.0008	-0.0013	-0.0011	-0.0014	-0.0010
	[-5.36]***	[-2.68]***	[-5.71]***	[-2.19]**	[-5.68]***
Industry Coverage	0.0030	0.0064	0.0028	0.0052	0.0029
	[5.42]***	[3.42]***	[4.37]***	[2.38]**	[4.51]***
Observations	1,411,350	182,865	1,072,150	127,073	1,127,944
R-squared	0.011	0.034	0.011	0.038	0.011
Firm FEs	Yes	Yes	Yes	Yes	Yes
Year-Qtr FEs	Yes	Yes	Yes	Yes	Yes

Table 5: Timeliness Regression Estimates

This table presents the relation between analyst ethnicity and timely earnings forecasts. We estimate OLS regressions in which the dependent variable is either Timely EPS, Forecast Lag, or Timely Recommend on the minority analyst. *Minority* is an indicator variable that identifies minority analysts. Timely EPS is a dummy takes a value of one if the analyst issues an earnings forecast for quarter t+1 on the day of or the day after the firm's quarter *t* earnings announcement date, and zero otherwise. Forecast lag is a dummy variable takes a value of one if the analyst issues a stock recommendation on the day of or the day after the firm's quarter t earnings announcement date, and zero otherwise. Timely Recommend is difference between the analyst earnings forecast date for quarter t+1 and the earnings announcement date for quarter *t.* Number of Concurrent Forecasts, Broker Size, Firm Experience, General Experience, Firm Coverage, and Industry Coverage are included as control variables. Appendix Table A.1 includes the definitions for all variables included in the regressions. All regressions include firm and year-quarter-fixed effects. Robust t-statistics are in parentheses below the coefficient and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Timely EPS (1)	Ln(1 + Forecast Lag) (2)	Timely Reco (3)
Minority	-0.0091	0.0415	-0.0018
	[-3.82]***	[6.39]***	[-3.56]***
Ln(1 + NConcurrent)	-0.1064	0.3974	-0.0051
	[-47.83]***	[46.80]***	[-22.33]***
Broker Size	0.0014	-0.0040	-0.0002
	[45.47]***	[-47.85]***	[-28.99]***
Firm Experience	-0.0005	0.0040	0.0001
	[-2.18]**	[6.42]***	[2.83]***
General Experience	0.0000	-0.0000	0.0000
	[0.27]	[-0.06]	[0.71]
Firm Coverage	0.0057	-0.0196	0.0001
	[32.56]***	[-40.39]***	[3.34]***
Industry Coverage	-0.0007	-0.0060	-0.0004
	[-1.13]	[-3.76]***	[-2.90]***
Observations	1,411,350	1,411,350	1,411,350
R-squared	0.234	0.244	0.020
Firm FEs	Yes	Yes	Yes
Year-Qtr FEs	Yes	Yes	Yes

Table 6: Thoroughness Regression Estimates

This table presents the relation between the ethnicity and the thoroughness of the analyst. We estimate OLS regressions in which the dependent variable is either NEPS Horizon, NEPS Component, or NTotal. The key independent variable is *Minority,* which is an indicator variable that identifies minority analysts. NEPs Horizon measures the number of earnings forecasts for different horizons (i.e., quarter t+1, quarter t+2, forthcoming year etc.) of the sample firm issued by the analyst on the date of the forecast for quarter t+1. The value is 1 if the analyst issues only an earnings forecast for quarter t+1. NEPS Component measures the number of types of earnings or earnings component forecasts (i.e., revenue, cash flows, gross margin etc.) of the sample firm issued by the analyst on the date of the forecast for quarter t+1. The value is 1 if the analyst issues only the earnings forecast without any earnings component forecasts. In Columns (1) to (3), we retain only the earnings forecasts for quarter t+1 issued either on the day or one day after the earnings announcement. Number of Concurrent Forecasts, Broker Size, Firm Experience, General Experience, Firms Coverage and Industries Coverage are included as control variables. Appendix Table A.1 includes the definitions for all variables included in the regressions. All regressions include firm and year-quarter-fixed effects. Robust *t*-statistics are in parentheses below the coefficient and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Ln(1+NEPS Horizon) (1)	Ln(1+NEPS Component) (2)	Ln(1+NTotal Forecasts) (3)
Minority	-0.0187	-0.0123	-0.0401
	[-6.55]***	[-4.10]***	[-8.13]***
Ln(1 + NConcurrent)	-0.0118	-0.0049	-0.0168
	[-10.06]***	[-4.95]***	[-9.27]***
Broker Size	-0.0008	0.0015	-0.0000
	[-18.93]***	[38.71]***	[-0.61]
Firm Experience	-0.0038	-0.0008	-0.0045
	[-12.08]***	[-2.44]**	[-8.49]***
General Experience	-0.0023	-0.0005	-0.0022
	[-14.20]***	[-2.60]***	[-8.18]***
Firm Coverage	0.0042	0.0013	0.0055
	[19.71]***	[7.03]***	[16.29]***
Industry Coverage	-0.0078	-0.0060	-0.0168
	[-10.75]***	[-8.76]***	[-14.70]***
Observations	900,003	900,003	900,003
R-squared	0.225	0.303	0.363
Firm FEs	Yes	Yes	Yes
Year-Qtr FEs	Yes	Yes	Yes

Table 7: Consistency Regression Estimates

This table presents the relation between the analyst ethnicity and the consistency of the forecast issued. The key independent variable is *Minority*, which is an indicator variable that identifies minority analysts. We estimate OLS regressions in which the dependent variable is consistency as measured as the standard deviation of forecast errors 8 quarters before the earnings announcement. All variables are created on a rolling eight-quarter window before the current quarter. Consistency is the standard deviation of the analyst forecast errors for the sample firm over the previous 8 quarters. Accuracy is the average forecast error over the previous 8 quarters. Lowball is the number of positive forecast errors (actual EPS - forecast EPS) minus the number of negative forecast errors (unclassified zero errors), scaled by the total number of forecast errors over the previous 8 quarters. Forecast Horizon, Bold, Firm Experience, General Experience, Firm Coverage, and Industry Coverage are included as control variables. Appendix Table A.1 includes the definitions for all variables included in the regressions.We break the full sample into two subsamples: local and non-local for both consistency and accuracy. All regressions include firm and year-quarter-fixed effects. Robust *t*-statistics are in parentheses below the coefficient and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Consistency			*Accuracy*		
	Full Sample	Local	Non-local	Full Sample	Local	Non-local
	(1)	(2)	(3)	(4)	(5)	(6)
Minority	-0.0093	-0.0158	-0.0080	0.0026	-0.0108	0.0062
	[-2.49]**	[-1.34]	[-1.93]*	[0.85]	[-0.86]	[1.87]*
Minority × Lowball	0.0256	0.0797	0.0275	-0.0201	0.0204	-0.0271
	[2.89]***	[2.92]***	[2.80]***	[-2.93]***	[0.76]	[-3.47]***
Lowball	0.0066	-0.0082	-0.0040	-0.0757	-0.0731	-0.0700
	[1.58]	[-0.67]	[-0.89]	[-30.96]***	[-10.15]***	[-26.19]***
Forecast Horizon	-0.1915	-0.2106	-0.1936	-0.0825	-0.0854	-0.0819
	[-63.19]***	[-23.28]***	[-57.87]***	[-44.06]***	[-13.27]***	[-38.93]***
Bold	-0.1157	-0.0963	-0.1117	-0.0515	-0.0407	-0.0506
	[-48.16]***	[-13.96]***	[-43.65]***	[-32.84]***	[-8.11]***	[-29.53]***
Brokerage Size	0.0056	0.0069	0.0067	0.0012	0.0049	0.0016
	[6.95]***	[2.42]**	[7.55]***	[1.95]*	[2.04]**	[2.19]**
Firm Experience	0.0837	0.1076	0.0808	0.0254	0.0207	0.0261
	[28.25]***	[11.49]***	[24.62]***	[13.21]***	[2.86]***	[12.14]***
Firm Coverage	0.0116	0.0129	0.0122	0.0062	0.0099	0.0060
	[5.10]***	[1.69]*	[4.83]***	[3.93]***	[1.58]	[3.42]***
Ln(Analyst Coverage)	0.0162	0.0125	0.0191	0.3596	0.3785	0.3758
	[10.54]***	[2.29]**	[11.12]***	[69.95]***	[24.97]***	[68.78]***
Observations	788,203	68,270	615,421	788,203	68,270	615,421
R-squared	0.107	0.199	0.109	0.294	0.367	0.312
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Conference Call Regression Estimates

This table presents the relation between firm ethnic diversity and diversity in information collected and beliefs. In Columns (1) and (2), we measure the diversity in information set as the number of question and number of words for all questions analysts asked at conference calls for quarter t. This data is collected from Capital IQ conference call data. In Columns (3)-(5), we measure the diversity in analysts beliefs as flips, divergences and the sum of the two. Flips and Divergences are defined as follows: Flip = Sign $(Y_i - X_i) \neq$ Sign $(Y_j - X_j)$ and $(X_i > X_j)$ and $(Y_i < Y_j)$; Divergence = Sign $(Y_i - X_i) \neq$ Sign $(Y_j - X_j)$ and $|Y_j - Y_i| > |X_j - X_i|$, where two analysts make forecasts of X_i and Y_i in the pre-announcement window and X_j and Y_j in the post announcement window. These measures are the ones as in Kandel and Pearson (1995). Size, M/B, Leverage, Income Vol., Turnover, Loss, Dividend Yield, No Dividend, D/P Ratio, Institutional Ownership (IOR), and Analyst Coverage are included as control variables. Appendix Table A.1 includes the definitions for all variables included in the regressions. Robust *t*-statistics are in parentheses below the coefficient and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Ln(1+ NQuestions) (1)	Ln(1+ NWords) (2)	Ln(1+ NFlip) (3)	Ln(1+ NDivergence) (4)	Ln(1+ NFlips & NDivergences) (5)
PMINO	0.0711	0.1587	0.1153	0.1121	0.1232
	[2.17]**	[1.95]*	[3.09]***	[2.47]**	[2.61]***
Size	0.0951	0.1659	0.1113	0.1293	0.1390
	[5.69]***	[4.41]***	[9.95]***	[9.71]***	[10.39]***
M/B	0.0011	0.0016	0.0001	-0.0001	0.0002
	[2.41]**	[1.63]	[0.26]	[-0.19]	[0.39]
Leverage	-0.1347	-0.2798	0.0408	0.0628	0.0510
	[-3.05]***	[-2.73]***	[1.13]	[1.44]	[1.17]
Income Vol.	1.8814	4.2861	1.1315	0.9033	1.2841
	[3.81]***	[3.64]***	[2.81]***	[1.92]*	[2.68]***
Turnover	0.1399	0.2088	0.1713	0.1963	0.2118
	[4.15]***	[2.60]***	[5.74]***	[5.67]***	[6.05]***
Loss	-0.0629	-0.1035	0.0371	0.0556	0.0603
	[-3.97]***	[-2.82]***	[2.29]**	[3.02]***	[3.15]***
Dividend Yield	0.7489	3.8877	-1.6465	2.7348	2.3199
	[0.26]	[0.61]	[-0.54]	[0.83]	[0.66]
No Dividend	-0.0062	0.0468	-0.0026	-0.0026	0.0008
	[-0.29]	[1.02]	[-0.14]	[-0.12]	[0.04]
D/P Ratio	-0.1967	-0.1508	-0.0876	-0.3867	-0.3387
	[-1.22]	[-0.43]	[-0.59]	[-2.45]**	[-1.99]**
IOR	0.1798	0.3882	-0.0357	-0.0180	-0.0078
	[5.34]***	[5.13]***	[-1.25]	[-0.53]	[-0.23]
Ln(Analyst Coverage)	0.4058	0.6359	0.7528	0.8842	0.9406
	[29.51]***	[20.05]***	[40.57]***	[41.35]***	[42.51]***
Observations	94,180	94,180	84,246	84,246	84,246
R-squared	0.568	0.550	0.412	0.451	0.460
Firm FEs	Yes	Yes	Yes	Yes	Yes
Year-Qtr FEs	Yes	Yes	Yes	Yes	Yes

Table 9: Economic Uncertainty and Conference Call Behavior

This table presents the relation between firm ethnic diversity and diversity in information collected and beliefs at times of economic uncertainty. High Uncertainty (High UI) is a dummy variable that equals one when the U.S. historical index is in the top tercile of available values. The uncertainty index is from Baker, Bloom, and Davis (2016) and is the policy uncertainty index. In Columns (1) and (2), we measure the diversity in information set as the number of question and number of words for all questions analysts asked at conference calls for quarter t. This data is collected from Capital IQ conference call data. In column (3) - (5) we measure the diversity in analysts beliefs as flips, divergences and inconsistencies. Flips and Divergences are measured are the ones as in Kandel and Pearson (1995). Size, M/B, Leverage, Income Vol., Turnover, Loss, Dividend Yield, No Dividend, D/P Ratio, Institutional Ownership (IOR), and Analyst Coverage are included as control variables. Appendix Table A.1 includes the definitions for all variables included in the regressions. Robust *t*-statistics are in parentheses below the coefficient and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Low UI	High UI	Low UI	High UI	Low UI	High UI
	Ln(1+NQuestions)		Ln(1+NWords)		Ln(1+ NFlips & NDivergences)	
	(1)	(2)	(3)	(4)	(5)	(6)
PMINO	-0.0625	0.1070	-0.2936	0.2419	-0.1320	0.2628
	[-0.50]	[2.63]***	[-1.10]	[2.47]**	[-1.59]	[3.48]***
Size	-0.0311	0.1105	-0.0534	0.2085	0.1522	0.1075
	[-0.49]	[5.69]***	[-0.43]	[4.78]***	[6.34]***	[5.08]***
M/B	0.0018	0.0005	0.0032	0.0002	-0.0003	0.0005
	[0.93]	[0.77]	[0.85]	[0.16]	[-0.23]	[0.57]
Leverage	-0.0277	-0.1678	0.2115	-0.3926	-0.0547	0.1319
	[-0.20]	[-3.10]***	[0.72]	[-3.15]***	[-0.65]	[1.95]*
Income Vol.	1.5864	2.0999	4.9760	4.2715	1.6049	-0.1245
	[1.05]	[3.45]***	[1.62]	[2.99]***	[1.72]*	[-0.17]
Turnover	0.1341	0.1227	0.0271	0.1678	0.2082	0.1170
	[1.00]	[3.01]***	[0.09]	[1.75]*	[2.67]***	[2.25]**
Loss	-0.0056	-0.0447	0.0447	-0.0693	0.0704	0.0330
	[-0.10]	[-2.33]**	[0.37]	[-1.57]	[1.69]*	[1.10]
Dividend Yield	7.1249	3.5831	5.5381	9.9977	6.0643	6.3625
	[0.83]	[0.90]	[0.38]	[1.10]	[0.75]	[1.16]
No Dividend	-0.0511	0.0162	-0.0973	0.0882	0.0239	0.0135
	[-0.47]	[0.66]	[-0.40]	[1.65]*	[0.49]	[0.40]
D/P Ratio	-0.5992	-0.2875	-0.6463	-0.3695	-0.2370	-0.4008
	[-1.05]	[-1.28]	[-0.60]	[-0.74]	[-0.89]	[-1.43]
IOR	0.2527	0.1740	0.4968	0.3734	-0.0589	0.0562
	[2.19]**	[4.61]***	[2.42]**	[4.38]***	[-0.79]	[1.24]
Ln(Analyst Coverage)	0.3588	0.3710	0.5648	0.5673	0.7836	0.9868
	[6.83]***	[22.50]***	[4.98]***	[15.07]***	[23.84]***	[29.08]***
Observations	3,880	54,143	3,880	54,143	22,022	31,949
R-squared	0.763	0.590	0.765	0.579	0.440	0.476
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Board Composition and Analyst Behavior

This table presents regressions of minority analysts on accuracy, timeliness and thoroughness of forecasts when there are minority board members. PMBoard measures the percentage of minority board members. High PMBoard is a dummy takes a value of one when PMBoard is great or equal to 15%, and zero otherwise. The dependent variable in columns (1) and (2) are the proportional mean absolute forecast error (PMAFE). In Columns (3) and (4) the dependent variable is Timely EPS is a dummy takes a value of one if the analyst issues an earnings forecast for quarter t+1 on the day of or the day after the firm's quarter t earnings announcement date, and zero otherwise. In columns (5) and (6) the dependent variable is NTotal Forecasts which is the number of EPS forecasts. Lagged PMAFE, Forecast Horizon, Brokerage Size, Forecast Frequency, Firm Experience, General Experience, Firms Coverage and Industries Coverage are included as control variables in Columns (1) and (2). Number of Concurrent Forecasts, Broker Size, Firm Experience, General Experience, Firms Coverage and Industries Coverage are included as control variables in Columns (3) to (6). All regressions, include firm and year-quarter-fixed effects. Appendix Table A.1 includes the definitions for all variables included in the regressions. Robust *t*-statistics are in parentheses below the coefficient and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	PMBoard	High PMBoard	PMBoard	High PMBoard	PMBoard	High PMBoard
	PMAFE		Timely EPS		Ln(1+NTotal Forecasts)	
	(1)	(2)	(3)	(4)	(5)	(6)
Minority	0.0180	0.0172	-0.0143	-0.0120	-0.0329	-0.0393
	[5.22]***	[5.59]***	[-4.58]***	[-4.37]***	[-5.22]***	[-6.88]***
Board Mino	0.0081	0.0027	0.0170	0.0067	-0.0036	0.0022
	[0.75]	[1.17]	[0.78]	[1.55]	[-0.11]	[0.33]
Minority × Board Mino	-0.0482	-0.0170	0.0506	0.0089	-0.1242	-0.0183
	[-1.91]*	[-2.46]**	[2.02]**	[1.45]	[-2.90]***	[-1.51]
Lag(PMAFE)	0.0766	0.0766				
	[28.12]***	[28.12]***				
Ln(1 + NConcurrent)			-0.1064	-0.1064	-0.0168	-0.0169
			[-37.77]***	[-37.78]***	[-8.59]***	[-8.59]***
Observations	1,130,991	1,130,991	1,130,991	1,130,991	794,538	794,538
R-squared	0.011	0.011	0.166	0.166	0.288	0.288
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Board Composition, Economic Uncertainty, and Earnings Predictability

This table presents earnings predictability regressions of minority analysts on future earnings when there are minority board members. The dependent variable is the earnings in the next quarter (*t+1*). Minority analysts (PMINO) are measured at the stock level as the percentage of analysts following a firm that has minority status. PMBoard measures the percentage of minority board members. High PMBoard is a dummy takes a value of one when PMBoard is great or equal to 15%, and zero otherwise. High Uncertainty (High UI) is a dummy variable that equals one when the U.S. historical index is in the top tercile of available values. The uncertainty index is from Baker, Bloom, and Davis (2016) and is the policy uncertainty index. Control variables include Earnings, Size, M/B, Leverage, Income Volatility, Turnover, Loss, Dividend Yield, No Dividend, D/P Ratio, Institutional Ownership (IOR), and Analyst Coverage. Appendix Table A.1 includes the definitions for all variables included in the regressions. All regressions include firm and year-quarter-fixed effects. Robust *t*-statistics are in parentheses below the coefficient and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Baseline (1)	High PMBoard = 0 (2)	High PMBoard = 1 (3)	Low UI (4)	High UI (5)
PMINO	-0.0018	-0.0018	-0.0024	-0.0004	-0.0013
	[-1.71]*	[-1.57]	[-1.08]	[-0.22]	[-0.73]
PMINO × Consensus	0.0078	0.0064	0.0162	0.0053	0.0109
	[2.94]***	[2.10]**	[2.89]***	[1.23]	[3.14]***
Consensus	0.0214	0.0225	0.0201	0.0275	0.0205
	[24.71]***	[23.62]***	[11.62]***	[19.24]***	[21.90]***
Earnings	0.4210	0.4118	0.3660	0.3335	0.3603
	[30.84]***	[28.36]***	[10.09]***	[16.56]***	[18.03]***
Observations	131,667	114,139	17,418	26,327	55,412
R-squared	0.803	0.802	0.829	0.845	0.802
Controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Year-Qtr FEs	Yes	Yes	Yes	Yes	Yes

Table 12: Combined Effects of Board Composition and Market Uncertainty on Earnings Predictability

This table presents earnings predictability regressions of minority analysts on future earnings when there are minority board members. The dependent variable is the earnings in the next quarter (*t+1*). Minority analysts (PMINO) are measured at the stock level as the percentage of analysts following a firm that has minority status. PMBoard measures the percentage of minority board members. High PMBoard is a dummy takes a value of one when PMBoard is great or equal to 15%, and zero otherwise. High Uncertainty (High UI) is a dummy variable that equals one when the U.S. historical index is in the top tercile of available values. The uncertainty index is from Baker, Bloom, and Davis (2016) and is the policy uncertainty index. Control variables include Earnings, Size, M/B, Leverage, Income Volatility, Turnover, Loss, Dividend Yield, No Dividend, D/P Ratio, Institutional Ownership (IOR), and Analyst Coverage. Appendix Table A.1 includes the definitions for all variables included in the regressions. All regressions include firm and year-quarter-fixed effects. Robust *t*-statistics are in parentheses below the coefficient and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

	Low UI	High UI	Low UI	High UI	Low UI	High UI
	Baseline		Triple: PMBoard		Triple: High PMBoard	
	(1)	(2)	(3)	(4)	(5)	(6)
PMINO	-0.0004	-0.0013	-0.0007	-0.0005	-0.0013	-0.0002
	[-0.22]	[-0.73]	[-0.34]	[-0.25]	[-0.67]	[-0.11]
Consensus	0.0275	0.0205	0.0284	0.0227	0.0280	0.0215
	[19.24]***	[21.90]***	[17.83]***	[20.28]***	[18.73]***	[21.59]***
PMINO × Consensus	0.0053	0.0109	0.0057	0.0075	0.0060	0.0082
	[1.23]	[3.14]***	[1.11]	[1.72]*	[1.32]	[2.13]**
Board Mino			0.0004	0.0090	0.0011	0.0018
			[0.07]	[1.94]*	[0.85]	[1.85]*
PMINO × Board Mino			0.0053	-0.0125	0.0069	-0.0065
			[0.34]	[-0.93]	[1.27]	[-1.76]*
Board Mino × Consensus			-0.0156	-0.0309	-0.0039	-0.0059
			[-1.44]	[-5.16]***	[-1.63]	[-4.89]***
PMINO × Consensus × Board Mino			-0.0020	0.0519	-0.0064	0.0162
			[-0.04]	[2.10]**	[-0.54]	[2.56]**
Earnings	0.3335	0.3603	0.3332	0.3596	0.3329	0.3599
	[16.56]***	[18.03]***	[16.56]***	[18.02]***	[16.56]***	[18.01]***
Observations	26,327	55,412	26,327	55,412	26,327	55,412
R-squared	0.845	0.802	0.845	0.802	0.846	0.802
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr FEs	Yes	Yes	Yes	Yes	Yes	Yes

Appendix A

Table A.1: Variable Definitions

This table provides detailed definitions of all variables and data sources.

Variable	Definition	Source
Panel A: Stock-level Variables		
Earnings	The operating income after depreciation (OIADPQ) divided by lagged total assets (ATQ).	COMPUSTAT
CAR[0, 1] or [2, 61]	The cumulative daily abnormal return during the [0, 1] or [2, 61] window around the earning announcement date based on Fama-French 3 factors plus momentum model.	CRSP
Consensus	The median of all outstanding forecasts of the stock issued within the 90 days prior to the earnings announcement. If an analyst made multiple forecasts during that period, we take her most recent forecast.	I/B/E/S
Suprise	Actual earnings minus consensus scaled by the end-of-month stock price.	I/B/E/S
PMINO	The number of minority analysts divided by the number of total analysts who cover the stock.	I/B/E/S, 2010 US Census
PMINOF	The number of forecasts from minority analysts divided by the number of all forecasts coverd the stock.	I/B/E/S, 2010 US Census
Size	The natural logarithm of total assets (ATQ).	COMPUSTAT
M/B	The market to book ratio as the market value of equity (PRCCQ × CSHOQ) divided by the book value of equity. The book value of equity depends on availability in the following order: the shareholders' equity (SEQQ), or commons/ordinary equity (CEQQ). If both items are missing, the shareholders' equity is total assets (ATQ) minus total liabilities (LTQ) and minority interests (MIBQ).	COMPUSTAT
Leverage	The sum of short-term debt (DLCQ) and long-term debt (DLTTQ), divided by total assets (ATQ).	COMPUSTAT
Income Vol.	The income volatility as the standard diviation of operating income before depreciation (OIBDPQ) over the 20 quarters (minimum 8 quarters available) prior to the fiscal quarter divided by the mean of total assets (ATQ).	COMPUSTAT
Turnover	The average monthly volume to number of shares outstanding over the past six months before the earning announcement month.	CRSP
Loss	A dummy takes a value of one when operating income after depreciation (OIADPQ) is negative, and zero otherwise.	COMPUSTAT
Dividend Yield	The sum of the past 12-month dividend cash amount (DIVAMT), divided by the book value of equity at the end of the fisical quarter.	COMPUSTAT, CRSP
No Dividend	A dummy takes a value of one when the past 12-month dividends is zero, and zero otherwise.	CRSP
D/P Ratio	The dividend-price (D/P) ratio, where D is the sum of the past 12-month dividends, and P is the end-of-month stock price.	CRSP

IOR	The institutional ownership ratio, defined as the total institutional ownership as the percent of shares outstanding.	Thomson Reuters
Analyst Coverage	The number of analysts covering the firm.	I/B/E/S
PMBoard	The percentage of minority directors on board.	BoardEx
High PMBoard	A dummy takes a value of one when PMBoard is great or equal to 15%, and zero otherwise.	BoardEx
NQuestions	The number of questions analysts asked at conference calls for quarter t.	Capital IQ
NWords	The number of words for all questions analysts asked at conference calls for quarter t.	Capital IQ
NFlip	Using Kandel and Pearson (1995) suppose 2 analysts make forecasts of Xi and Yi in the pre-announcement window and Xj and Yj in the post announcement window then a: Flip= Sign (Yi - Xi)≠ Sign (Yj – Xj) and (Xi > Xj) and (Yi < Yj).	I/B/E/S
NDivergence	Using Kandel and Pearson (1995) suppose 2 analysts make forecasts of Xi and Yi in the pre-announcement window and Xj and Yj in the post announcement window then a: Divergence= Sign (Yi - Xi)≠ Sign (Yj – Xj) and |Yj -Yi| > |Xj -Xi|.	I/B/E/S
NFlips & NDivergences	The number of pairs of forcasts as either "flip" or "divergence".	I/B/E/S
High/Low Uncertainty Index (UI)	Period of high uncertainty are marked by a dummy variable that equals one when the U.S. historical uncertainty index is in the top/bottom tercile of available values.	www.policyuncertainty.com
Panel B: Analyst-level Variables		
Timely EPS	A dummy takes a value of one if the analyst issues an earnings forecast for quarter t+1 on the day of or the day after the firm's quarter t earnings announcement date, and zero otherwise.	I/B/E/S
Timely Recommend	A dummy takes a value of one if the analyst issues a stock recommendation on the day of or the day after the firm's quarter t earnings announcement date, and zero otherwise.	I/B/E/S
Forecast Lag	The difference between the analyst earnings forecast date for quarter t+1 and the earnings announcement date for quarter t.	I/B/E/S
PMAFE	The proportional mean absolute forecast error for the firm's EPS, defined as the difference between absolute forecast error of the analyst and the mean absolute forecast error by all analysts providing EPS forecasts for the firm, normalized by the mean absolute forecast error.	I/B/E/S
Minority	A dummy that takes a value of one if the analyst is a minority, and zero otherwise.	I/B/E/S, 2010 US Census
Forecast Horizon	The number of days between the forecast date and the earning announcement date.	I/B/E/S
Brokerage Size	The number of analysts reporting EPS forecasts for the broker in the quarter.	I/B/E/S
Forecast Frequency	The number of EPS forecasts the analyst issued during the forecast period.	I/B/E/S
Firm Experience	The number of years for which the analyst has provided EPS forecasts for the firm.	I/B/E/S
General Experience	The number of years for which the analyst has provided any EPS forecasts.	I/B/E/S
Firm Coverage	The number of firms for which the analyst issues an earnings forecast in the quarter.	I/B/E/S
Industry Coverage	The number of industries for which the analyst issues an earnings forecast in the quarter. The industry is defined by two-digit SIC code.	I/B/E/S
NEPS Horizons	The number of earnings forecasts for different horizons (i.e., quarter t+1, quarter t+2, forthcoming year etc.) of the sample firm issued by the analyst on the date of the forecast for quarter t+1. The value is 1 if the analyst issues only an earnings forecast for quarter t+1.	I/B/E/S

NEPS Components	The number of types of earnings or earnings component forecasts (i.e., revenue, cash flows, gross margin etc.) of the sample firm issued by the analyst on the date of the forecast for quarter t+1. The value is 1 if the analyst issues only the earnings forecast without any earnings component forecasts.	I/B/E/S
NConcurrent	The number of concurrent announcements, which is the analyst has other firms in her coverage portfolio announcing earnings on the same day as the sample firm. If the sample firm is the only firm in the analyst's portfolio announcing earnings, then the value is 0.	I/B/E/S
Consistency	The standard deviation of the analyst forecast errors for the sample firm over the previous eight quarters.	I/B/E/S
Accuracy	The average forecast error over the previous eight quarters.	I/B/E/S
Lowball	the number of positive forecast errors (actual EPS - forecast EPS) minus the number of negative forecast errors (unclassified zero errors), scaled by the total number of forecast errors over the previous eight quarters.	I/B/E/S
Bold	The absolute value of the distance between the analyst forecast and the consensus forecast (defined as the average of the other analysts' forecasts).	I/B/E/S
All-Star	A dummy that takes a value of one if the analyst is selected to the first, second, third, or runner-up teams in the Institutional Investor All-America Research Team in the prior year, and zero otherwise.	Institutional Investor magazine
Local	A dummy that takes a value of one if the analyst is at the firm's headquarter state, and zero otherwise.	I/B/E/S, 10K/Q Filings

Table A.2: Analysts' Characteristics Distribution

Panel A presents the distribution of analyst ethnicity. Panel B reports the number of All-Star analysts over 3 year time windows, and Panel C reports summary statistics for the number of local analysts every 3 years. Local analysts are those that reside in the state where the firm is headquartered. Appendix Table A.1 includes the detailed definition for all variables

Panel A: Race/Ethnicity

	N	% Total
Non-minority	7,631	83.44
Minority	1,514	16.56
Asian	1,126	12.31
Hispanic	208	2.27
Africa American	180	1.97
Total	9,145	100

Panel B: AllStar Nomination

Period	NonStar	All-Star	Total
1995-1997	4,324	628	4,952
1998-2000	6,051	813	6,864
2001-2003	6,284	729	7,013
2004-2006	6,487	629	7,116
2007-2009	6,214	585	6,799
2010-2012	6,128	625	6,753
2013-2015	5,863	579	6,442
2016-2018	4,998	602	5,600
Total	46,349	5,190	51,539
Non-minority	39,944	4,742	44,686
Minority	6,405	448	6,853

Panel C: Local Analysts

Period	Non-local	Local	Total
1995-1997	38,139	5,277	43,416
1998-2000	45,347	7,337	52,684
2001-2003	44,851	7,902	52,753
2004-2006	55,610	7,924	63,534
2007-2009	57,688	7,390	65,078
2010-2012	62,297	6,392	68,689
2013-2015	64,726	5,169	69,895
2016-2018	45,999	3,889	49,888
Total	414,657	51,280	465,937
Non-minority	368,560	44,757	413,317
Minority	46,097	6,523	52,620

Table A.3: Earnings and Return Predictability: Excluding Asian Analysts

The table presents earnings (Panel A) and returns (Panel B) predictability regressions of minority analysts on future earnings after excluding Asian analysts. In Panel A, the dependent variable is the earnings in the next quarter (*t+1*). The dependent variables in Panel B are the cumulative abnormal returns over days [0, 1] and [2, 61] after the earnings announcement. Minority analysts (PMINO) are measured at the stock level as the percentage of analysts following a firm that has minority status. Minority analysts forecast (PMINOF) measure the percentage of forecasts that are issued by minority analysts. Industry-adjusted minority analysts are defined as the percentage of analysts in an industry (3-digit SIC code) that have minority status. The adjusted percentage minority is calculated for both stock and forecast level measures. Control variables include *Size, M/B, Leverage, Income Vol., Turnover, Loss, Dividend Yield, No Dividend, D/P Ratio, IOR,* and *ln(Analyst Coverage)*. In Panel A regressions, include firm-fixed effects and year-quarter-fixed effects. In Panel B, all control variables interact with *Surprise,* which is measured as the actual earnings less the consensus forecast and included as additional control variables in the regression. Also, all regressions include year-quarter-fixed effects. Robust *t*-statistics are in parentheses below the coefficient and are based on standard errors clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. Appendix Table A.1 includes the detailed definition for all variables included in the regressions.

Panel A: Earnings Predictability					
	Baseline	Full Sample		Minority Subsample	
	(1)	(2)	(3)	(4)	(5)
PMINO		-0.0028		-0.0042	
		[-1.63]		[-1.80]*	
PMINO × Consensus		0.0121		0.0193	
		[2.86]***		[3.94]***	
PMINOF			-0.0023		-0.0037
			[-1.42]		[-1.81]*
PMINOF × Consensus			0.0099		0.0162
			[2.56]**		[3.62]***
Consensus	0.0237	0.0233	0.0234	0.0230	0.0232
	[27.27]***	[26.80]***	[26.83]***	[19.72]***	[19.80]***
Earnings	0.4457	0.4455	0.4455	0.4204	0.4206
	[38.69]***	[38.64]***	[38.65]***	[25.84]***	[25.85]***
Observations	176,725	176,725	176,725	78,512	78,512
R-squared	0.791	0.791	0.791	0.800	0.800
Stock-level Controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Year-Qtr FEs	Yes	Yes	Yes	Yes	Yes

Panel B: Market Reaction

	CAR[0, 1] (1)	CAR[2, 61] (2)	CAR[0, 1] (3)	CAR[2, 61] (4)	CAR[0, 1] (5)	CAR[2, 61] (6)
PMINO			0.0018	-0.0063		
			[0.67]	[-0.90]		
PMINO × Surprise			0.1030	0.4477		
			[1.01]	[1.74]*		
PMINOF					0.0018	-0.0066
					[0.69]	[-0.96]
PMINOF × Surprise					0.0843	0.4165
					[0.88]	[1.67]*
Surprise	0.2227	0.0394	0.2194	0.0249	0.2199	0.0256
	[16.32]***	[2.01]**	[15.87]***	[1.24]	[15.95]***	[1.27]
Observations	176,725	176,725	176,725	176,725	176,725	176,725
R-squared	0.059	0.060	0.059	0.060	0.059	0.060
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr FEs	Yes	Yes	Yes	Yes	Yes	Yes