Brokerage office diversity and analysts' forecast performance

Abstract

This paper investigates the impact of office-level ethnic diversity on individual analysts' forecasting performance. Drawing on a hand-collected dataset of analysts' ethnic backgrounds, we find that analysts in offices with higher ethnic diversity produce earnings forecasts that are more accurate, timely, and frequent. These results remain robust when controlling for mean-adjusted analyst and firm characteristics, as well as year and location fixed effects, and when utilizing brokerage firm mergers as an exogenous shock that alters the ethnic composition of analysts within an office. Further analysis reveals that the positive effects of office-level ethnic diversity are more pronounced when a greater proportion of colleagues share a country of origin with (1) the covered firms' subsidiary locations or (2) their primary import/export countries, and when analysts have less experience, shorter tenures, or non-star status. Finally, we show that forecast revisions issued by analysts in highly diverse offices are significantly more informative than those from less diverse offices. Overall, this study suggests that office-level ethnic diversity enhances analysts' performance by improving information access.

1. Introduction

There is ongoing debate on the role of diversity in the corporate world. On the one hand, public policies and corporate initiatives often portray diversity as a catalyst for organizational success, arguing that individuals with varied backgrounds and characteristics enhance decision-making and problem-solving (Cox and Blake, 1991; Shachaf, 2008; Loyd et al., 2013; Rao and Tilt, 2016). On the other hand, skepticism about diversity has been on the rise, as evidenced by firms scaling back their diversity programs and the emergence of anti-diversity shareholder proposals—trends that align with research suggesting possible detrimental effects of diversity (Bassett-Jones, 2005; Mannix and Neale, 2005; Netki, 2008; Darmadi, 2013; Xu et al., 2022; Wang et al., 2024).[1] This study aims to contribute to this debate. Drawing on a hand-collected dataset of analysts' ethnic backgrounds at the brokerage office level, we investigate whether office level ethnic diversity enhances analysts' earnings forecast performance and, if so, through which mechanisms.

We focus on brokerage office level diversity for two reasons. First, much extant research on diversity focuses on diversity at the firm level (Upadhyay and Zeng, 2014; Parrotta et al., 2014; Kong et al., 2023), implicitly assuming that diversity is uniform across different geographic locations within the same firm or that effective collaboration occurs over broad distances. In reality, a brokerage house may exhibit limited diversity at the overall firm level but considerable variation when examined at the local office level, or vice versa. For example, our hand collected data reveals that while PRUDENTIAL EQUITY GROUP had a moderately and consistently high broker-level ethnic diversity score, its Houston office had no diversity at all by 2002, only to surge dramatically in 2003 with the hiring of more South Asian analysts. Meanwhile, its San Francisco office saw a sharp 36% decline in diversity in 2002. As illustrated by this example, diversity at the office level may be a more crucial determinant

[1] Early in 2020, U.S. President Trump had signed anti-DEI proposal—Executive Order 13950, however, such order is overturned by President Biden (Kalkman, 2021). Currently, there's onging debate on the effectiveness of DEI program. Many companies such as Ford, Walmart, McDonald, Apple and Meta Platform Inc. have publicly announced to curtail or terminate their DEI programs to advocate diversity, equity and inclusion (APNews, 2025; AXIOS, 2025). According to NBC analysis, Republican lawmakers in more than 30 states have introduced or passed more than 100 bills to either restrict or regulate diversity, equity and inclusion initiatives from 2020.

of analysts' performance. This is consistent with prior studies suggest that employees tend to interact most with colleagues in close proximity (Oerlemans and Meeus, 2005; Eriksson, 2011; Molina-Morales et al., 2014), meaning that office boundaries may limit analysts' access to information beyond their immediate work environment.

Second, firm-level diversity often intertwines with intangible factors such as organizational culture or policies, which themselves can drive outcomes (Gordon and DiTomaso, 1992; Lee and Yu, 2003; Rashid et al., 2003). By focusing on the brokerage office, the more granular setting in which analysts most frequently interact, we reduce the risk of confounding firm-level influences and directly assess how office-level heterogeneity shapes performance.

In this paper, we focus on ethnic differences within brokerage office level. Ethnicity is closely related to language, culture norms, etiquette, and individual's approaches to work (Riordan and Shore, 1997; Schilpzand and Martins, 2010). Individuals have different knowledge and skills based on their own ethnicity, leading to different thinking patterns, preferences and perspectives, finally resulting in different impacts on individuals' decision-making (Guiso et al., 2006; Guiso et al., 2009; Liu, 2016).

In this paper, we argue that brokerage office-level ethnic diversity enhances individual analysts' performance. Diverse ethnic backgrounds bring varied knowledge and cognitive approaches (Ferdman and Sagiv, 2012; Elrehail et al., 2017; Huang et al., 2022). In offices with higher ethnic diversity, analysts are exposed to a broader range of perspectives and insights, helping them overcome inertial thinking and individual biases (Cox and Blake, 1991; Hong and Page, 2004; Huang et al., 2022). As a result, these analysts may gain an informational advantage over their counterparts in less ethnically diverse offices, potentially leading to improved forecasting performance.

It is possible that our prediction may not be supported. Prior research suggests that diversity can lead to conflicts among heterogeneous groups, which may impair communication and collaboration and adversely affect individual analysts' performance (Mannix and Neale, 2005). Moreover, the insights generated by a diverse workforce may be difficult and costly to interpret and apply, thereby limiting their practical usefulness for individual analysts (Cronin and Weingart, 2007).

To test our prediction, we collected data on both analysts' ethnicity and office locations for the period from 2000 to 2007. To determine analysts' ethnicity, we follow prior literature (Hambrick et al., 1996; Easterly and Levine, 1997; Alesina et al., 1999; Alesina et al., 2003; Ottaviano and Peri, 2005, 2006) and employ Onolytics software to ascertain each analyst's ethnic background using their names. To determine analysts' office locations, we manually collected all published office locations from Nelson's Directory of Investment Research. Finally, following prior studies, we compute office-level ethnic diversity using the ethnolinguistic fractionalization (ELF) index, which measures diversity within each office (Alesina et al., 1999; Alesina et al., 2003).[2]

First, as illustrated in Figure 1, we find a substantial variation in ethnic diversity across offices over our sample period. For example, in 2005, the broker-level ELF index for Morgan Stanley is 0.7422, which is relatively high among brokers in our sample. For offices in Boston and Chicago, the ELF index is 0 with all analysts are homogeneous with the same ethnic background of EUROPEAN and ENGLISH respectively. However, for offices in New York and San Francisco, analysts have various ethnic backgrounds of ENGLISH, EUROPEAN, CELTIC, SOUTH ASIAN, etc, leading to a high ELF index of 0.7017 and 0.6250 respectively.[3]

Next, we examine the impact of brokerage office-level ethnic diversity on analysts' performance. We show that analysts working in brokerage office with higher ethnic diversity produce earnings forecasts that are more accurate, more timely, and more frequent. These results are robust if we control for mean-adjusted analysts' characteristics and firm characteristics and if we include year fixed effect and location fixed effect respectively. Consistent with prior studies (Chen et al., 2015; Hong and Kacperczyk, 2010; Kelly and Ljungqvist, 2012), we utilize brokerage firm merger events as an exogenous shock to the number of analysts in a brokerage house that leads to change of ethnic diversity of analysts at the office level and obtain consistent results.

We then examine the mechanisms through which analysts benefit from office-level ethnic diversity. If diversity offers relevant skills and knowledge, we expect its positive effects to be

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[2] ELF index measures diversity on a 0 to 1 scale, where 0 indicates complete homogeneity and 1 represents maximum diversity.

[3] We show more examples in Appendix B.

more pronounced when these ethnicity-related resources align with the specific demands of analysts' forecasting tasks. To test this, we narrow our focus to analysts' countries of origin (as identified by Ancestry.com) and the geographic locations of covered firms' operational attributes. This approach enables us to match analysts' ethnicity-related expertise to the tasks they perform. We exclude analysts who have the same country of origin as the country of a firm's non-us subsidiary or the firms' major trading country since these analysts are more likely to have relevant skills and knowledge when following the matched firms. We find that analysts produce more accurate and timely forecastsand update them more frequently when their offices include a greater proportion of colleagues whose countries of origin overlap with (1) the covered firms' subsidiary locations or (2) their primary import or export countries. Overall, these results suggest that analysts derive stronger benefits from office-level ethnic diversity when the related skills or knowledge of their colleagues are directly relevant to their forecasting tasks.

Further, we investigate the type of analysts who derive more advantages from office-level ethnic diversity. We find that improvements in forecast accuracy, timeliness, and frequency are more pronounced for analysts who are less experienced, have shorter tenures, or non-star analysts. These results suggest that junior analysts benefit more from the diverse perspectives offered by an ethnically diverse office.

Finally, we examine the broader capital market implications of these findings. We show that forecast revisions issued by analysts in highly diverse offices are significantly more informative than those from less diverse offices. This suggests that investors place greater value on the outputs of analysts working in environments with higher levels of ethnic diversity, subsequently valuing their forecasts more highly.

Our study contributes to literature in several ways. First, our study contributes to the analyst literature by exploring a new determinant of analysts' forecast performance. Prior literature has documented that firm characteristics, analyst characteristics and brokerage characteristics affect analysts' forecast performance (Clement, 1999; Clement and Tse, 2005; Bradley et al., 2017; Li et al., 2020). Studies focusing on brokerage characteristics have shown that analysts' forecast performance is positively related to brokerage size, brokerage in-house economic experts, brokerage political network and corporate culture (Clement, 1999; Hugon et al., 2016; Christensen et al., 2017; Pacelli 2019). However, these papers have an implicit assumption that offices are homogeneous across firms and brokerage resources are shared across offices at relatively costs. Using hand-collected data of analysts' office location, we demonstrate significant variations in ethnic diversity across offices within the same brokerage firms, and such variations influence analysts' performance.

Second, our study contributes to broad literature on the impact of diversity. Prior literature investigating the role of diversity at the firm level presents mixed evidence. Several studies argue that diversity provides diverse perspectives and insights and demonstrate its positive impact on firm's and individual's performance (Upadhyay and Zeng, 2014; Parrotta et al., 2014; Parrotta et al., 2016; Condie et al., 2023). Others contend diversity causes conflicts and hinders communication and collaboration, thus having a negative impact (Darmadi, 2013; Koopmans adn Veit, 2014; Zou et al. 2021; Kong et al., 2023). In this paper, we use more granular data and study diversity at the office level. Our results illustrate that diversity at the office level enhances individual analysts' performance and the mechanisms through office-level diversity operates to have an impact.

In practice, our study has managerial implications for brokerage offices to promote ethnic diversity. Our main results illustrate that analysts working in offices with higher level of ethnic diversity have better forecasts performance, suggesting that ethnic diversity has economic values. Further, our results suggest not only diversity matters, but also the alignment between ethnic related knowledge and specific task matters. Therefore, brokerage firms aiming to improve employees' performance may consider incorporating such an alignment when designing the recruitment plan and workplace diversity policy.

The rest of our study is structured as below. Section 2 provides literature review and hypothesis development. Section 3 presents the empirical design. Section 4 presents the main results, along with channel test, cross-section test, robustness test and an endogeneity test. Section 5 provides additional tests on economic results. Finally, Section 6 concludes our study.

2. Literature Review and Hypothesis

2.1 Ethnic Diversity

Diversity can be a double-edged sword for both organizations and individuals. On the positive side, diversity brings together people with varied ideas, perspectives, and skills, which can enhance performance at both the firm and individual levels (Cox et al., 1991; Upadhyay & Zeng 2014; Parrotta et al. 2014). Past research highlights these benefits among top management teams, auditors, and boards of directors, demonstrating enhancement in decision-making, and overall performance (Talke et al., 2010; Nielson and Nielson, 2013; Fernández-Temprano and Tejerina-Gaite, 2020; Condie et al., 2023). However, diversity also means that team members may have contrasting cultural, linguistic, or social backgrounds, potentially leading to miscommunication, lack of cooperation, conflict, discrimination, and distrust (Montalvo and Reynal-Querol, 2005; Koopmans adn Veit, 2014; Zou et al. 2021; Kong et al., 2023). These issues can culminate in turnover, ultimately harming performance.

This dual nature of diversity applies especially to ethnicity, where ethnic differences affect language, culture, etiquette, approaches to work, and individual's self-identification (Riordan and Shore, 1997; Schilpzand and Martins, 2010). Prior studies suggest that one's ethnic background imparts a unique set of knowledge, skills, and thinking patterns that begin early in life and become deeply ingrained (Tse et al., 1988; Hope et al., 1999). In a business context, these variations might include different communication styles or culturally specific norms. For example, individuals from certain Asian cultures, especially Confucian environment place a strong emphasis on business ethnics and social harmony (Chung et al., 2008) and tend to be more conservative in decision-making (Ning et al., 2024), whereas others may prioritize different values or practices.

When teams are ethnically diverse, they draw on a broader range of informed perspectives, often resulting in better outcomes. For instance, firms with higher ethnic diversity show stronger innovation, improved information disclosure, and more effective internationalization (Upadhyay & Zeng, 2014; Parrotta et al., 2016; Cao et al., 2021; Quintana-García et al., 2022). At the individual level, research suggests that members of diverse groups can collaborate more effectively (Cox et al., 1991), leading to better individual performance (Manevska et al., 2024). In auditing contexts, Condie et al. (2023) find that greater ethnic diversity promotes talent retention among audit professionals, thereby improving audit quality.

However, ethnic diversity may result in conflict between different ethnic groups may hinder collaboration, thus having a negative impact on firms' and individuals' performance (Zou et al. 2021). This suggests that the benefits of ethnic diversity can be limited if conflicts arise between different ethnic groups, stifling collaboration and negatively impacting economic development and firms' and individual performance (Easterly and Levine, 1997; Koopmans adn Veit, 2014; Zou et al., 2021; Kong et al., 2023).

2.2 The link between office-level ethnic diversity and analysts' performance

Prior research has demonstrated that analysts' performance is closely tied to their individual abilities and accumulated experience. For example, Bradley et al. (2017) find that an analyst's prior industry background significantly affects forecast accuracy, while Mikhail et al. (1997), Clement (1999) and Clement et al. (2007) show that analysts' general, firm-specific and task-specific experience correlates with more accurate forecasts. This line of literature underscores the importance of analysts' personal expertise in driving their forecasting outcomes.

In contrast, another stream of literature examines how analysts leverage others' capabilities to enhance their own performance. Early studies in this area focused on brokerage house size, observing that larger firms tend to be associated with better analyst performance—suggesting that size serves as a proxy for valuable resources analysts can tap into (Clement, 1999).

More recently, scholars have zoomed in on the resources available within a brokerage firm. For instance, Huang et al. (2022) investigate firm-wide industry skills heterogeneity, documenting that greater information sharing among analyst colleagues who cover economically related industries along a supply chain improves analyst performance. However, the implicit assumption is that analysts can access these resources across geographic regions at relatively low cost. Fang and Hope (2021) study the composition of analyst teams working on specific forecasts, reporting that teams with higher diversity perform better. However, such team composition may be endogenously determined by the attributes of the forecasted firms and the analysts. For example, an analyst in charge of forecasting multiple firms may decide how to allocate talents cross different forecasting tasks. Yet, the composition at the office level is unlikely to be determined by any single analyst.

In this paper, we focus on office-level ethnic diversity, arguing that the diversity within a specific office is crucial to analysts' interactions. Prior studies suggest that individuals tend to foster communication and collaboration in close proximity (Oerlemans and Meeus, 2005; Eriksson, 2011; Irving et al., 2020). When colleagues work in the same location, face-to-face interaction becomes more frequent and effective, facilitating knowledge sharing, building trust, and nurturing collaborative relationships (Argyle and Dean, 1965; Kabo et al., 2014). If an office possesses high ethnic diversity, analysts are more likely to tap into a wide range of cultural and linguistic insights. These collective skills and perspectives then feed into individual forecasts, ultimately improving forecast outcomes. In other words, analysts based in an office with higher ethnic diversity are likely to enjoy an informational advantage over those in less diverse offices, resulting in more accurate, timely, and frequent forecasts.

Based on this reasoning, we formally state our first hypothesis:

H1: Analysts working in brokerage offices with higher levels of ethnic diversity produce more accurate earnings forecasts.

H2: Analysts working in brokerage offices with higher levels of ethnic diversity produce more timely earnings forecasts.

H3: Analysts working in brokerage offices with higher levels of ethnic diversity produce more frequent earnings forecasts.

However, the diversity of brokerage offices may exhibit no effect, or even negative effect on analysts' forecast performance. When interacting with colleagues from diverse ethnic backgrounds, analysts gain access to a broader range of information. However, information overload or noise may impair analysts' interpretation accuracy, leading to poorer forecasting performance (Cronin and Weingart, 2007). Further, the different ethnic background may bring distrust and conflicts in the workplace, which deters further communication and collaboration (Mannix and Neale, 2005; Koopmans and Veit, 2014).

3. Empirical Design

3.1 Measuring ethnic diversity

We begin by obtaining analysts' surnames and first initials from the I/B/E/S Recommendation Detail History file for the period 1993-2017. We eliminate observations where the analyst's name ('ANALYST' in I/B/E/S) is missing or if the name provided refers to an industry, a research department or an analyst team. This process provides an initial list of 16,993 unique analysts' surnames. We then manually collect the full first names of analysts by searching Zoominfo.com, LinkedIn.com, Factiva, and other websites. To increase the reliability of the classification of analysts' ethnicity, we attempt to identify analysts' full forenames wherever possible. To ensure satisfactory accuracy of collecting analyst' full names, we require an exact match among analysts' full names, the brokerage house where the analysts are employed, and the corresponding time periods during which the analysts worked at the brokerage house.[4] Using this process, the full names of 11,592 analysts, and the surnames and first initials of 5,401 analysts are identified.

To measure ethnic diversity within a brokerage office at a given time, we construct an ethnolinguistic fractionalization (*ELF*) index based on each employed analysts' ethnic group classification identified by the Onolytics software. This method has been extensively used by prior studies (Hambrick et al., 1996; Easterly and Levine, 1997; Alesina et al., 1999; Alesina et al., 2003; Ottaviano and Peri, 2005, 2006).[5] The Onolytics software analyzes both forenames and surnames and returns with a probability score that the names belong to particular ethnic groups. For analysts for whom full forename information is unavailable, we use the software to assign ethnicity based on surnames only. In the case of divergent name classification where the forename and surname indicate different ethnicity, the software assigns the ethnic group based on the highest probability score. We identify different ethnic groupings under Onolytics program at multiple hierarchical levels from a macro level of 16 groups to a more granular level

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[4] Similar to Bradley et al. (2020) and Cohen et al. (2010), analysts' name changes due to marriage or divorce, are possibly not accounted for in our classification. However, there is no obvious reason to believe that this would systematically bias our results.

[5] The Onolytics/OnoMap software was developed in 2009 by researchers at the Department of Geography at University College London, and covers over 500,000 forenames and 1,000,000 surnames drawn from public name registries of 28 countries.

of 189 types. The program is unable to identify the likely ethnic origin for about 15.64% (i.e. either unclassified or are not found in Onolytics dictionaries) of the unique analyst names obtained from I/B/E/S. The remaining analysts are matched to 14 ethnic groups (based on the macro level of grouping) as depicted in Figure 2: African (0.21%), Celtic (17.06%), East Asian & Pacific (2.84%), English (42.48%), European (10.08%), Greek (0.33%), Hispanic (1.51%), International (0.25%), Japanese (0.11%), Jewish and Armenian (3.63%), Muslim (1.64%), Nordic (0.93%), Sikh (0.46%), South Asian (2.82%).[6]

We then construct the office-level ethnic diversity index *ELF_bci* to represent the brokerage office-level ethnic diversity.[7] We manually collect information on analysts' office locations (the city data) from the Nelson's Directory of Investment Research for the periods 2000-2007.[8]

We calculate our independent variable *ELF_bci* as below:

$$ELF\_bci = 1 - \sum_i (S_i)^2$$

Where S_i denotes the share of each ethnic group *i* in a brokerage house. Specifically, S_i is calculated as $coverage_{ijtk}/coverage_{jtk}$, where $coverage_{ijtk}$ is the number of analysts representing ethnic group *i* working at brokerage firm *k* in city *j* in year *t*, and $coverage_{jtk}$ is the number of analysts working at brokerage firm *k* in city *j* in year *t*. The *ELF_bci* measure has a theoretical maximum value of one when every individual in a brokerage house belongs to different ethnic groups and a minimum of zero when all individuals fall into the same group. A higher *ELF_bci* index indicates a greater level of ethnic diversity.

3.2 Measuring analysts' forecast performance

[6] In the main test, we assign analysts with missing ethnic group as one distinct ethnic group. In our sample, we have a total of 15 ethnic groups.

[7] We also extend our research to country-level diversity score by constructing ELF index of country-level. Our results are robust and significant in untabulated table.

[8] The Nelson Publishing Inc. stopped producing its Directory of Investment Research after 2008.

Following prior literature, we measure analysts' performance through three different dimensions: accuracy, timeliness and frequency.

First, we use analysts' proportional mean absolute forecast errors (*PMAFE*) to measure their forecast performance (Clement, 1999; Call et al., 2009; Green et al., 2014; Bradley et al., 2017). Following prior literature (Clement, 1999; Bradley et al., 2017), we identify all annual earnings forecasts issued by an analyst during the first 11 months of the fiscal year to capture the forecasts of active analysts, and then keep the forecasts with a minimum forecast horizon of 30 days prior to the earnings announcement date, and calculate each analysts' proportional mean forecast error as below:

$$PMAFE_{ijt} = (AFE_{ijt} - MAFE_{jt}) / MAFE_{jt}$$

where AFE_{ijt} is the absolute value of analyst *i*'s forecast for firm *j* minus firm *j*'s actual EPS in year *t*. $MAFE_{jt}$ is mean absolute forecast error of all analysts following firm *j* in year *t*. This measure expresses an analyst's absolute forecast errors relative to those of all analysts covering a firm in a given year and thus controls for differences across covered firms, time, and industries (Clement, 1999; Call et al., 2009; Bradley et al., 2017). This relative measure also allows comparison with a vast body of prior work examining analysts' forecast errors. A higher level of $PMAFE$ means more forecast errors. Therefore, we prefer analysts with lower level of $PMAFE$.

Second, we follow Cooper, Day and Lewis (2001) and construct the Leader-Follower Ratio (*LFR*), which captures lead analysts' superior skill in collecting and processing information and releasing their earnings forecasts before competing analysts. It is calculated as the cumulative number of days by which analyst *i*'s forecast of firm *j* lags the prior two other analysts' forecasts divided by the cumulative number of days by which the same forecast leads the next two forecasts made by other analysts. We use *LFR* to represent analysts' forecast timeliness.

Third, we measure forecast frequency (*FREQ*) as the number of forecasts an analyst issues for a covered firm during a given year.

3.3 Empirical Model

To test our hypothesis that analysts who work in offices with higher level of ethnic diversity provide capital market participants with better earnings forecasts, we follow the approach in Clement (1999) and Call et al. (2009) and estimate Equation (1) using OLS regressions with standard errors adjusted for clustering at the analyst and firm levels.

$$Forecast\ Performance_{ijt} = \alpha + \beta_1 ELF\_bci + Controls + \varepsilon \qquad \text{Equation (1)}$$

The dependent variable *Forecast Performance* refers to accuracy, timeliness and frequency as defined above. The control variables are drawn from Clement (1999) and Call et al. (2009). We control for analysts' and brokerage characteristics, including analyst general experience (*GEXP*), analyst firm-specific experience (*FEXP*), the brokerage firm size (*BSIZE*), the number of firms the analyst follows (*NOFIRM*) and the number of industries the analyst follows (*NOIND*). We also control for forecast characteristics including the age of the forecast (*AGE*). Following prior studies, all of control variables are mean adjusted.

3.4 Data and Sample

We collect analyst data from I/B/E/S, public firms' financial data from Compustat, and stock return data from CRSP. For our main regression tests, the sample period spans from 2000 to 2007.[9] That is because our city specific measures of ethnic diversity require information regarding analysts' office location, which is only available on the Nelson's Directory of Investment Research from 2000 to 2007.[10]

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[9] Our sample begins in 2000 because we rely on Nelson's Directory of Investment Research for analysts' locations, and this is the earliest period for which we can access to the Nelson's Directory of Investment Research. Although Nelson provides location information through 2008, our sample ends in 2007 because the financial crisis may confound our results due to significant changes in analyst team composition (e.g., increased turnover) and performance. Our findings remain robust when extending the sample to 2017, provided we assume analysts do not change their locations after 2007 and we supplement any missing data with information from LinkedIn.

[10] While the location data is also available on the individual analysts' LinkedIn websites, the availability depends on analysts' self-disclosure, as a result, is significantly lower than what is available on the Nelson's Directory. We however perform robustness check on the extended sample using LinkedIn data.

We assume analysts do not change their locations afterwards and fill up missing locations with those collected from LinkedIn or use LinkedIn location only, in all cases, our results are qualitatively the same.

4. Results

4.1 Main test

Table 1 shows the distribution of overall sample by year. We recognize 9,228 unique analysts from 618 unique brokers, making forecasts for 7,873 firms between 2000 and 2007. Table 2 reports the descriptive statistics. The mean of *ELF_bci* is 0.582, with a standard deviation of 0.217. The minimum of *ELF_bci* is 0, indicating that analysts working in that office have the same ethnic background. The maximum of *ELF_bci* is 0.864. All the other control variables are generally consistent with those reported in the prior literature (Clement 1999; Bradley et al. 2017).

Table 3 reports the results of Equation (1). In column (1), we find a negative and significant ($p < 0.01$) coefficient on *ELF_bci*, suggesting that analysts issue more accurate earnings forecasts when working in offices with higher level of ethnic diversity. In columns (2) and (3), we find positive and significant ($p < 0.01$) coefficients on *ELF_bci*, suggesting that office-level ethnic diversity improves analysts' forecast timeliness and frequency.

In sum, the results support our hypotheses and illustrate that higher level of brokerage office-level ethnic diversity enhances analysts' forecasts performance in terms of accuracy, timeliness and frequency.

4.2 Channel tests

To explore the underlying mechanism through which office level ethnic diversity affect analysts' earnings forecast performance, we conduct two tests. If the previously documented main results are mainly due to analysts gaining information advantages from working with colleagues who have different ethnic backgrounds, we predict that the positive impacts of ethnic diversity should be more pronounced when analysts' colleagues' ethnic backgrounds align with the attributes of forecasting tasks.[11]

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[11] In our main test, we use the software Onolytics to classify analysts' ethnic background based on analysts' surnames. As an ethnic original can correspond to multiple region across the world, to test our prediction, we use a narrower but more precise way to determine ethnic origin by focusing on analysts' country of origin, and a narrower attribute of forecasting tasks—geographic location of covered firms' subsidiaries, and of their major import and export countries, to allow mapping of analysts' country of origin to attributes of the covered firm.

4.2.1 Location of subsidiaries

We begin our analysis by focusing on the subsidiaries of analysts' covered firms. We posit a stronger relation between brokerage firm diversity and analysts' performance in cases when the analyst has a different ethnic background from that of the firm's subsidiaries (i.e. unrelated analysts), but there is a higher proportion of analysts' colleagues employed from the same brokerage office share the same ethnic background of the subsidiaries (i.e. related colleagues), compared to cases when both the covered analysts and their colleagues have an unrelated ethnic background.

We obtain a firm's subsidiary data from seek Edgar and identify the country in which the subsidiary locates. We then identify the analyst's country of origin by searching the analyst's surname at Ancestry.com (http://www.ancestry.com/learn/facts/) from immigration passenger lists for years 1820–1957.[12] We require the analyst's country of origin to be different to the country of a firm's non-us subsidiary so that the analysts are less likely to have in-depth knowledge of the ethnic background of the firm's subsidiaries and are more likely to solicit help from their colleagues who have the related e background. We then construct two sub-samples based on the median of the proportion of colleagues whose country of origin align with the country in which analyst's covered firm's non-us subsidiary locates (related colleagues).

Table 4 reports the results. In Panel A, in column (1), the coefficient on *ELF_bci* is negative and significant ($p < 0.01$) in the related colleagues sub-sample defined based on the location of a firm's subsidiary but insignificant in the unrelated colleagues sub-sample. In columns (3) and (4), the coefficients are both positive and significant ($p < 0.01$), however, the coefficient in column (3) is far larger than that reported in in column (4), suggesting a more significant improvement in analysts' forecast timeliness. In column (5), the coefficient is positive and significant ($p < 0.05$), while insignificant in column (6), suggesting that analysts tend to issue forecasts more frequently if their colleagues have the same ethnic background as the followed firms' subsidiaries. F-test shows that the coefficients are significantly different between these two sub-samples. The results indicate that when analysts working with

[12] We collect the country data of the firm's subsidiary. In this test, we classify ethnic relatedness based on whether an individual's country of origin (ancestor) is the same as the country in which the firm's non-us subsidiary locates.

colleagues whose ethnic backgrounds align with the covered firms' subsidiaries issue more accurate earnings forecasts and their forecasts are more timely and frequently.

4.2.2 Industry import and export countries

We then examine the alignment between analysts' colleagues' ethnic background and the major trading countries of the analysts' covered firms. We obtain the import and export data for the manufacturing industry from the Schott's data library.[13] In this dataset, countries that trade with US for each four-digit 1987-version SIC manufacturing industries in a given year are identified. We restrict our sample to manufacturing industries only (sic codes between 2000 and 3999). We then calculate the proportion of colleagues from the analyst's working office who have the same country of origin as the country that trades with the industry to which the analyst's covered firm belongs (related colleagues), and construct two sub-samples based on the proportion. The first sub-sample includes cases where the proportion of related colleagues is higher than the proportions' median in the current year. Otherwise, the observation is classified in the second sub-sample.

Table 4 reports the results in panel B. The coefficients on *ELF_bci* are more significant in sub-samples of related colleagues. Overall, the channel test results suggest that analysts produce higher quality earnings forecasts when their colleagues share an ethnic background related with the firms that analysts cover.

4.3 Cross-sectional tests

We further explore whether the relation between brokerage office-level ethnic diversity and analysts' forecast performance varies with analyst-specific characteristics (Clement, 1999; Bradley et al., 2017; Li et al., 2020). In the cross-sectional test, we examine the role of analysts' experience, tenure, and all-star status. If diversity provides valuable information to analysts, we expect such information is more valuable to those who are in need of help. This includes those who are early in their career and who are less proficient in executing their forecasting tasks.

4.3.1 Experience

[13] The data is available for the periods from 2000 to 2005 and can be downloaded at https://faculty.som.yale.edu/peterschott/international-trade-data/

We separate the samples into two sub-samples based on analysts' experience. Table 5 reports the results separately for analysts who are with less than 12 years (the sample median) of general experience (i.e., junior analysts) and more than 12 years of experience (i.e., senior) in panel A. We show that the effect of *ELF_bci* on analysts' forecast performance is most pronounced for junior analysts in columns (1), (3) and (5).

4.3.2 Tenure

In Table 5 panel B, we find that in sub-sample where analysts' tenure at a brokerage firm is less than or equal to 4 years (the sample median), ELF_bci has a negative and significant ($p < 0.01$) coefficient. In column (5), we find a positive and significant ($p < 0.01$) coefficient on *ELF_bci*, suggesting that analysts with fewer tenure issue forecasts more frequently. These effects are significantly different across the two sub-samples. With regard to forecast timeliness, we do not find any differences in the coefficients on *ELF_bci* across the two sub-samples.

Overall, these results suggest that fresh employees are more affected by an ethnic diverse working environment, which is intuitive because these analysts have to adapt to the new working environment and will benefit more from communication and the exchange of information and perspectives among colleagues.

4.3.3 All-star

Finally, we construct two sub-samples where the all-star sample includes analysts being ranked as an all-star14, and the non-star sample consists of the remaining analysts. In columns (1) and (2) of Table 5 panel C, when considering analysts' forecast error, we find that coefficient on *ELF_bci* is negative and significant ($p < 0.01$) in non-star sample and insignificant in all-star sample. Next, we examine the relation between ethnic diversity and forecast timeliness and frequency. The coefficients on *ELF_bci* are positive and significant ($p < 0.01$) in non-stall sample in columns (3) and (5), while insignificant for all-star sample in columns (4) and (6). The results indicate that the effect of brokerage ethnic diversity on analysts' forecast performance is stronger for average analysts whose abilities to analyze information and obtain additional information are limited.

[14] An analyst is an all-star if she is named to *Institutional Investor*'s all-star team in current year.

4.4 Robustness tests

4.4.1 Alternative Independent Variables

In order to deal with the measurement errors, we use a different dictionary and a more granular way to determine an analyst's ethnic group in the robustness test. Each analyst's surname is assigned to a specific country of origin based on the origins data collected by Ancestry.com (http://www.ancestry.com/learn/facts/) from immigration passenger lists from 1820-1957. We re-construct brokerage office-level ethnic diversity scores ELF_bci_{ance} based on ethnic groups classified under this approach, and re-estimate Equation (1). The results reported in Table 6 panel A corroborate our main findings.

4.4.2 Fixed Effects

In the main regression model, the dependent and control variables are mean adjusted to control for firm and year fixed effects following the prior literature (Clement, 1999; Call et al., 2009). For robustness check, we include location fixed effects and year fixed effects respectively in the main model and re-estimate Equation (1). Our results remain robust while controlling for these fixed effects as shown in Table 6 panel B.

4.5 Endogeneity

We have attempted to address endogeneity by including a number of control variables, using mean-adjusted measures that controls for firm and year fixed effects, and controlling for location or year fixed effects. To strengthen our inferences that brokerage office-level ethnic diversity leads to an improvement on analysts' forecast performance, we employ a quasi-natural experiment based on brokerage firm merger events (Hong and Kacperczyk, 2010; Kelly and Ljungqvist, 2012; Chen et al., 2015). Brokerage firm mergers will lead to an exogenous change in the number of analysts and thereby the number of ethnic groups, resulting in an increase or decrease in ELF scores. Following prior studies, we first obtain a sub-sample of brokerage firms that acquire another brokerage firm during our sample period. We identify a total of 29 brokerage firm merger events. Within this sub-sample, we create a binary variable, *ELF_bci_endogeneity*, which equals one (zero) if the increase in the brokerage office-level ethnic diversity score (*ELF_bci*) is higher (lower) than the average increase rate in the current year as a result of a brokerage firm merger event. Then we re-estimate Equation (1) using *ELF_bci_endogeneity* as an independent variable.

Table 7 reports the results. Consistent with our main regression, we find that the coefficient on *ELF_bci_endogeneity*is negative and significant ($p < 0.05$) for forecast error model in column (1) and the coefficients on *ELF_bci_endogeneity* is positive and significant ($p < 0.01, p < 0.05$) for timeliness and frequency models in columns (2) and (3). This result suggests that an exogenous increase in brokerage firm ethnic diversity results in more accurate, timely and frequent forecasts.

5. Additional tests

5.1 Economic impacts

We also explore how market reacts to earnings forecast revisions issued by analysts who work in brokerage offices with various levels of ethnic diversity. If the capital market values the importance of brokerage ethnic diversity, we expect that market reacts strongly towards the revisions of analysts employed by a more ethnically diverse broker. We estimate the following regression model—Equation (2) to examine the market reactions.

$$CAR_{ijt} = \alpha + \beta_1 ELF\_bci + \beta_2 ABSFR + Controls + Fixed\ Effects + \varepsilon \qquad \text{Equation (2)}$$

Where *CAR* is the cumulative abnormal return in the two-day (0,1) window around the forecast revision made on day *t* by analyst *i* for firm *j*. Abnormal return is calculated as the firm's return less the CRSP value-weighted market return.[15] *ABSFR* is the absolute value of the difference an analyst's revised forecast at time *t* and the previous forecast at time *t-1* scaled by the absolute value of the forecast at time *t-1*. We also control for analyst and firm characteristics and year fixed effects. In the *CAR* test, we consider the direction and the magnitude of forecast revisions. Following prior studies (Gleason and Lee, 2003; Ivkovic and Jegadeesh, 2004; Green et al., 2014; Bradley et al., 2017), we estimate Equation (2) separately for positive (upward revisions) and negative (downward revisions) news.

Table 8 reports the results. In column (1), we find that the coefficient on *ELF_bci* is positive and significant ($p < 0.1$), illustrating that upward forecast revisions issued by analysts employed by a more ethnic diverse office are significantly more informative than those issued by other analysts, which means that the capital market values ethnic diversity within brokerage offices. Similar results are obtained for downward revisions. Altogether, the evidence suggests that capital market participants place greater emphasize on earnings forecast revisions issued by analyst working in brokerage offices with higher level of ethnic diversity.

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[15] In obtaining CAR, we move day 0 to the next 1 or 2 trading days if the revision is issued on non-trading days to capture the missing values on weekend.

6. Conclusion

Ethnicity is closely related to individual's language, culture norms and preferences and thinking patterns, thus affecting how analysts form their predictions (Schilpzand and Martins, 2010). We examine the relation between brokerage office-level ethnic diversity and analysts' forecast performance. Our results illustrate that analysts issue earnings forecasts more accurately, timely and frequently when working in offices with higher level of ethnic diversity. Our results remain robust with several tests including an exogenous shock to ethnic diversity resulting from brokerage firm merger events.

We further identity two possible channels by which ethnic diversity improves analysts' performance. A stronger improvement is observed in offices which have higher proportion of related colleagues—colleagues whose ethnic background aligns with either the origin of firms' subsidiaries or major trading countries, suggesting that the improvements are mainly driven by communication and collaboration between analysts and their colleagues.

We also find that the positive relation is more pronounced for non-star analysts with less experience and shorter tenure, as these analysts benefit more from the additional resources and insights provided by a diverse office environment in making predictions.

While not the primary focus of our study, ethnic diversity can potentially offer other benefits. For additional tests, we explore the economic results and illustrate that the capital market values the level of ethnic diversity in brokerage firm as they react more actively to forecast revisions issued by analysts working in brokers with higher level of ethnic diversity.

In conclusion, this study provides valuable insights into how office level ethnic diversity enhances the quality of analysts' earnings forecasts. The results contribute to literature in several ways. The findings that brokerage office-level ethnic diversity enhances analysts' working performance contributes not only to analysts literature on determinants on analysts forecast performance, but also to the broad literature studying diversity. The granular data on brokerage office level also enable us to explore the underlying mechanisms. The results place great emphasize on the alignment between ethnic background and covered firms' subsidiaries and major trading partners. In practice, the findings of this study are intended to offer actionable insights for brokers regarding hiring practices. Employing analysts from diverse ethnic backgrounds can enhance forecasting performance, thereby enabling brokers to leverage the benefits of ethnic diversity.

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Figure 1.

This figure reports the diversity score during our sample period, 2000 to 2007. The pink lines indicate office-level ethnic diversity score in different offices in US under the same broker. The blue line illustrates the broker-level diversity score. We take Prudential Equity Group, LLC, Morgan Stanley and JPMorgan as examples.

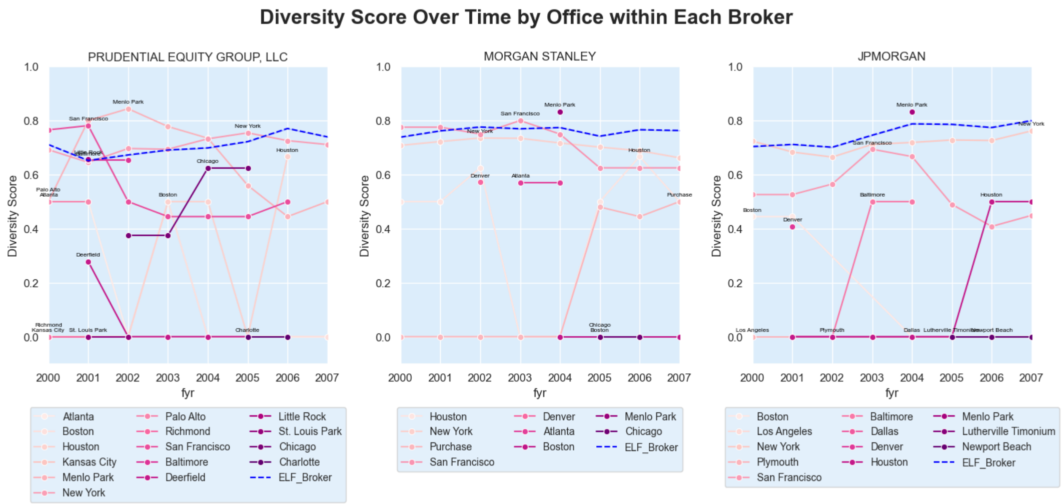


Figure 2.
This figure reports the distribution of analysts' ethnic groups. We identify different ethnic groupings under Onolytics program at multiple hierarchical levels from a macro level of 16 groups to a more granular level of 189 types. The program is unable to identify the likely ethnic origin for about 15.64% (i.e. either unclassified or are not found in Onolytics dictionaries) of the unique analyst names obtained from I/B/E/S. The remaining analysts are matched to 14 ethnic groups (based on the macro level of grouping).

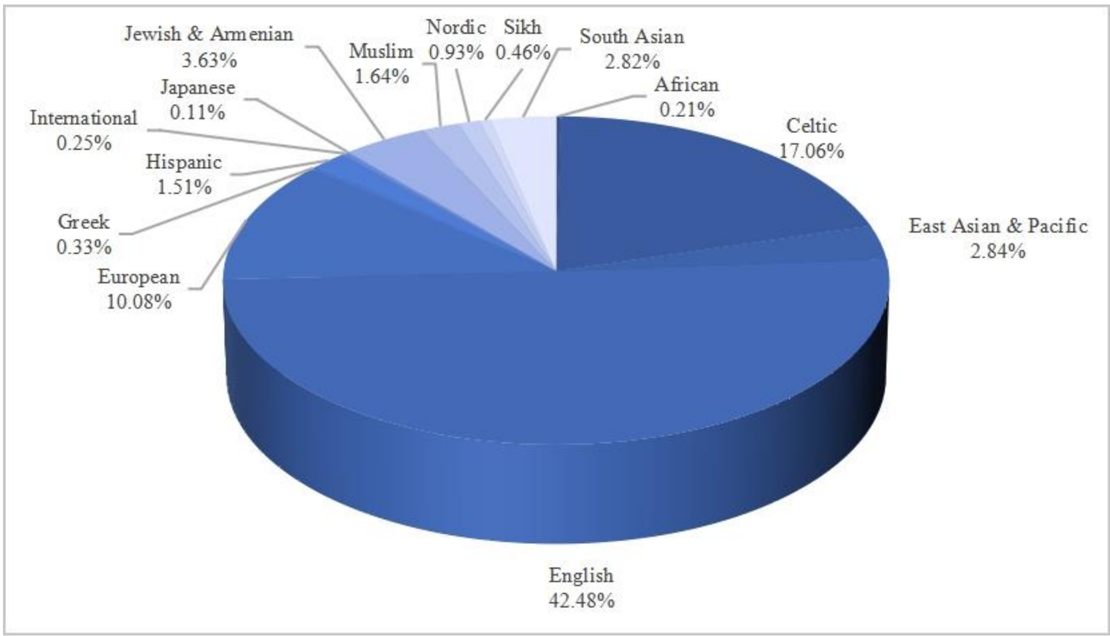


Table 1.

The distribution of sample by year

The tables illustrates the yearly distribution of our sample from 2000 to 2007. In total, we recognize 9,228 unique analysts from 618 different broker firms. Our sample contains forecasts to 7,873 different firms between 2000 and 2007.

Year	N	Firm	Analysts	Broker
2000	33,180	5,021	4,683	316
2001	31,168	4,323	4,775	300
2002	31,824	4,180	4,844	270
2003	30,835	4,136	4,720	355
2004	33,671	4,452	4,411	395
2005	35,646	4,460	4,433	398
2006	37,015	4,761	4,469	367
2007	38,072	4,789	4,561	344
Total	271,411			

Table 2.

Descriptive Statistics

This table reports summary statistics for the main variables used in the analyses. *PMAFE* is analysts' proportional mean absolute forecast errors. *LFR* is the Leader-Follower Ratio and is calculated as the cumulative number of days by which analyst's forecast of specific firm lags the prior two other analysts' forecasts divided by the cumulative number of days by which the same forecast leads the next two forecasts made by other analysts. *FREQ* is the number of forecasts an analyst issues for a covered firm during a given year. *ELF_bci* is the index to measure brokerage office-level ethnic diversity. The control variables include analysts characteristics, broker characteristics and forecast characteristics and are all mean adjusted. *GEXP* is analysts' general experience. *FEXP* is analyst firm-specific experience. *BSIZE* is the brokerage firm size. *NOFIRM* is the number of firms the analyst follows. *NOIND* is the number of industries the analyst follows. *AGE* is the age of the forecast.

Variable	N	MEAN	SD	MIN	P25	P50	P75	MAX
PMAFE	271,411	-0.052	0.884	-1	-0.633	-0.227	0.184	3.853
LFR	242,992	10.551	61.997	-134	-18.000	1.455	27.612	219.25
FREQ	271,936	0.187	3.745	-8.079	-2.444	0.000	2.714	9.706
ELF_bci	271,411	0.582	0.217	0	0.500	0.658	0.724	0.864
GEXP	271,411	0.186	6.441	-18.545	-5.000	0.000	5.476	20.462
FEXP	271,411	0.041	3.380	-13.333	-1.667	-0.273	0.930	21.533
BSIZE	271,411	1.368	64.938	-244.667	-43.222	-8.706	33.828	321.5
NOFIRM	271,411	0.191	7.412	-48	-4.143	-0.333	3.541	87.436
NOIND	271,411	0.012	1.835	-10.5	-1.000	-0.200	0.684	20.077
AGE	271,411	-2.730	64.056	-221	-41.536	-14.857	12.875	299.44

Table 3.

Brokerage office-level ethnic diversity and analysts' forecast performance

This table reports the OLS regression results of the effect of brokerage office-level ethnic diversity on analysts' forecast performance. The dependent variable in column (1) to (3) is analysts' proportional mean absolute forecast errors, Leader-Follower Ratio (Timeliness) and the number of forecasts an analyst issues for a covered firm during a given year (Frequency), respectively. The key independent variable is *ELF_bci*, a city-level diversity index to evaluate brokerage office-level ethnic diversity. P-values are reported in parentheses and standard errors are double-clustered by analyst and firm. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
	Error	**Timeliness**	**Frequency**
	PMAFE	**LFR**	**FREQ**
ELF_bci	-0.0416***	9.7231***	0.5050***
	(0.000)	(0.000)	(0.000)
GEXP	-0.0006	-0.0273	0.0079**
	(0.197)	(0.557)	(0.027)
FEXP	-0.0006	0.1952***	0.1179***
	(0.362)	(0.005)	(0.000)
BSIZE	-0.0001***	0.0543***	0.0050***
	(0.006)	(0.000)	(0.000)
NOFIRM	-0.0033***	-0.0713	0.0437***
	(0.000)	(0.427)	(0.000)
NOIND	0.0077***	-0.9267***	-0.1003***
	(0.000)	(0.000)	(0.000)
AGE	0.0060***	-0.0322***	-0.0238***
	(0.000)	(0.000)	(0.000)
CON	-0.0111	4.6559***	-0.1923***
	(0.117)	(0.000)	(0.003)
Observations	271,411	242,992	271,936
Adjusted R-squared	0.19	0.008	0.204
F	941.4***	56.29***	1573***

Table 4.

Brokerage office-level ethnic diversity, analysts' forecast performance, and colleagues' background alignment

This table reports the OLS regression results of the channel test. In panel A and panel B, we consider two alignment scenarios: (1) when a greater proportion of colleagues share a country of origin with the covered firms' subsidiary locations or (2) when a greater proportion of colleagues share a country of origin with the covered firms' primary import/export countries We separate all of our samples into two sub-samples: Match and Mismatch based on the alignment between colleagues' backgrounds and the origins of the subsidiaries and the major trading partners, and conduct OLS regression respectively. P-values are reported in parentheses and standard errors are double-clustered by analyst and firm. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: Alignment between analysts' colleagues share ethnic backgrounds and the origins of the covered firms' subsidiaries

	(1)	(2)	(3)	(4)	(5)	(6)
	Error		Timeliness		Frequency	
	High	Low	High	Low	High	Low
ELF_bci	-0.1022**	-0.0029	24.2532***	6.6215***	0.4973**	0.1132
	(0.031)	(0.870)	(0.000)	(0.003)	(0.046)	(0.445)
GEXP	0.0007	0.0006	-0.1792**	0.0090	-0.0106*	0.0073
	(0.419)	(0.414)	(0.048)	(0.895)	(0.074)	(0.167)
FEXP	-0.0017	-0.0013	0.2923**	0.0541	0.1184***	0.1038***
	(0.198)	(0.268)	(0.011)	(0.610)	(0.000)	(0.000)
BSIZE	-0.0000	-0.0002***	0.0525***	0.0561***	0.0044***	0.0053***
	(0.651)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NOFIRM	-0.0039***	-0.0028***	-0.1439	-0.2137**	0.0468***	0.0330***
	(0.002)	(0.002)	(0.294)	(0.012)	(0.000)	(0.000)
NOIND	0.0132***	0.0106***	-1.4623***	-0.0726	-0.1368***	-0.0929***
	(0.000)	(0.000)	(0.001)	(0.857)	(0.000)	(0.000)
AGE	0.0063***	0.0061***	-0.0217***	-0.0357***	-0.0258***	-0.0241***
	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)
CON	0.0143	-0.0365***	-1.9706	5.6462***	-0.0790	0.1102
	(0.641)	(0.001)	(0.467)	(0.000)	(0.634)	(0.225)
Chi-test	7.53***		43.94***		7.03***	
F-test	Prob > chi2 = 0.0061		Prob > chi2 = 0.0000		Prob > chi2 = 0.0080	
Observations	46,024	69,308	43,392	62,944	46,065	69,401
Adjusted R-squared	0.194	0.198	0.012	0.007	0.202	0.199
F	274.8***	369.4***	22.41***	19.65***	646.3***	605.2***

Table 4. -Continued.

Panel B: Alignment between analysts' colleagues share ethnic backgrounds and the primary import and export countries of the covered firms

	(1)	(2)	(3)	(4)	(5)	(6)
	Error		Timeliness		Frequency	
	High	Low	High	Low	High	Low
ELF_bci	-0.1538**	-0.0255	23.0564***	3.2419	1.0285**	0.0943
	(0.013)	(0.457)	(0.004)	(0.522)	(0.016)	(0.730)
GEXP	0.0002	-0.001	-0.0542	-0.3509*	-0.003	0.0075
	(0.905)	(0.536)	(0.752)	(0.066)	(0.769)	(0.571)
FEXP	-0.0005	0.0002	0.5001**	-0.0606	0.1098***	0.1140***
	(0.801)	(0.946)	(0.045)	(0.823)	(0.000)	(0.000)
BSIZE	-0.0006***	-0.0002	0.0771***	0.0373***	0.0063***	0.0039***
	(0.000)	(0.188)	(0.000)	(0.006)	(0.000)	(0.000)
NOFIRM	-0.0017	-0.0071***	0.0595	0.2855	0.0552***	0.0855***
	(0.341)	(0.001)	(0.848)	(0.287)	(0.002)	(0.000)
NOIND	-0.0015	0.0165*	-1.7582*	-1.5221*	-0.0950**	-0.2053***
	(0.804)	(0.056)	(0.074)	(0.097)	(0.017)	(0.000)
AGE	0.0065***	0.0070***	0.0064	-0.0345**	-0.0244***	-0.0246***
	(0.000)	(0.000)	(0.654)	(0.027)	(0.000)	(0.000)
CON	0.0372	-0.031	0.847	11.7647***	-0.3904	0.0184
	(0.346)	(0.105)	(0.868)	(0.000)	(0.167)	(0.905)
chi-test	4.95**		15.16***		14.56***	
F-test	Prob > chi2 = 0.0261		Prob > chi2 =0.0001		Prob > chi2 = 0.0001	
Observations	18,640	11,482	16,662	10,278	18,678	11,504
Adjusted R-squared	0.215	0.251	0.011	0.006	0.196	0.208
F	123.4***	126.6***	8.02***	2.847**	304.2***	184.8***

Table 5.

Brokerage office-level ethnic diversity, analysts' forecast performance, and analysts' characteristics

This table reports the OLS regression results of how analyst characteristics impact the effect of brokerage office-level ethnic diversity on forecast performance. We consider analysts' general experience, tenure and whether analyst has all-star status. In panel A, we separate all of our sample into junior analysts and senior analysts based on analysts' general experience. We classify an analyst as junior analyst if the general experience is more than 12 years (the sample median), otherwise, the analyst is classified as senior analyst. In panel B, we separate all of our sample into junior analysts and senior analysts based on analysts' tenure. We classify an analyst as junior analyst if the general experience is more than 4 years (the sample median), otherwise, the analyst is classified as senior analyst. In panel C, we separate all of our sample into all-star sample in which the analysts are ranked as an all-star, and the non-star sample consists of the remaining analysts. P-values are reported in parentheses and standard errors are double-clustered by analyst and firm. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: Analysts' general experience and forecast performance

	(1)	(2)	(3)	(4)	(5)	(6)
	Error		Timeliness		Frequency	
	Junior	Senior	Junior	Senior	Junior	Senior
ELF_bci	-0.0727***	0.0035	12.0026***	6.5132**	0.7220***	0.2479
	(0.000)	(0.845)	(0.000)	(0.011)	(0.000)	(0.140)
GEXP	0.0012	-0.0023**	0.7751***	-1.6356***	0.0054	-0.0009
	(0.147)	(0.013)	(0.000)	(0.000)	(0.402)	(0.916)
EXP	0.0002	-0.001	-1.0030***	0.4287***	0.2651***	0.0770***
	(0.866)	(0.193)	(0.000)	(0.000)	(0.000)	(0.000)
BSIZE	0.0000	-0.0003***	0.0530***	0.0549***	0.0051***	0.0049***
	(0.798)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NOFIRM	-0.0061***	-0.0016*	-0.2524***	-0.0229	0.0631***	0.0289***
	(0.000)	(0.064)	(0.001)	(0.860)	(0.000)	(0.000)
NOIND	0.0104***	0.0060**	-1.0005***	-0.7403*	-0.1068***	-0.1045***
	(0.000)	(0.022)	(0.000)	(0.065)	(0.000)	(0.000)
AGE	0.0059***	0.0060***	-0.0362***	-0.0279***	-0.0228***	-0.0253***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CONS	0.0122	-0.0282**	4.6994***	17.2693***	-0.1337*	0.0232
	(0.198)	(0.019)	(0.000)	(0.000)	(0.079)	(0.840)
chi-test	26.69***		20.96***		59.36***	
F-test	Prob > chi2 = 0.0000		Prob > chi2 = 0.0000		Prob > chi2 = 0.0000	
Observations	149,024	122,387	132,041	110,951	149,340	122,596
Adjusted R-squared	0.19	0.191	0.012	0.016	0.209	0.21
F	774.4***	506.1***	55.31***	45.26***	1388***	835.3***

Table 5. -Continued.

Panel B: Analysts' tenure and forecast performance

	(1)	(2)	(3)	(4)	(5)	(6)
	Error		Timeliness		Frequency	
	Junior	Senior	Junior	Senior	Junior	Senior
ELF_bci	-0.0714***	-0.002	9.2976***	10.0278***	0.7143***	0.1566
	(0.000)	(0.923)	(0.000)	(0.000)	(0.000)	(0.331)
GEXP	-0.0009*	-0.0008	0.1692***	-0.2390***	0.0035	-0.0175***
	(0.069)	(0.240)	(0.003)	(0.003)	(0.400)	(0.002)
EXP	0.0004	-0.0016*	0.1717	0.2606***	0.1557***	0.0889***
	(0.650)	(0.058)	(0.139)	(0.003)	(0.000)	(0.000)
BSIZE	-0.0001*	-0.0002***	0.0716***	0.0432***	0.0057***	0.0041***
	(0.054)	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)
NOFIRM	-0.0055***	-0.0022**	-0.1535*	-0.0129	0.0696***	0.0218***
	(0.000)	(0.018)	(0.090)	(0.923)	(0.000)	(0.003)
NOIND	0.0088***	0.0069**	-1.0194***	-0.8222**	-0.0989***	-0.1145***
	(0.000)	(0.015)	(0.003)	(0.017)	(0.000)	(0.000)
AGE	0.0060***	0.0059***	-0.0361***	-0.0277***	-0.0216***	-0.0264***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CONS	-0.0055	-0.0252**	5.6748***	4.4637***	-0.3965***	0.3252***
	(0.508)	(0.042)	(0.000)	(0.004)	(0.000)	(0.001)
chi-test	21.62***		0.37		81.89***	
F-test	Prob > chi2 = 0.0000		Prob > chi2 = 0.5439		Prob > chi2 = 0.0000	
Observations	142,547	128,864	125,886	117,106	142,845	129,091
Adjusted R-squared	0.193	0.188	0.011	0.007	0.184	0.229
F	742.9***	567***	48.63***	21.39***	1438***	950.2***

Table 5. -Continued.

Panel C: Analysts' all-star status and forecast performance

	(1)	(2)	(3)	(4)	(5)	(6)
	Error		Timeliness		Frequency	
	Non-star	All-star	Non-star	All-star	Non-star	All-star
ELF_bci	-0.0370***	0.0323	9.5483***	-0.7701	0.4665***	-0.4278
	(0.002)	(0.413)	(0.000)	(0.900)	(0.000)	(0.153)
GEXP	-0.0004	0.0011	0.0056	-0.6183***	0.0091**	-0.0408***
	(0.350)	(0.382)	(0.908)	(0.000)	(0.013)	(0.000)
EXP	0.0001	-0.0016	0.1566**	0.2107	0.1227***	0.0822***
	(0.933)	(0.191)	(0.044)	(0.116)	(0.000)	(0.000)
BSIZE	0.0000	-0.0003***	0.0479***	0.0329***	0.0046***	0.0016*
	(0.893)	(0.007)	(0.000)	(0.008)	(0.000)	(0.051)
NOFIRM	-0.0033***	0.0003	-0.1053	-0.0215	0.0436***	0.0217**
	(0.000)	(0.825)	(0.303)	(0.889)	(0.000)	(0.018)
NOIND	0.0076***	0.0065	-0.7791***	-1.9872***	-0.0984***	-0.0769**
	(0.000)	(0.156)	(0.003)	(0.004)	(0.000)	(0.038)
AGE	0.0061***	0.0044***	-0.0336***	-0.0034	-0.0234***	-0.0279***
	(0.000)	(0.000)	(0.000)	(0.736)	(0.000)	(0.000)
CONS	-0.0057	-0.1359***	4.0942***	19.4850***	-0.2298***	1.2951***
	(0.430)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
chi-test	6.77***		17.49***		44.49***	
F-test	Prob > chi2 = 0.0093		Prob > chi2 = 0.0000		Prob > chi2 = 0.0000	
Observations	239,114	32,297	212,201	30,791	239,616	32,320
Adjusted R-squared	0.199	0.091	0.007	0.008	0.199	0.166
F	957.6***	85.58***	43.52***	6.401***	1654***	215.9***

Table 6.

Robustness Tests

This table reports the results for robustness checks. In panel A, we change the independent variable to *ELF_bci2*. We use a different dictionary to determine an analyst's ethnic group and re-construct the city-level ethnic diversity index. We re-estimate Equation (1) using ELF_bci_{ance}. In panel B, we control for location fixed effect and year fixed effect. P-values are reported in parentheses and standard errors are double-clustered by analyst and firm. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: Robustness: alternative measures of ethnic group

	(1)	(2)	(3)
	Error	**Timeliness**	**Frequency**
	PMAFE	**LFR**	**FREQ**
ELF_bci_{ance}	-0.0269**	7.3940***	0.1820*
	(0.030)	(0.000)	(0.087)
GEXP	-0.0001	-0.0413	0.0045
	(0.833)	(0.410)	(0.243)
FEXP	-0.0008	0.1719**	0.1119***
	(0.240)	(0.016)	(0.000)
BSIZE	-0.0002***	0.0562***	0.0049***
	(0.001)	(0.000)	(0.000)
NOFIRM	-0.0030***	-0.1824**	0.0365***
	(0.000)	(0.017)	(0.000)
NOIND	0.0082***	-0.8326***	-0.1034***
	(0.000)	(0.001)	(0.000)
AGE	0.0059***	-0.0339***	-0.0244***
	(0.000)	(0.000)	(0.000)
CON	-0.0306***	7.0830***	0.1244**
	(0.000)	(0.000)	(0.023)
Observations	236,397	212,284	236,861
Adjusted R-squared	0.183	0.008	0.200
F	822.1***	46.19***	1455***

Table 6. -Continued.

Panel B: Robustness: different fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Error		Timeliness		Frequency	
ELF_bci	-0.0542***	-0.0411***	7.3415***	5.0183***	0.4309***	0.5039***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
GEXP	-0.0000	-0.0005	-0.0803	-0.0204	0.0006	0.0078**
	(0.978)	(0.201)	(0.108)	(0.592)	(0.869)	(0.027)
FEXP	-0.0011	-0.0006	0.1880***	0.1680***	0.1132***	0.1179***
	(0.101)	(0.364)	(0.008)	(0.002)	(0.000)	(0.000)
BSIZE	-0.0002***	-0.0001***	0.0476***	0.0545***	0.0052***	0.0050***
	(0.000)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)
NOFIRM	-0.0019***	-0.0033***	-0.2202***	-0.0188	0.0376***	0.0437***
	(0.004)	(0.000)	(0.005)	(0.749)	(0.000)	(0.000)
NOIND	0.0088***	0.0076***	-0.6900**	-0.7872***	-0.0958***	-0.1002***
	(0.000)	(0.000)	(0.012)	(0.000)	(0.000)	(0.000)
AGE	0.0057***	0.0060***	-0.0297***	-0.0319***	-0.0240***	-0.0238***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CON	-0.0166*	-0.0113	6.4397***	7.3895***	-0.0460	-0.1917***
	(0.071)	(0.110)	(0.000)	(0.000)	(0.566)	(0.003)
Location FE	Yes		Yes		Yes	
Year FE		Yes		Yes		Yes
Observations	238,932	271,411	214,888	242,992	239,401	271,936
Adjusted R-squared	0.175	0.190	0.018	0.144	0.203	0.204
F	797.7***	939.7***	28.32***	75.44***	1573***	1387***

Table 7.

Endogeneity

This table reports the results for endogeneity test. We use broker merger events as exogenous shocks, leading to changes in brokerage office-level ethnic diversity. We calculate the change rate of ethnic diversity for each broker in given year. Change rate is the value of the difference between *ELF_bci* at time t and at time t-1 scaled by the value of *ELF_bci* at time t. We then construct a dummy variable (*ELF_bci_endogeneity*) based on the change rate. The *ELF_bci_endogeneity* equals one (zero) if the change rate of brokerage office-level ethnic diversity score (*ELF_bci*) is higher (lower) than the average change rate in given year as a result of a brokerage firm merger event. P-values are reported in parentheses and standard errors are double-clustered by analyst and firm. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
	Error	**Timeliness**	**Frequency**
	PMAFE	**LFR**	**FREQ**
ELF_bci_endogeneirty	-0.0559**	14.7890***	0.2926**
	(0.036)	(0.000)	(0.041)
GEXP	0.0032	-0.2533	0.0118
	(0.164)	(0.173)	(0.352)
FEXP	0.0052	0.4002	0.1210***
	(0.202)	(0.132)	(0.000)
BSIZE	0.0003	0.0264**	0.0049***
	(0.178)	(0.041)	(0.000)
NOFIRM	-0.0042	-0.3658	0.0397**
	(0.117)	(0.324)	(0.044)
NOIND	-0.0110	0.1338	0.1139**
	(0.297)	(0.886)	(0.035)
AGE	0.0062***	-0.0270	-0.0298***
	(0.000)	(0.147)	(0.000)
CON	-0.0555***	2.8043	0.3358***
	(0.002)	(0.101)	(0.005)
Observations	7,807	7,049	7,818
Adjusted R-squared	0.162	0.020	0.214
F	67.55***	6.899***	193.1***

Table 8.

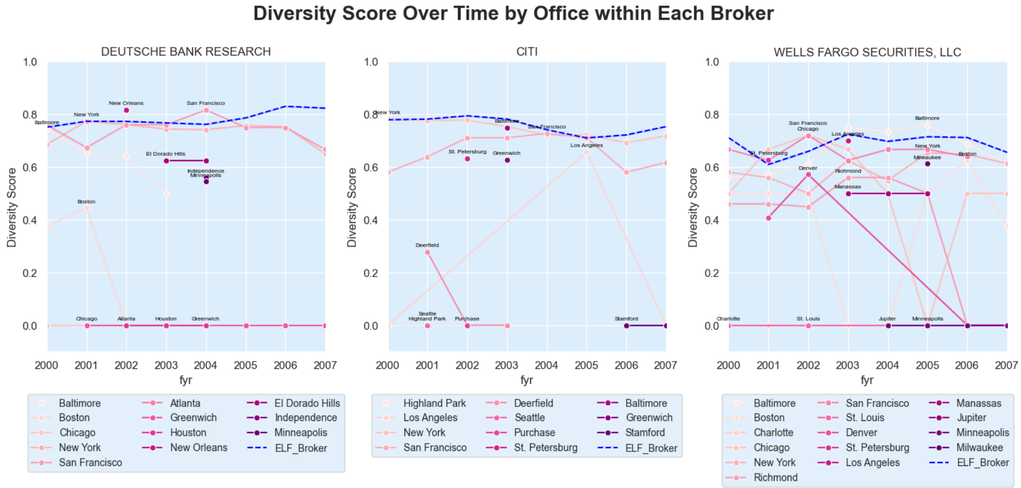
Ethnic diversity and market reactions

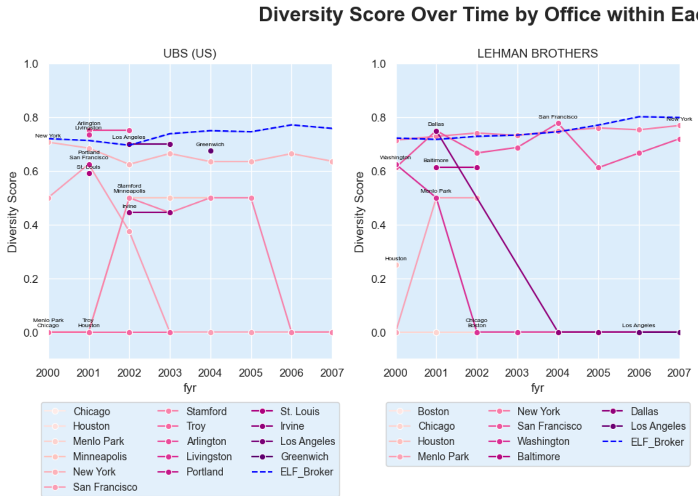
This table reports the results for how market reacts to forecast revisions issued by analysts who work in brokerage offices with various levels of ethnic diversity. *CAR* is the cumulative abnormal return in the two-day (0,1) window around the forecast revision. *ABSFR* is the absolute value of the difference an analyst's revised forecast at time t and the previous forecast at time t-1 scaled by the absolute value of the forecast at time t-1. We consider the direction and the magnitude of forecast revisions and estimate Equation (2) separately for positive (upward revisions) and negative (downward revisions) news. P-values are reported in parentheses and standard errors are double-clustered by analyst and firm. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1)	(2)
	Positive News	Negative News
ELF_bci	0.2000**	-0.6254***
	(0.027)	(0.000)
ABSFR	0.1141**	-0.0929***
	(0.018)	(0.000)
GEXP	0.0001	-0.0051
	(0.984)	(0.194)
FEXP	0.0023	0.0099**
	(0.492)	(0.038)
BSIZE	0.0010***	-0.0016***
	(0.000)	(0.000)
NOFIRM	-0.0018	0.0009
	(0.585)	(0.838)
NOIND	-0.0157	0.0071
	(0.153)	(0.617)
AGE	0.0011***	0.0001
	(0.002)	(0.900)
SIZE	-0.2193***	0.6111***
	(0.000)	(0.000)
BTM	-0.7675***	-1.3227***
	(0.000)	(0.000)
ANFOLLOW	-0.1637***	-0.6825***
	(0.005)	(0.000)
LAGPMAFE	-0.5144***	0.7957***
	(0.000)	(0.000)
LAGRET	-0.1510***	-0.1957***
	(0.001)	(0.000)
CONS	3.9950***	-4.3803***
	(0.000)	(0.000)
Year FE	Yes	Yes
Observations	297,771	296,232
Adjusted R-squared	0.014	0.033

Appendix A.

Here, we present more examples and their diversity scores over time.





Appendix B.

1.JPMorgan

In 2007, the diversity score for JPMorgan is 0.7998, which is extremely high and ranks 11 among all brokers in our sample. However, several offices of JPMorgan employ analysts with same ethnic background. For example, in offices in Boston and Dallas, the diversity score is 0, with all employed analysts have the same ethnic background of ENGLISH and EUROPEAN respectively. For office in San Francisco, the diversity score is 0.4444. However, for office in New York, the diversity level reaches the peak, with a score of 0.7617. The analysts in New York office have different ethnic background of GREEK, ENGLISH, EUROPEAN, HIPANIC, CELTIC and so on.

2.Prudential Equity Group, LLC

In 2001, the broker-level diversity score for Prudential Equity Group, LLC is 0.652. However, the diversity score across offices is quite different. For offices in Boston, Houston and St. Louise Park, the diversity score is 0 with all analysts share the same ethnic background of ENGLISH. The diversity scores in offices in New York, Baltimore and Little Rock are around 0.65, which are similar to the broker-level diversity score. However, for offices in San Francisco, the diversity score is 0.7813. Analysts employed by this office have ethnic background worldwide, such as ENGLISH, CELTIC, EUROPEAN, EAST ASIAN AND PACFIC and so on.

3.H.C. WAINWRIGHT & CO., INC.

In 2001, the broker-level diversity score for H.C. WAINWRIGHT & CO., INC. is 0.4425, which is relatively low and ranks in the bottom 25% among all brokers, illustrating that analysts employed by this broker tend to have similar ethnic background. For offices in Newton, the diversity score is 0 with all analysts have the same ethnic background of ENGLISH. For offices in New York, the diversity score is only 0.2778. Analysts working in New York office mainly have an ethnic background of ENGLISH and EUROPEAN. However, for office in Boston, the broker employ analysts with diverse ethnic background, leading to a high diversity scores of 0.6667. Among them, 40% of analysts employed have ethnic background of ENGLISH, 40% of them are CELTIC and MUSLIM with 20% each and the rest of analysts have UNCLASSIFIED ethnic background.

4.MORGAN KEEGAN & COMPANY (HIST)

For Morgan Keegan & Company (hist) in 2003, the broker-level ethnic diversity score is 0.4959, which ranks in the bottom 20% among all brokerage firms. For offices in Houston, Nashville and New York, the diversity scores are all 0. Analysts employed by Nashville and New York office have the ethnic background of ENGLISH. For Houston office, all analysts come from SOUTH ASIAN. However, the diversity score for offices in Memphis is 0.5123, which is relatively high. In Memphis office, 56.25% of analysts employed have ethnic background of ENGLISH, 12.5% of analysts have ethnic background of SOUTH ASIAN, and 18.75% of analysts have ethnic background of CELTIC.

5.KEYBANC CAPITAL MKTS

In 2004, the broker-level diversity score is 0.5178 for brokerage firm Keybanc Capital Mkts. For offices in El Segundo and Los Angeles, analysts have the same ethnic background of ENGLISH with a diversity score of 0. The office-level diversity level is around the broker-level for offices in Cleveland and Chicago, with the score of 0.4750 and 0.5 respectively. However, office in New York has a relatively high diversity score of 0.6667. Within this office, analysts employed have diverse ethnic background. Among them, 50% are ENGLISH, 16.67% are MUSLIM, and 16.67% are CELTIC.

6.Others

Some brokerage firms show strong preference on analysts with specific ethnic background and are reluctant to promote diversity within offices. For example, SOLEIL-LANGENBERG &

CO. LLC has a broker-level diversity score of 0 in 2003 with every offices worldwide employ analysts who have the same background of ENGLISH. Similar situation can be observed in other brokers. THOMPSON, DAVIS, & CO. in 2003 only employ analysts with an ethnic background of CELTIC. In 2006, the offices in Granada Hills and Tarzana employ MUSLIMS analysts, leading to a diversity score of 0.