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Analysts' foreign ancestral origins and firms' information environment

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Abstract

Purpose – The purpose of this study is to examine whether and how analysts' foreign ancestral origins would have an effect on analysts' earning forecasts in particular and ultimately on firms' information environment in general.

Design/methodology/approach – By inferring analysts' ancestral countries based on their surnames, this study empirically examines whether analysts' ancestral countries affect their earnings forecast errors.

Findings – Using novel data on analysts' foreign ancestral origins from more than 110 countries, this study finds that relative to analysts with common American surnames, analysts with common foreign surnames tend to have higher earnings forecast errors. The positive relation between analyst foreign surnames and earnings forecast errors is more likely to be observed for African-American analysts and analysts whose ancestry countries are geographically apart from the USA. In contrast, this study finds that when analysts' foreign countries of ancestry are aligned with that of the CEOs, analysts exhibit lower earnings forecast errors relative to analysts with common American surnames. More importantly, the results show that firms followed by more analysts with foreign surnames tend to exhibit higher earnings forecast errors.

Originality/value – Taken together, findings of this study are consistent with the conjecture that geographical, social and ethnical proximity between managers and analysts affect firms' information environment. Therefore, this study contributes to the determinants of analysts' earnings forecast errors and adds to the literature on firms' information environment.

Keywords Analyst, Ancestry, Forecast error, Social network, Information environment

Paper type Research paper

1. Introduction

Both academic researchers and regulators are particularly concerned that managers may provide financial analysts and institutional investors with differential access to management's private information (Cox, 2005; Mayo, 2006; Mayew, 2008). However, studies show that some analysts are still able to retain a competitive informational advantage even after Regulation Fair Disclosure (Regulation FD) [1] (e.g. Mayew, 2008; Mayew, Sharp, & Venkatachalam, 2013; Green, Jame, Markov, & Subasi, 2014). In line with the discrimination, the hypothesis posits that managers are more (less) likely to grant analysts with favorable (unfavorable) views preferential access to private managerial information (Francis, Chen, Philbrick, & Willis, 2004; Gintschel & Markov, 2004; Chen & Matsumoto, 2006), Mayew (2008) shows that managers discriminate among analysts during earnings conference calls.

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The results of previous studies are generally consistent with managers' intentional informational discrimination toward some analysts (Francis & Philbrick, 1993; Francis *et al.*, 2004; Gintschel & Markov, 2004; Chen & Matsumoto, 2006; Mayew, 2008; Soltes, 2014). However, we conjecture that some analysts' competitive informational disadvantage may be the result of managers' unintentional discrimination arising from managers' unconscious bias and social categorization, which in turn may induce a bias against interacting with all analysts equally [2], [3]. Thus, to the extent that analysts favored by managers are likely to have better access to firms' private information and/or a better understanding of firms' public information, we predict that unfavored analysts' informational disadvantage increases with the managers' preferences resulted from their unconscious bias.

People with foreign ancestry represent a significant portion of the American workforce, including the financial analyst profession [4]. The homophily principle introduced by Lazarsfeld and Merton (1954, p. 23) posits a "tendency for friendship to form between those who are alike." The social psychology literature also suggests that people tend to favor others with similar ethnicities and cultures (e.g. Lazarsfeld & Merton, 1954; Byrne, 1971; Eve, 2010; Chiesi, 2014; Barwick, 2017). In line with this view, it is well-established that social categorization between individuals, such as between managers and analysts, may play an important role in the information transmission between them (Granovetter, 1983; Autant-Bernard, Billand, Frachisse, & Massard, 2007; Brochet, Miller, Naranjo, & Yu, 2019). As a result of the greater level of difficulty in establishing social and informational networks with corporate executives by analysts due to, for example, managers' unconscious bias toward people with different ethnicities, the earnings forecast accuracy of financial analysts with foreign ancestry is likely to decrease with the geographical, social, ethnical or racial distance of their countries of ancestry. However, it is also plausible that analysts with foreign ancestry may produce more accurate earnings forecasts, as they may have stronger incentives to work hard and dedicate greater efforts in processing and analyzing firm information given their informational disadvantage.

To empirically examine the competing conjectures, we first infer the analysts' countries of ancestry by matching each analyst's surname with the most common/popular surnames of each country around the world. Accordingly, we classify an analyst as either an analyst with a common surname in America (USA or Canada) or as an analyst with foreign ancestry if her surname is identified as an uncommon surname in the USA or Canada but matched with a common surname of another country. Using 41,863 earnings forecasts between 2000 and 2015 issued by financial analysts with their surnames successfully matched, we find that earnings forecasts issued by analysts with foreign ancestry [5] are significantly less accurate than those issued by analysts with common US or Canadian surnames. This result holds after controlling for various analyst and firm characteristics along with firm- and year-fixed effects. The finding also indicates a substantial economic magnitude. For example, relative to analysts with common US or Canadian surnames, analysts with common surnames linked to foreign ancestry tend to exhibit earnings forecast errors that are on average 7% to 7.5% greater.

We perform a series of additional analyses to further reinforce our conclusion. *First,* Byrne (1971) suggests that people who are ethnically or racially similar are likely to trust and interact with each other, thereby facilitating network building and information sharing. Research (e.g. Ginther *et al.*, 2011) generally suggests that Americans' unconscious bias is more pervasive for African-Americans. If managers' unconscious bias toward analysts does exist, we expect to see greater forecast errors for African-American analysts. Therefore, we partition analysts into African-American analysts and non-African-American analysts and find evidence supporting less accurate earnings forecasts for African-American analysts. *Second,* we examine the effect of geographical proximity between analysts' and chief executive officers' (CEOs') countries of ancestry on the forecast errors of analysts. Following the view that geographical proximity is positively associated with social distance (Maggioni, Nosvelli, & Uberti, 2007), we examine whether the forecasts of analysts whose ancestral countries are geographically farther from the US are likely less accurate. We find supporting evidence that the geographical distance of an analyst's ancestral country to the USA is positively associated with higher earnings forecast errors. *Third,* we identify the match between CEOs' and analysts' foreign ancestry. With such a match, it presumably reduces managers' unconscious bias toward analysts with foreign ancestry. Consistent with this prediction, our results indicate that when both the CEO and analyst share the same foreign ancestry, the earnings forecast errors of the analysts with foreign ancestry decrease [6].

We further perform various robustness checks to rule out possible alternative explanations of our findings. For example, we exclude all firms with securities cross-listed in foreign countries, firms with foreign institutional ownership, and more directly firms with analysts working in foreign locations. These tests reduce the concern that the variable of interest in our study (i.e. American analysts with foreign ancestry) likely captures non-American analysts (i.e. foreign analysts) who presumably tend to face a greater information costs in forecasting firms in the USA. In addition, we examine whether our results are driven by different levels of cultural and language barriers faced by analysts (Reiter, 2021). We use country-level power distance and official language in analysts' ancestral countries to proxy for the cultural and communication barriers of analysts, respectively. We find that there is no significant difference in their earnings forecast errors between analysts with foreign ancestry from countries with different levels of power distance and between analysts whose ancestral countries are English- or non-English-speaking. These findings reduce the concern that our finding of greater forecast errors of analysts with foreign ancestry are driven by certain attributes of analysts (such as analysts' tendency to approach managers proactively and their communication difficulty).

In addition to untabulated analyses, we further distinguish analysts with common foreign surnames into those who are currently working for large vs small brokerage houses and find that both groups of analysts are associated with higher earnings forecast errors. This finding rules out an alternative explanation that the higher earnings forecast errors of analysts with common foreign surnames documented in our study is driven by their incentives to issue optimistic earnings forecasts for career advancement (e.g. moving up to a high-status brokerage house). We also extend our sample by including analysts without common surnames in any of the 195 countries in our surname database and find that both analysts with common foreign surnames and analysts with uncommon surnames tend to exhibit higher earnings forecast errors than analysts with common US or Canadian surnames. This result suggests that analysts with surnames that are less likely identifiable as common US or Canadian surnames likely encounter similar informational barriers resulted from managers' unconscious bias and social categorization as analysts with common foreign surnames.

Finally, and more importantly, we examine whether and how the presence of analysts with foreign ancestry affects the general information environment of a firm. To do this, we examine whether and to what extent the average analysts' earnings forecast errors of a firm vary with the proportion of analysts with foreign ancestry following the firm or industry. We find that average analysts' earnings forecasts errors tend to increase with the percentage of analysts with foreign ancestry following the firm or industry. This finding is important as it suggests that firms and industries that are more intensively covered by analysts with foreign ancestry can have a deteriorated information environment. In other words, managers' unconscious bias toward analysts with different ancestry can indeed have a real consequence to firms' information environment.

Our study contributes to several strands of accounting and finance literature. First, because of the crucial role that financial analysts play in collecting, analyzing, interpreting and disseminating information to the market and ultimately allocating economic resources, the determinants of the earnings forecast performance of financial analysts are of significant interest to academic researchers and investors (e.g. Ramnath, Rock, & Shane, 2008). As a result, a large body of literature explores the effects of various analyst characteristics on their earnings forecast accuracy, such as analysts' political contributions, gender, pre-analyst experience and involvement in the IPO process (e.g. Jiang, Kumar, & Law, 2016; Dambra, Field, Gustafson, & Pisciotta, 2018; Bradley, Gokkaya, & Liu, 2017). In contrast to the literature focusing on the attributes of analysts, a key contribution of our study is to present evidence that managers' unconscious bias and the potential social categorization resulted from such bias can play a role in explaining the heterogeneity of earnings forecast performance across analysts.

Second, recent studies using individuals' surnames to identify their ancestral origins find that cultural traits associated with different ancestries affect individuals' behavior and corporate policies (e.g. Kumar, Niessen-Ruenzi, & Spalt, 2015; Liu, 2016; Ellahie, Tahoun, & Tuna, 2017; Brochet *et al.*, 2019; Giannetti & Zhao, 2019) [7]. Our study extends the literature related to capital market participants' names to financial analysts – an important information intermediary in capital markets – and examine the potential implications of analysts' names for their forecast accuracy.

Finally, we extend the recent and developing work suggesting the importance of private communication and proximity between analysts and managers in analyst output (Soltes, 2014; Brown, Call, Clement, & Sharp, 2015; Du, Yu, & Yu, 2017; Fang & Huang, 2017). We attribute the finding that analysts with common foreign surnames issue less accurate earnings forecasts than analysts with common US or Canadian surnames to analysts' informational disadvantage resulted from managers' unconscious bias toward analysts with different geographical, social, ethnical or racial distance. Our findings thus shed light on factors affecting analysts' earnings forecast performance and firms' information environment.

The rest of this paper is organized as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 discusses the sample, variable measurement and research design for testing whether and how analysts' earnings forecast errors vary with their ancestral country. Section 4 presents the empirical results regarding analysts' earnings forecast errors according to their ancestral origins. Section 5 concludes the paper.

2. Literature review and hypothesis development

2.1 A negative relation between analysts' foreign ancestry and earnings forecast accuracy

The important role of networking in facilitating information exchange and sharing is well recognized in the literature (Granovette, 1983). Wolff and Moser (2009) argue that simple informal interactions, such as going out for drinks, or staying in contact with friends after work, are all the essential, voluntary and crucial means of facilitating information transmission. Management's body language or vocal cues can also be another possible channel through which analysts can obtain additional information (Mayew & Venkatachalam, 2012). More formal types of interactions include visiting company headquarters, attending investor office meetings and broker-hosted investor conferences (Bushee, Jung, & Miller, 2011; Green *et al.*, 2014). Even without obtaining material nonpublic information from managers (which is prohibited by Regulation FD), it is possible that analysts could create material information by "piecing together public information and nonmaterial information from management" (Green *et al.*, 2014, p. 241) [8]. Anecdotal evidence suggests that private conversations or communications with management remain a very important and valuable input to analysts' earnings forecasts in the post-Regulation FD environment (Green *et al.*, 2014; Soltes, 2014; Brown *et al.*, 2015).

Similarly, Soltes (2014, p. 247) states that "Even with restrictions on managers' ability to convey material information to analysts, private interaction continues to thrive by offering analysts additional context to interpret firm news and the opportunity to better understand a firm's operations." In the same vein, Brown *et al.* (2015) conclude that private communication with management is a more useful input to analysts' earnings forecasts than their own primary research and information provided by management through financial reporting. Analysts who can interact with firm executives are also likely to have access to the communication channel with division-level executives such as regional or production line managers (Soltes, 2014).

In contrast, Francis *et al.* (2004) note that managers' discrimination actions against analysts can take many forms, such as excluding analysts from meetings, outings and conference calls with top company executives, and failing to respond to analysts' questions or even barring analysts from asking questions during conference calls. Similarly, Mayew (2008) finds that analysts issuing more favorable stock recommendations for a firm have a higher probability to ask a question during the firm's conference call. Therefore, if analysts can establish an effective communication network with client company managers, they are likely to have an advantage in making earnings forecasts.

However, social networks and informal relations do not form automatically, and thus private and direct interactions with managers are unlikely available for all analysts [9]. For example, of the analysts surveyed by Brown *et al.* (2015), only roughly 53.2% say that they have direct contact with the CEO or CFO of the firm they cover at least five times a year in making their earnings forecasts. Lazarsfeld and Merton (1954) find that people tend to develop friendships with those who are categorically similar to themselves. For example, studies show that alumni ties can be an effective way to establish connections and networks between different types of capital market participants (Cohen, Frazzini, & Malloy, 2010; Fang & Huang, 2017).

Chiesi (2014) suggests that trustworthiness is more easily established among people with similar ethnicities and social identities. This phenomenon of homogeneity in networking can also be explained by homophily – individuals' preference to interact with those who are (ethnically) similar (Barwick, 2017). As a result, individual ethnicity groups tend to have their own networks due to the ease of communication and mutual trust and may also distrust and exclude outsiders who do not share the same traits and heritage as the groups (Gudykunst, 1995; Faist, 2000). Sociological research also consistently shows that the preference for similar others can have a significant effect on interaction and information exchange (McPherson, Smoth-Lovin, & Cook, 2001). More recently, by presenting the evidence that corporate inside traders tend to share a common surname ancestry, Ahern (2017) suggests that potential social categorization between individuals can be a valid proxy of information transmission.

The discussion above suggests that CEOs' unconscious bias and the tendency of social categorization may partially contribute to certain analysts' greater level of difficulty in establishing social networks and informal relations with CEOs, especially for analysts with foreign ancestry. Therefore, in this study, our first prediction is that analysts with foreign ancestry are likely to exhibit greater earnings forecast errors (i.e. a negative relation between analysts with foreign ancestry and earnings forecast accuracy) compared to analysts who do not have foreign ancestry.

2.2 A positive relation between analysts with foreign ancestry and earnings forecast accuracy

Despite their competitive disadvantage in social and informational networking, analysts with foreign ancestry may be able to provide more accurate earnings forecasts than analysts without foreign ancestry due to their extrinsic motivation and hard work. Analysts with foreign ancestry are likely to be more motivated and harder working than analysts without foreign ancestry, as they may appreciate their jobs as financial analysts more (Vasquez *et al.*, 2006; Leong & Grand, 2008; Kameny *et al.*, 2014; Leong & Tang, 2016). In addition, although having better social and informational networks facilitates information sharing and transmission, it does not always guarantee analysts better earnings forecast performance. For example, it is plausible that analysts with foreign ancestry are more likely to dedicate greater efforts in processing and analyzing firm information given their informational disadvantage, which, in turn, produce more accurate earnings forecasts. Following these discussions, we predict a positive relation between analysts' foreign ancestry and earnings forecast accuracy.

Given the competing views on the relation between analysts' ancestry and earnings forecast errors, we state our hypothesis in competing forms.

H1a. Analysts with foreign surnames are negatively associated with analysts' earnings forecast accuracy.

H1b. Analysts with foreign surnames are positively associated with analysts' earnings forecast accuracy.

2.3 Analysts' foreign ancestry and firms' information environment

Despite the competing views on the relation between analysts' ancestry and earnings forecast errors discussed above, we further posit that our predictions can have an important implication for the general information environment of firms as well. That is, to the extent that analysts with foreign surnames tend to make more/less accurate earnings forecasts than those without, we predict that firms' information environment can vary with the level of concentration of analysts with foreign surnames. Thus, we state our second hypothesis in the following forms.

H2a. Firms with a greater concentration of analysts with foreign surnames have an average lower level of analysts' earnings forecast accuracy.

H2b. Firms with a greater concentration of analysts with foreign surnames have an average higher level of analysts' earnings forecast accuracy.

3. Research design

3.1 Data and sample selection

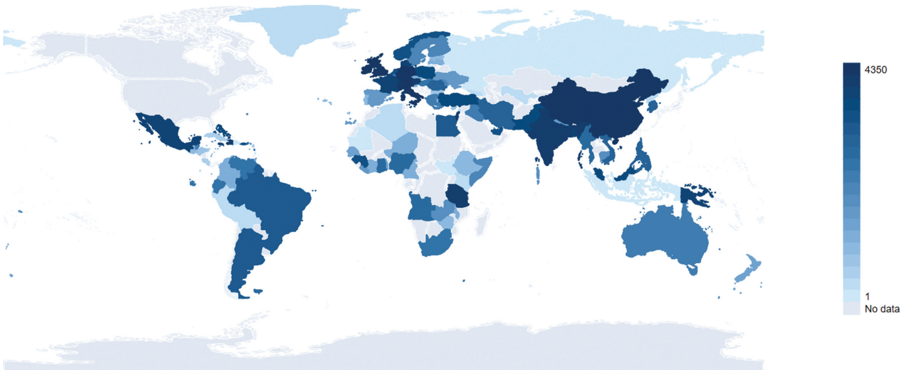
Studies suggest that a person's family surname tends to be sticky and to reflect the person's ancestry (Hanks, 2003), even if the individual's family migrated to the USA many generations prior (e.g. Jobling, 2001; Goldstein & Stecklov, 2016). Following Ahern (2017), in our study, we use analysts' surnames as an indirect proxy of social interactions and social networks because a direct observation or empirical identification of information transmission between individuals is challenging.

To test our hypotheses, we start from the Thomson Reuters' Institutional Brokers' Estimate System (I/B/E/S) database because this database contains analysts' codes, surnames and initials [10]. We further collect 1-year-ahead earnings forecasts and the actual earnings of US firms between 2000 and 2015 from the I/B/E/S databases for those who work for US brokerage firms. We then create a database containing the most common surnames of every country based on the information collected from Forebears.io (Forebears hereafter) or Ancestry.com, which are two major depositories of surname origins (Pan, Siegel, & Wang, 2017; Jung, Kumar, Lim, & Yoo, 2019; Pacelli, 2019) [11], [12]. We assign an analyst to a specific ancestral country when his or her surname is on the country's 200 most common surname list. If a surname appears as the most common surname in more than one country, we assign the analyst to the country with a higher incidence of people who bear the name. We supplement our surname search using Ancestry.com in cases where we are unable to identify the country of origin of a surname.

The variable of interest in our study is financial analysts who work for US brokerage firms located within the US but who are likely the descendants of immigrants. Most of these analysts probably live in the US, having both studied and grown up there. We label our variable of interest as analysts with foreign ancestry (or analysts with common foreign surnames) to reduce the confusion that our study is about foreign analysts domiciled outside of the country in which the firm that they are following is located, as this (i.e. the performance outcome of foreign analysts) has been examined in previous studies (e.g. Bae, Stulz, & Tan, 2008; Agarwal & Hauswald, 2010).

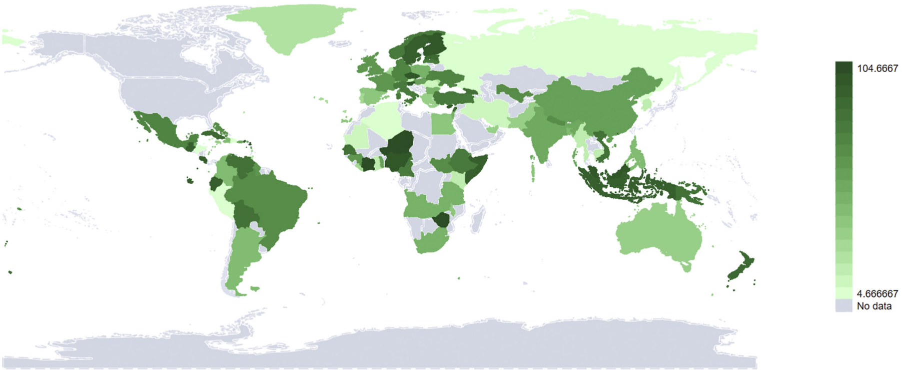
We classify an analyst as having foreign ancestry if his or her surname is not in the 200 most common surname list of either the USA or Canada but indeed is a common surname in a foreign country. We exclude an analyst from our final sample if we cannot find a match for her surname (i.e. when an analyst's surname is not a common one in all of the 195 countries in the surname database we constructed). As a result, we exclude earnings forecasts made by analysts for whom we cannot identify ancestral countries (in additional tests, we also examine the earnings forecast errors of these analysts). Table A1 provides the distribution of analysts with foreign ancestry by their ancestral countries/regions and Table A2 provides a list of the 10 most frequent analyst surnames by continent (in descending order). Figures 1 and 2 illustrate the distribution of analysts with foreign ancestry and the average level of analyst earnings forecast errors by country.

As an analyst may make multiple earnings forecast during the year, we follow prior studies (e.g. Zhang, 2008) and focus on the last earnings forecast issued before the annual earnings announcement date to minimize the influence of forecast horizon on forecast errors [13]. Our analyst firm-year sample is then merged with Compustat financial data, CRSP stock price data and Thomson Reuters' 13F institutional ownership data. After eliminating the observations with missing values for control variables used in our main regression analyses, we obtain a final sample consisting of 41,863 earnings forecasts (i.e. the unit of analysis of our study) associated with 3,877 distinct firms during the sample period of 2000–2015. In total, 30,613 of the 41,863 observations are associated with analysts with foreign ancestry.



Note(s): This figure plots the distribution of earnings forecasts made by analysts with common foreign surnames by country based on Table A1, Column 2. The number in the legend represents the number of forecasts by analysts

Figure 1. Distribution of analysts without common foreign surnames by country of ancestral origins for 2000–2015



Note(s): This figure plots the average earnings forecast errors of analysts with common foreign surnames by country based on Table A1, Columns 4, 5 and 6. We first rank each of the earnings forecast measure by country, and then obtain the average rank of all three measures. The higher the rank and the darker the color (as indicated in the legend), the higher the average forecast error across all the three measures

Figure 2. Average earnings forecast errors of analysts with common foreign surnames by country of ancestral origins for 2000–2015

3.2 Regression model and variable construction

Our baseline analysis of the relation between analysts with foreign ancestry and earnings forecast errors relies on the following regression model:

$$FError_{ijt} = \alpha_0 + \alpha_1 Foreign\_Ancestry_{ijt} + \sum \omega_i Control_{ijt} + Firm - fixed\ effect + Year - fixed\ effect + \varepsilon_{ijt} \quad (1)$$

where i, j and t index analyst, firm and year, respectively. *FError* is one of the three measures of absolute forecast error: scaled (*AbsFError*), unscaled (*AbsFError_Alt1*) and demeaned (*AbsFError_Alt2*). Following previous studies (e.g. Jung *et al.*, 2019), *AbsFError* is measured as the absolute value of the difference between the actual annual earnings per share (EPS) and the last annual EPS forecast issued by the analyst scaled by the opening stock price. *AbsFError_Alt1* is defined as the absolute value of the difference between the actual annual EPS minus the last annual EPS forecast issued by the analyst (Loh & Mian, 2006). *AbsFError_Alt2* is defined as the absolute price-scaled annual EPS forecast error of the analyst minus the average absolute price-scaled annual EPS forecast error of all of the analysts for the firm-year (Bae *et al.*, 2008). To facilitate interpretation, we multiply all three analyst earnings forecast error measures by 100 in the regression analyses. The variable of interest in this model is *Foreign_Ancestry*, which is an indicator variable that equals 1 if an analyst i does not have a common surname (i.e. based on the top 200 common surnames in each country) in either the USA or Canada, but instead she is with a common surname of another country.

Following the literature, we include an array of control variables that may affect analyst earnings forecast errors, such as those measuring analyst characteristics, forecast horizon and firm-level characteristics. To control for analyst characteristics, we include two analyst portfolio complexity variables, *NFirm* and *NIndustry*, defined as the natural logarithm of the number of firms and industries that analyst i followed in year t, respectively (Clement, 1999). We include analysts' firm-specific experience (*FirmExp*), calculated as the number of years that an analyst has followed a specific firm (Mikhail, Walther, & Willis, 2003; Drake & Myers, 2011). Furthermore, we control for forecast horizon (*Horizon*), defined as the natural logarithm of the difference in days between the forecast day and the earnings announcement day, as earnings forecast errors increase with forecast horizon (Mikhail *et al.*, 2003; Jacob, Rock, & Weber, 2008).

To control for a firm's information environment, we follow prior studies and include firm size (*FirmSize*), the natural logarithm of total assets (Chae, 2005; Dhaliwal, Radhakrishnan, Tsang, & Yang, 2012), and analyst following (*AnalystFollowing*), the natural logarithm of the number of analysts who follow a firm (Healy, Hutton, & Palepu, 1999; Bushman, Piotroski, & Smith, 2005). To control for other firm-level determinants of earnings forecast error, we include the book-to-market ratio (*Book-to-Market*) and intangible assets (*IntangibleAssets*) to capture the value relevance of information conveyed by firms' financial reports. *Book-to-Market* is calculated as the ratio of the book value of equity to the market value and *IntangibleAssets* is calculated as the proportion of intangible assets to total assets.

Pope (2003) suggests that earnings predictability decreases with the increased use of transitory, potentially difficult-to-detect accruals and flexible accounting choices. Therefore, we include *AbnormalAccruals*, which is estimated using the performance-adjusted modified Jones model (Kothari, Leone, & Wasley, 2005). In this estimation, we require at least 10 observations available for each industry-year based on their 3-digit SIC industry classifications. We control for auditor quality using the indicator variable *Big4*, which equals 1 if a firm is audited by a Big Four auditor in a given year and 0 otherwise (Behn, Choi, & Kang, 2008). In addition, we control for stock turnover (*StockTurnover*), the total number of shares traded in a given year to its total number of outstanding shares (Hameed, Morck, Shen, & Yeung, 2015). We further control for institutional ownership (*InstitutionalOwner*), measured as the proportion of a firm's outstanding shares held by institutional shareholders (Frankel, Kothari, & Weber, 2006).

Next, we control for firms' market performance. We include firms' lagged return volatility (*ReturnVolatility*), calculated as the standard deviation of the monthly returns of firm j for year $t-1$, and lagged monthly return (*StockReturn*), calculated as the average monthly return of firm j for year $t-1$ (Bhushan, 1989; Chen, Matsumoto, & Rajgopal, 2011). To control for firm accounting performance, we also add the indicator variable *Loss* in the model, which equals 1 if a firm reports negative earnings in a given year and 0 otherwise (Hwang, Jan, & Basu, 1996). Furthermore, we include earnings volatility (*EarningsVolatility*), calculated as the natural logarithm of the time-series standard deviation of the EPS of firm j in year t using the 10 previous years as a rolling window (Dhaliwal *et al.*, 2012). Table A3 provides detailed variable definitions [14].

3.3 Sample distribution and descriptive statistics

Panel A of Table 1 reports the sample distribution and descriptive statistics across 23 industries based on the industry classification suggested by Barth, Beaver, and Landsman (1998). The average ratio of the number of forecasts by analysts with foreign ancestry to the number of forecasts by analysts with non-foreign ancestry is 2.7 times across all industries, suggesting the presence of a non-trivial fraction of analysts with foreign ancestry. Untabulated results suggest that approximately 42% of the analysts in our sample are descendants of Europeans (followed by the USA/Canada, Asia, other North America such as Mexico, Jamaica, Bahamas and Haiti, Africa and South America). This is consistent with the fact that the British and other Europeans started settling in the USA in 1600.

Table 1 also reveals a considerable variation in the ratio of forecasts by analysts with foreign ancestry to forecasts by analysts who do not have foreign ancestry across industries, with the highest ratio in the food industry (14.49, industry #17) and the lowest ratio in the mining and construction industry (0.974, #13) [15]. The last three columns show the mean

Panel A: By industry

(1) Industry	(2) *N*	(3) %	(4) No. of forecasts by analysts with common foreign surnames	(5) No. of forecasts by analysts with common US/CA surnames	(6) (4)/(5)	(7) *AbsFError*	(8) *AbsFError Alt1*	(9) *AbsFError Alt2*
1. Computers	8,681	20.74	6,749	1,932	3.493	1.110	0.180	−0.005
2. Extractive	3,529	8.43	2,532	997	2.540	1.689	0.453	0.011
3. Services	3,282	7.84	2,235	1,047	2.135	0.989	0.175	−0.013
4. Transportation	3,059	7.31	2,523	536	4.707	1.427	0.240	−0.015
5. Retail	2,636	6.30	2,194	442	4.964	1.094	0.190	−0.024
6. Pharmaceuticals	2,630	6.28	2,120	510	4.157	1.573	0.242	−0.018
7. Instruments	2,220	5.30	1,599	621	2.575	0.792	0.163	0.022
8. Utilities	2,017	4.82	1,081	936	1.155	0.758	0.180	−0.004
9. Financial	1,960	4.68	1,361	599	2.272	1.239	0.379	−0.035
10. Machinery	1,592	3.80	1,102	490	2.249	1.051	0.235	0.029
11. Chemicals	1,533	3.66	1,140	393	2.901	1.042	0.253	0.015
12. Textiles/Print/Publish	1,361	3.25	1,050	311	3.376	1.245	0.234	0.003
13. Mining/Construction	1,157	2.76	571	586	0.974	1.814	0.380	−0.019
14. Electrical equipment	1,068	2.55	751	317	2.369	1.285	0.215	0.019
15. Retail/Wholesale	992	2.37	654	338	1.935	0.752	0.172	−0.017
16. Transport equipment	930	2.22	627	303	2.069	1.089	0.292	0.017
17. Food	790	1.89	739	51	14.490	0.578	0.130	−0.027
18. Restaurant	710	1.70	434	276	1.572	0.523	0.118	−0.017
19. Metal	603	1.44	319	284	1.123	1.662	0.330	0.083
20. Rubber/Glass/Etc	456	1.09	347	109	3.183	1.412	0.256	−0.041
21. Insurance/Real estate	318	0.76	248	70	3.543	1.384	0.224	−0.065
22. Misc	194	0.46	148	46	3.217	1.413	0.177	0.076
23. Others	145	0.35	89	56	1.589	1.805	0.206	−0.025
Total/Overall	41,863	100.00	30,613	11,250	2.721	1.185	0.237	−0.004

Panel B: By year

(1) Year	(2) *N*	(3) %	(4) No. of forecasts by analysts with common foreign surnames	(5) No. of forecasts by analysts with common US/CA surnames	(6) (4)/(5)	(7) *AbsFError*	(8) *AbsFError Alt1*	(9) *AbsFError Alt2*
2000	2,753	6.58	1,902	851	2.235	1.213	0.227	0.019
2001	2,631	6.28	1,893	738	2.565	1.378	0.242	0.069
2002	2,331	5.57	1,727	604	2.859	0.950	0.162	0.007
2003	2,307	5.51	1,764	543	3.249	1.229	0.144	0.013
2004	2,559	6.11	1,940	619	3.134	0.784	0.180	0.020
2005	2,795	6.68	2,079	716	2.904	0.966	0.209	0.015
2006	2,906	6.94	2,118	788	2.688	0.946	0.213	0.013
2007	2,887	6.90	2,118	769	2.754	0.981	0.214	−0.046
2008	2,683	6.41	1,989	694	2.866	1.697	0.353	−0.017
2009	2,460	5.88	1,817	643	2.826	2.169	0.289	−0.046
2010	2,704	6.46	1,951	753	2.591	1.146	0.236	−0.019
2011	2,735	6.53	2,021	714	2.831	0.963	0.235	−0.026

(*continued*)

Table 1.
Sample distribution

Table 1.

Panel B: By year								
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year	*N*	%	No. of forecasts by analysts with common foreign surnames	No. of forecasts by analysts with common US/CA surnames	(4)/(5)	*AbsFError*	*AbsFError Alt1*	*AbsFError Alt2*
2012	2,568	6.13	1,919	649	2.957	1.335	0.258	0.002
2013	2,512	6.00	1,811	701	2.583	1.171	0.256	−0.049
2014	2,479	5.92	1,740	739	2.355	0.919	0.257	−0.009
2015	2,553	6.10	1,824	729	2.502	1.183	0.300	−0.010
Total/ Overall	41,863	100.00	30,613	11,250	2.721	1.185	0.237	−0.004

value of the scaled (*AbsFError*), unscaled (*AbsFError_Alt1*) and demeaned (*AbsFError_Alt2*) absolute earnings forecast errors by each industry, respectively. Similarly, we observe a significant variation in earnings forecast errors across industries. Panel B of Table 1 presents the sample distribution by year. The ratio of foreign ancestry to non-foreign ancestry analysts remains generally stable over the sample period, but analyst earnings forecast errors show considerable fluctuations across years, with a tendency to peak during the years surrounding financial crises.

Panel A of Table 2 shows the summary statistics. The mean value of absolute 1-year-ahead earnings forecast errors (*AbsFError*) is approximately 1.2% of the opening price, which is consistent with the statistics reported in the literature [16]. The means of *AbsFError_Alt1* and *AbsFError_Alt2* are 0.237% and −0.004%, respectively, which are also consistent with prior studies (e.g. Loh & Mian, 2006; Bae *et al.*, 2008). With respect to the other analyst-level variables, the means of *NFirm* and *NIndustry* are 2.671 and 1.021, indicating that analysts on average follow approximately 14 firms and 3 industries. Analysts on average have over 5 years of firm-specific forecasting experience (*FirmExp*). The mean value of *Horizon* is 5.156. The firm-level variables are also generally consistent with prior studies. For example, an average firm in the sample is followed by approximately 21 analysts (*AnalystFollowing* = 3.034). On average, institutional shareholders (*InstitutionalOwner*) hold 64.3% of the total shares outstanding. Approximately 92% of the firms in the sample are audited by the Big Four (*Big4*) and 20.5% of the firms report loss (*Loss*) in the previous year.

Panel B of Table 2 reports the univariate comparison of the earnings forecast errors and analyst characteristics between the analysts with foreign and non-foreign ancestry. Across all three measures of earnings forecast error, the mean difference of earnings forecast error is consistently and significantly positive, indicating a higher earnings forecast error for analysts with common foreign surnames. This provides preliminary support for H1a. In addition, analysts with foreign ancestry tend to have less firm-specific experience and cover fewer firms and industries in their portfolios, suggesting the importance of having these variables controlled in multivariate analyses.

Table 3 presents the Pearson correlations for the variables used in our main regression analyses. Consistent with H1a, the correlation between *Foreign_Ancestry* and each of our three analyst earnings forecast error measures is significantly positive. A significantly positive correlation between analysts with foreign ancestry and analyst earnings forecast errors lends preliminary evidence to the conjecture that managers' unconscious bias and social categorization can potentially hinder the ability of financial analysts with foreign ancestry in establishing social and informational networks with corporate executives. This in turn affects analysts' earnings forecast accuracy.

Panel A: Main variables

Variable	*N*	Mean	Std. dev	25%	50%	75%
AbsFError	41,863	1.185	2.563	0.100	0.333	1.036
AbsFError_Alt1	41,863	0.237	0.416	0.030	0.090	0.250
AbsFError_Alt2	41,863	−0.004	1.075	−0.232	−0.024	0.159
Foreign_Ancestry	41,863	0.731	0.443	0.000	1.000	1.000
FARatio_Firm	41,863	0.731	0.319	0.500	0.800	1.000
FARatio_Indus	41,863	0.733	0.137	0.665	0.752	0.811
FA_Distance	41,863	6.271	4.585	0.000	6.830	8.992
Horizon	41,863	5.156	0.731	4.727	5.313	5.677
AnalystFollowing	41,863	3.034	0.635	2.639	3.135	3.497
FirmSize	41,863	7.837	1.782	6.527	7.802	9.092
Book-to-Market	41,863	0.474	0.377	0.234	0.390	0.617
IntangibleAssets	41,863	0.183	0.194	0.015	0.117	0.296
StockTurnover	41,863	2.657	1.999	1.282	2.092	3.388
ReturnVolatility	41,863	11.337	6.995	6.629	9.437	13.787
StockReturn	41,863	1.054	3.101	−0.680	1.142	2.814
Loss	41,863	0.205	0.404	0.000	0.000	0.000
EarningsVolatility	41,863	−0.060	0.900	−0.663	−0.115	0.473
AbnormalAccruals	41,863	0.113	1.858	−0.167	−0.022	0.100
InstitutionalOwner	41,863	0.643	0.277	0.521	0.726	0.849
Big4	41,863	0.920	0.271	1.000	1.000	1.000
NFirm	41,863	2.671	0.507	2.398	2.708	2.996
NIndustry	41,863	1.021	0.655	0.693	1.099	1.609
FirmExp	41,863	5.299	5.128	2.000	3.000	7.000

Panel B: Comparative statistics

Variables	*Foreign_Ancestry* = 1 (1)	*Foreign_ Ancestry* = 0 (2)	*Difference* (3) = (1)–(2)
AbsFError (%)	1.203	1.135	*0.067***
AbsFError_Alt1	23.953	22.828	*1.125**
AbsFError_Alt2 (%)	0.001	−0.017	*0.018***
NFirm	2.659	2.704	*−0.045****
Nindus	1.018	1.029	*−0.011*
FirmExp	5.266	5.390	*−0.124***

Note(s): Panel A presents the summary statistics for variables used in our main regression analyses. All variables are defined in Table A2. Panel B presents the mean difference in main variables between analyst-firm-years for analysts with common foreign surnames (*Foreign_Ancestry* = 1) and analyst-firm-years for analysts with common US/Canada surnames (*Foreign_Ancestry* = 0). ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively

Table 2.
Summary statistics

4. Regression results

4.1 Main results

Table 4 reports the regression results for Equation (1). For each of the forecast error measures (*AbsFError*, *AbsFError_Alt1* and *AbsFError_Alt2*), we run both the baseline regression, which only includes the test variable *Foreign_Ancestry* and the firm- and year-fixed effects (Columns 1, 3 and 5), and the full model, which includes the full set of control variables (Columns 2, 4 and 6). In all columns, the coefficients on *Foreign_Ancestry* are consistently positive and significant regardless of whether control variables are included. This result supports H1a, which predicts that analysts with foreign ancestry (i.e. with common foreign surnames) make less accurate earnings forecasts than analysts with non-foreign ancestry (i.e. analysts with common US/Canada surnames).

Table 3.
Pearson correlation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) *AbsFError*											
(2) *AbsFError_Alt1*	*0.686*										
(3) *AbsFError_Alt2*	*0.440*	*0.419*									
(4) *Foreign_Ancestry*	*0.012*	*0.012*	*0.010*								
(5) *FARatio_Firm*	*0.012*	*0.011*	0.006	*0.720*							
(6) *FARatio_Indus*	*0.014*	−0.007	0.001	*0.318*	*0.441*						
(7) *FA_Distance*	*0.016*	*0.019*	*0.014*	*0.829*	*0.597*	*0.256*					
(8) *Horizon*	*0.152*	*0.172*	*0.080*	−0.007	−0.006	−0.006	−0.006				
(9) *AnalystFollowing*	*−0.181*	0.001	*−0.042*	*0.058*	*0.080*	*0.045*	*0.060*	*−0.049*			
(10) *FirmSize*	*−0.168*	*0.069*	*−0.053*	0.000	0.000	*−0.042*	*−0.015*	*−0.083*	*0.622*		
(11) *Book_to_Market*	*0.225*	*0.179*	*0.057*	*−0.042*	*−0.059*	*−0.083*	*−0.044*	*−0.019*	*−0.203*	*−0.010*	
(12) *IntangibleAssets*	*−0.114*	*−0.121*	*−0.038*	−0.004	−0.006	*0.036*	−0.002	*0.028*	*0.021*	*0.096*	*−0.021*
(13) *StockTurnover*	*0.069*	*0.141*	*0.044*	*0.053*	*0.073*	*0.035*	*0.075*	−0.004	*0.294*	*−0.064*	−0.006
(14) *ReturnVolatility*	*0.300*	*0.156*	*0.114*	0.007	*0.010*	*−0.013*	*0.009*	*0.027*	*−0.166*	*−0.402*	*0.234*
(15) *StockReturn*	*0.024*	*−0.062*	*0.018*	0.003	0.005	0.009	0.000	*0.019*	*−0.035*	*−0.025*	*−0.176*
(16) *Loss*	*0.340*	*0.174*	*0.121*	*0.010*	*0.014*	0.009	*0.023*	*0.033*	*−0.127*	*−0.286*	*0.167*
(17) *EarningsVolatility*	*0.130*	*0.244*	*0.054*	0.003	0.004	−0.036	*0.011*	*−0.022*	*0.141*	*0.259*	*0.082*
(18) *AbnormalAccruals*	0.002	−0.004	−0.003	*0.013*	*0.018*	*0.046*	*0.018*	0.002	*−0.011*	*−0.014*	*−0.011*
(19) *InstitutionalOwner*	*−0.119*	*−0.030*	*−0.044*	0.001	0.002	0.005	0.001	*−0.008*	*0.176*	*0.167*	*−0.072*
(20) *Big4*	*−0.071*	−0.006	*−0.021*	*0.017*	*0.023*	*0.010*	*0.013*	−0.005	*0.210*	*0.223*	*−0.067*
(21) *NFirm*	*−0.022*	0.000	−0.007	*−0.039*	*−0.049*	*−0.080*	*−0.058*	*−0.031*	*−0.023*	*0.051*	*0.015*
(22) *NIndus*	*−0.029*	*−0.027*	*−0.016*	−0.007	*−0.021*	*0.036*	*−0.064*	0.003	*−0.193*	*−0.046*	*0.027*
(23) *FirmExp*	*−0.054*	−0.002	*−0.016*	*−0.011*	*−0.014*	*−0.037*	−0.001	*−0.067*	*0.134*	*0.328*	0.001

	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(13) *StockTurnover*	*−0.103*										
(14) *ReturnVolatility*	*−0.143*	*0.327*									
(15) *StockReturn*	*−0.016*	*−0.072*	*−0.062*								
(16) *Loss*	*−0.067*	*0.111*	*0.439*	*−0.086*							
(17) *EarningsVolatility*	*−0.082*	*0.156*	*0.022*	*0.015*	*0.078*						
(18) *AbnormalAccruals*	0.003	−0.005	−0.004	*−0.008*	*−0.009*	*0.015*					
(19) *InstitutionalOwner*	*0.087*	*0.039*	*−0.138*	*0.042*	*−0.113*	*0.058*	*0.020*				
(20) *Big4*	*0.030*	*0.074*	*−0.120*	*0.017*	*−0.068*	*0.094*	*0.014*	*0.085*			
(21) *NFirm*	*−0.010*	*−0.024*	*−0.072*	*−0.017*	*−0.029*	−0.001	−0.005	*0.016*	*0.009*		
(22) *NIndus*	*0.111*	*−0.074*	*−0.067*	−0.006	*−0.106*	*−0.071*	*0.022*	*0.017*	*−0.036*	*0.380*	
(23) *FirmExp*	−0.004	*−0.077*	*−0.204*	0.006	*−0.113*	*0.070*	*−0.009*	*0.091*	*0.067*	*0.117*	*0.047*

Note(s): This table presents Pearson correlations of main variables. The correlation coefficients that are statistically significant at 10% are in italic

Table 4. Analysts with common foreign surnames and earnings forecast accuracy

Dep. Var	*AbsFError* (1)	*AbsFError* (2)	*AbsFError Alt1* (3)	*AbsFError Alt1* (4)	*AbsFError Alt2* (5)	*AbsFError Alt2* (6)
Foreign_Ancestry	0.0700*** (0.0016)	0.0751*** (0.0004)	0.8869** (0.0291)	1.1850*** (0.0020)	0.0279** (0.0425)	0.0313** (0.0174)
Horizon		0.4861*** (0.0000)		11.085*** (0.0000)		0.4147*** (0.0000)
AnalystFollowing		−0.1617** (0.0143)		−0.9631 (0.3710)		0.0409 (0.1230)
FirmSize		−0.1457*** (0.0055)		10.681*** (0.0000)		0.0191 (0.3424)
Book-to-Market		0.6512*** (0.0000)		5.7327*** (0.0004)		−0.0662* (0.0764)
IntangibleAssets		−0.6248*** (0.0001)		−20.111*** (0.0000)		0.0150 (0.8198)
StockTurnover		−0.0021 (0.9009)		1.7931*** (0.0000)		−0.0072 (0.3099)
ReturnVolatility		0.0481*** (0.0000)		0.7745*** (0.0000)		0.0044** (0.0187)
StockReturn		0.0645*** (0.0000)		−0.3127*** (0.0034)		0.0025 (0.3585)
Loss		0.9456*** (0.0000)		12.263*** (0.0000)		−0.0213 (0.3866)
EarningsVolatility		0.1664*** (0.0000)		0.6687 (0.2197)		−0.0195 (0.1402)
AbnormalAccruals		−0.0132** (0.0451)		−0.2172* (0.0735)		−0.0074*** (0.0099)
InstitutionalOwner		−0.1973*** (0.0035)		−0.8292 (0.4646)		−0.0091 (0.7235)
Big4		0.0718 (0.3860)		0.5162 (0.6909)		0.0428 (0.2284)
NFirm		−0.0474* (0.0600)		−1.0722** (0.0188)		−0.0385*** (0.0065)
NIndus		0.0346 (0.1220)		0.4546 (0.2708)		0.0360*** (0.0073)
FirmExp		0.0065*** (0.0002)		0.0326 (0.4117)		0.0010 (0.3772)
Constant	0.8463*** (0.0000)	−1.2512*** (0.0015)	17.143*** (0.0000)	−130.97*** (0.0000)	−0.0066 (0.7604)	−2.4046*** (0.0000)
Observations	41,863	41,863	41,863	41,863	41,863	41,863
R-squared	0.4883	0.5379	0.4131	0.4742	0.1419	0.2131
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Note(s): This table presents the regression results of the relation between analysts with common foreign surnames and analyst forecast accuracy. p-values (two-tailed) based on robust standard errors clustered by firm and year are reported in parentheses. See Table A2 for variable definitions. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively

4.2 Racial proximity

Prior research suggests that Americans tend to have more unconscious prejudice toward African-Americans. For example, Ginther *et al.* (2011) find that researchers who are African Americans tend to have fewer opportunities to garner research grants from the National Institutes of Health, although they are similarly qualified. In our study, we postulate that managers' unconscious bias in granting information access to analysts with foreign ancestry affects analysts' earnings forecast accuracy. If the alleged unconscious bias does exist, it is likely that such a bias can be observed for African-American analysts. Therefore, we split analysts with common foreign surnames into two groups: African-American analysts (*FA_Africa*) and non-African-American analysts (*FA_NonAfrica*). Results in Panel A of Table 5 show that African-American analysts indeed tend to have greater earnings forecast errors than non-African-American analysts, which is consistent with the notion that managers' unconscious bias towards African-American analysts can lead to analysts' differential information access [17].

4.3 Geographical proximity

Studies suggest that geographical proximity is an important determinant of social distance, which contributes to effective social network building (Breschi & Lissoni, 2006; Maggioni *et al.*, 2007; Boguná, Krioukov, & Claffy, 2009; Skyrms & Pemantle, 2009). Geographical proximity can serve as a proxy for information cost (Jongwanich, 2017, p. 73). In light of this view, to the extent that managers' unconscious bias toward analysts with foreign ancestry varies with the social distance between managers and financial analysts, we posit that when analysts' ancestral countries are geographically far away from the USA, analysts may have greater informational disadvantage. Therefore, we expect to find greater earnings forecast errors among analysts whose ancestral countries are far from the USA.

Using geographical distance data from distancefroto.net, we measure geographical proximity (*FA_Distance*) as the distance (in thousands of kms) between analysts' ancestral countries and the USA (using the capital city as the center point in each). We further classify analysts with foreign ancestry into two groups using the indicator variables *FA_Far* and *FA_Close*. *FA_Far* (*FA_Close*) equals 1 if the distance between an analyst's ancestral country and the USA as measured by *FA_Distance* is above (equal to or below) the sample average and 0 otherwise. Consistent with our prediction that greater geographical distance increases managers' unconscious bias, results reported in Panel B of Table 5 show that *FA_Far* loads positively and significantly, whereas the coefficients on *FA_Close* are not significant in all three columns. As a robustness test, in untabulated analysis, instead of using two indicator variables (*FA_Far* and *FA_Close*), we use the continuous variable (*FA_Distance*) directly and find it loads positively and significantly for all three earnings forecast error measures as well. To the extent that low geographical proximity increases the social distance between analysts with common foreign surnames and executives, this result thus provides supporting evidence that a higher barrier in forming networks between analysts and executives likely explains our result.

4.4 Ancestral proximity between analysts and client firms' CEOs

Byrne (1971) suggests that the more similar two people are, the more likely they are to trust and interact with each other. For example, Brouer, Duke, Treadway, and Ferris (2009) find that line managers tend to give more opportunities and promotion information to employees who are ethnically similar to them than to ethnically dissimilar colleagues. As such, it is plausible that analysts with foreign ancestry are less likely to be affected by a CEO's unconscious bias if the CEO of the firm they follow also shares the same ancestral origin, thereby alleviating the analysts' networking disadvantage and improving their forecast

Table 5. Concentration of analysts with common foreign surnames and earnings forecast accuracy

Panel A: Continuous concentration measure						
Dep. Var	*AbsFError_Avg*		*AbsFError Alt1_Avg*		*AbsFError Alt2_Avg*	
	(1)	(2)	(3)	(4)	(5)	(6)
FARatio_Firm	0.0924* (0.0714)		1.6229** (0.0209)		0.0199 (0.3422)	
FARatio_Indus		1.0188*** (0.0005)		17.2832*** (0.0002)		0.0033 (0.9706)
Horizon	0.6341*** (0.0000)	0.6370*** (0.0000)	9.7135*** (0.0000)	9.7631*** (0.0000)	0.4631*** (0.0000)	0.4631*** (0.0000)
AnalystFollowing	−0.5129*** (0.0000)	−0.5168*** (0.0000)	−7.4971*** (0.0000)	−7.5629*** (0.0000)	0.0178 (0.3558)	0.0182 (0.3178)
FirmSize	0.0258 (0.1752)	0.0286 (0.1859)	4.3346*** (0.0000)	4.3837*** (0.0000)	0.0067 (0.3730)	0.0067 (0.3655)
Book-to-Market	0.8017*** (0.0000)	0.7953*** (0.0000)	6.8162*** (0.0000)	6.7071*** (0.0000)	−0.0689** (0.0287)	−0.0690** (0.0298)
IntangibleAssets	−0.8046*** (0.0000)	−0.8131*** (0.0000)	−14.8999*** (0.0000)	−15.0453*** (0.0000)	0.0431 (0.2483)	0.0425 (0.2757)
StockTurnover	−0.0147 (0.3417)	−0.0144 (0.4138)	2.2142*** (0.0000)	2.2208*** (0.0000)	−0.0002 (0.9736)	−0.0000 (0.9934)
ReturnVolatility	0.0796*** (0.0000)	0.0804*** (0.0000)	0.6931*** (0.0000)	0.7072*** (0.0000)	0.0037* (0.0698)	0.0037* (0.0768)
StockReturn	0.0217** (0.0164)	0.0212** (0.0473)	−0.7138*** (0.0000)	−0.7229*** (0.0000)	0.0028 (0.4096)	0.0028 (0.3925)
Loss	1.5742*** (0.0000)	1.5760*** (0.0000)	13.8408*** (0.0000)	13.8710*** (0.0000)	0.0019 (0.9403)	0.0019 (0.9424)
EarningsVolatility	0.2610*** (0.0000)	0.2616*** (0.0000)	5.9126*** (0.0000)	5.9228*** (0.0000)	0.0008 (0.9307)	0.0009 (0.9232)
AbnormalAccruals	0.0025 (0.7883)	0.0012 (0.8733)	−0.1349 (0.3378)	−0.1566 (0.2411)	−0.0076* (0.0570)	−0.0075** (0.0283)
InstitutionalOwner	−0.6369*** (0.0000)	−0.6327*** (0.0000)	−3.8026*** (0.0001)	−3.7323*** (0.0002)	−0.0008 (0.9735)	−0.0010 (0.9672)
Big4	−0.1012 (0.1675)	−0.0992 (0.2166)	−0.6596 (0.4632)	−0.6242 (0.5359)	0.0010 (0.9740)	0.0011 (0.9734)
NFirm	−0.1602*** (0.0025)	−0.1582*** (0.0038)	−2.4079*** (0.0013)	−2.3737*** (0.0050)	−0.0460** (0.0329)	−0.0461** (0.0324)
NIndus	−0.0101 (0.8053)	−0.0151 (0.7787)	1.0307* (0.0812)	0.9446 (0.2559)	0.0204 (0.2177)	0.0202 (0.2725)
FirmExp	0.0207*** (0.0000)	0.0209*** (0.0001)	−0.1606** (0.0262)	−0.1568* (0.0734)	0.0034* (0.0712)	0.0035* (0.0921)
Constant	−2.0398*** (0.0000)	−2.7196*** (0.0000)	−49.3269*** (0.0000)	−60.8214*** (0.0000)	−2.4306*** (0.0000)	−2.4199*** (0.0000)
Observations	20,227	20,227	20,227	20,227	20,227	20,227
R-squared	0.2685	0.2692	0.2179	0.2087	0.0796	0.0796
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Dichotomous concentration measure						
Dep. Var	*AbsFError_Avg*		*AbsFError Alt1_Avg*		*AbsFError Alt2_Avg*	
	(1)	(2)	(3)	(4)	(5)	(6)
FA_HighFirmRatio	0.0672*(1) (0.0994)		1.2015**(5) (0.0423)		0.0107(9) (0.5050)	
FA_LowFirmRatio	−0.0250(2) (0.6346)		−0.1349(6) (0.8713)		−0.0011(10) (0.9505)	
FA_HighIndRatio		0.1025**(3) (0.0318)		1.1934*(7) (0.0576)		−0.0063(11) (0.7572)
FA_LowIndRatio		−0.0794(4) (0.1175)		−0.5675(8) (0.4632)		−0.0001(12) (0.9973)
Horizon	0.6348*** (0.0000)	0.5946*** (0.0000)	9.7241*** (0.0000)	10.0759*** (0.0000)	0.4632*** (0.0000)	0.4476*** (0.0000)

(*continued*)

Table 5.

Panel B: Dichotomous concentration measure						
Dep. Var	*AbsFError_Avg*		*AbsFError Alt1_Avg*		*AbsFError Alt2_Avg*	
	(1)	(2)	(3)	(4)	(5)	(6)
AnalystFollowing	−0.5065*** (0.0000)	−0.1297 (0.1581)	−7.4058*** (0.0000)	−0.1835 (0.8756)	0.0187 (0.3309)	0.0715** (0.0266)
FirmSize	0.0268 (0.1588)	−0.1637** (0.0280)	4.3508*** (0.0000)	9.4592*** (0.0000)	0.0068 (0.3635)	0.0259 (0.3854)
Book-to-Market	0.8013*** (0.0000)	0.6149*** (0.0000)	6.8099*** (0.0000)	5.0659*** (0.0075)	−0.0690** (0.0286)	−0.0967* (0.0527)
IntangibleAssets	−0.8044*** (0.0000)	−0.7507*** (0.0012)	−14.8981*** (0.0000)	−18.0906*** (0.0000)	0.0429 (0.2498)	0.0370 (0.6815)
StockTurnover	−0.0148 (0.3403)	0.0078 (0.7108)	2.2140*** (0.0000)	2.0374*** (0.0000)	−0.0002 (0.9791)	−0.0037 (0.6945)
ReturnVolatility	0.0796*** (0.0000)	0.0544*** (0.0000)	0.6933*** (0.0000)	0.7912*** (0.0000)	0.0037* (0.0699)	0.0053** (0.0292)
StockReturn	0.0217** (0.0164)	0.0660*** (0.0000)	−0.7137*** (0.0000)	−0.3720*** (0.0007)	0.0028 (0.4090)	0.0046 (0.1998)
Loss	1.5732*** (0.0000)	1.1252*** (0.0000)	13.8290*** (0.0000)	13.5630*** (0.0000)	0.0018 (0.9434)	−0.0091 (0.7824)
EarningsVolatility	0.2614*** (0.0000)	0.1981*** (0.0000)	5.9182*** (0.0000)	0.9261 (0.1338)	0.0009 (0.9234)	−0.0196 (0.2651)
AbnormalAccruals	0.0026 (0.7758)	−0.0186** (0.0205)	−0.1330 (0.3448)	−0.2661** (0.0310)	−0.0076* (0.0581)	−0.0099*** (0.0043)
InstitutionalOwner	−0.6363*** (0.0000)	−0.2664*** (0.0009)	−3.7939*** (0.0001)	−1.3558 (0.2844)	−0.0008 (0.9742)	−0.0224 (0.5114)
Big4	−0.1007 (0.1699)	0.1049 (0.3096)	−0.6498 (0.4699)	1.1348 (0.3942)	0.0011 (0.9709)	0.0771 (0.1195)
NFirm	−0.1605*** (0.0025)	−0.1605*** (0.0035)	−2.4106*** (0.0013)	−2.4101*** (0.0046)	−0.0461** (0.0328)	−0.0460** (0.0325)
NIndus	−0.0094 (0.8188)	−0.0105 (0.8447)	1.0401* (0.0785)	1.0234 (0.2159)	0.0204 (0.2169)	0.0202 (0.2711)
FirmExp	0.0208*** (0.0000)	0.0208*** (0.0001)	−0.1595** (0.0272)	−0.1590* (0.0696)	0.0035* (0.0698)	0.0035* (0.0943)
Constant	−2.0392*** (0.0000)	−2.0010*** (0.0000)	−49.2807*** (0.0000)	−48.7876*** (0.0000)	−2.4266*** (0.0000)	−2.4238*** (0.0000)
Observations	20,227	20,227	20,227	20,227	20,227	20,227
R-squared	0.2685	0.5992	0.2169	0.5551	0.0796	0.3371
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
F test of equality of coefficients						
Test condition	(1) = (2)	(3) = (4)	(5) = (6)	(7) = (8)	(9) = (10)	(11) = (12)
p-value	0.0529*	0.0002***	0.0777*	0.0187**	0.4546	0.7371

Note(s): Panel A presents the regression results examining whether the relation between analysts with common foreign surnames and analyst forecast accuracy varies with the concentration of such analysts in a firm or an industry. In Panel B, *FA_HighFirmRatio* (*FA_LowFirmRatio*) equals 1 if the proportion of analysts with common foreign surnames for a firm is above (equal to or below) the sample mean, and 0 otherwise. Similarly, *FA_HighIndRatio* (*FA_LowIndRatio*) equals 1 if the proportion of analysts with common foreign surnames for an industry is above (equal to or below) the sample mean, and 0 otherwise. In Panels A and B, *NFirm*, *NIndus* and *FirmExp* are the average values based on all sample analysts covering the firm in a given year. All the tests in this table are performed using firm-year observations. In Panel A (B), *p*-values (two-tailed) based on robust standard errors clustered by firm (industry) and year are reported in parentheses. See Table A2 for variable definitions. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively accuracy. To test this conjecture, we apply our method in inferring analysts' countries of ancestry based on their surnames to all of the CEOs' surnames. This allows us to identify the ancestral country of each CEO in our sample.

We then split the analysts with foreign ancestry into three groups based on the ancestral country of the CEOs of the firms they follow: (1) *FA_Non-FACEO = 1/0*, which indicates that an analyst with foreign ancestry is following a firm whose CEO does not have foreign ancestry; (2) *Different_Foreign_Ancestry = 1/0*, which indicates an analyst with foreign ancestry is following a firm whose CEO also has foreign ancestry, but their ancestral countries are different (i.e. although both the analysts and CEO have common foreign surnames, they are not from the same foreign country); and (3) *Same_Foreign_Ancestry = 1/0*, which indicates an analyst with foreign ancestry following a firm whose CEO also shares the same ancestral country (i.e. both the analysts and CEO have common foreign surnames linked to the same foreign country) [18]. Among all these three groups, the networking disadvantage should be greatest (least) for the first (third) group of analysts due to the presumably greater (lower) level of cultural alignment (Brass, Galaskiewicz, Greve, & Tsai, 2004).

We then augment Equation (1) by replacing *Foreign_Ancestry* with these three newly created indicator variables. Table 5 Panel C presents the results, which show that *Same_Foreign_Ancestry* loads significantly negatively across all models. This finding supports our conjecture that analysts with foreign ancestry are less likely to be affected by managers' unconscious bias when they have the same ancestral country as the CEO of the firm they follow. In addition, the coefficient on *Different_Foreign_Ancestry* is insignificant, whereas that on *FA_Non-FACEO* is significantly positive. The insignificant result of *Different_Foreign_Ancestry* is interesting as it suggests that when the CEOs of firms are also with foreign surnames, it creates no differential effect on analysts with or without foreign ancestry, unless the analyst shares the same ancestral origin as that of the CEOs.

4.5 The concentration of analysts with foreign ancestry and firms' information environment

Our findings support the conclusion that financial analysts with foreign ancestry tend to make less accurate earnings forecasts than analysts without foreign ancestry in the USA. Following this finding, we further predict that firms with a greater concentration of analysts with foreign ancestry will generally exhibit weaker information environments (H2a). Following the literature (e.g. Lang, Lins, & Maffett, 2012; Horton, Serafeim, & Serafeim, 2013; Li & Zaiats, 2017), we measure firms' information environment by the average level of analysts' earnings forecast accuracy of all analysts following the firm [19].

To empirically examine this prediction, we create two variables to capture the concentration of analysts with foreign ancestry at both the firm and industry level: *FARatio_Firm* and *FARatio_Indus*, respectively. *FARatio_Firm* (*FARatio_Indus*) is defined as the ratio of the number of analysts with foreign ancestry to the total number of analysts following the same firm (industry). As this test examines the impact of analysts' earnings forecasts on firms' information environment, the unit of analysis is the firm-year. Panel A of Table 5 reports our results. Columns 1, 3 and 5 show the results examining the relationship between the firm-level concentration of analysts with foreign ancestry and the firm-year average analysts' earnings forecast accuracy. Similarly, Columns 2, 4 and 6 show results when the concentration of analysts with foreign ancestry is measured for each two-digit SIC industry. Consistent with the prediction of H2a, we find that firms followed by greater proportions of analysts with foreign ancestry (measured by both firm- and industry-level) tend to have greater earnings forecast errors on average.

As a robustness check, we further use indicator variables to indicate whether a firm or industry has a high proportion of analysts with foreign ancestry following it. *FA_HighFirmRatio* (*FA_LowFirmRatio*) equals 1 if the proportion of analysts with foreign ancestry following a firm is above (equal to or below) the sample mean and 0 otherwise. Similarly, for the industry-level analysis, we use *FA_HighIndRatio* (*FA_LowIndRatio*) to indicate whether the proportion of analysts with foreign ancestry for the industry is above (equal to or below) the sample mean of *FARatio_Indus*. Consistent with Panel A and supporting H2a, Panel B shows that the average analyst earnings forecast errors for a firm is generally higher when the proportion of analysts with foreign ancestry following the firm or the industry to which the firm belongs is greater.

4.6 Robustness tests

4.6.1 Analyst's surname favorability. Using the ancestral countries associated with analysts' surname and the favorability rating toward each foreign country, Jung *et al.* (2019) find that earnings forecast revisions provided by analysts with surnames from more favorable countries are associated with stronger market reactions. To the extent that analysts with foreign ancestry residing in less favorable countries are likely to be affected more by the unconscious bias from managers in granting information access to analysts, country-level favorability can partially contribute to our finding.

To exclude this possibility, we create two dichotomous variables to compare the earnings forecast errors across analysts whose ancestral countries are perceived by Americans as less vs more favorable. Specifically, *FA_MoreFavorable* (*FA_LessFavorable*) is an indicator variable that equals 1 if the perceived favorability of the analysts' ancestral countries is above (equal to or below) the mean favorability of all countries with available data, and zero otherwise [20].

Results reported on Panel D of Table 6 show little evidence suggesting that the country-level favorability matters in explaining our finding. For instance, we find our inference continues to hold for all analysts with common foreign surnames regardless of the favorability of their countries of ancestry. In other words, our results indicate no substantial difference between analysts with foreign surnames linked to countries favored more by US investors and those with foreign surnames linked to countries favored less by US investors. These findings lend strong support to the conjecture that managers' unconscious bias likely can persist for a long period of time and thus it is less likely to be affected by the time-variant perceived favorability of a foreign country [21].

4.6.2 The influence of information costs of analysts. Previous research (e.g. Bae *et al.*, 2008) documents that local analysts make more precise earnings forecasts than foreign analysts who reside outside of the country, suggesting an information advantage of local analysts over foreign analysts. Therefore, a potential concern is that the observed positive relation between analysts' foreign ancestry and their earnings forecast errors may be partially driven by the possibility that some such analysts are actually foreign analysts domiciled in foreign countries (i.e. non-American analysts) who presumably face greater information costs in their earnings forecast exercises. We perform several robustness tests to address this concern.

First, we exclude all firms with securities cross-listed on foreign stock exchanges. Baker, Nofsinger, and Weaver (2002) show that firms cross-listing their stocks on exchanges outside their domestic markets tend to have higher visibility and greater analyst coverage. Thus, excluding firms with cross-listings from our sample reduces the concern that it consists of a large number of firms with foreign analysts. For this purpose, we hand-check all cross-listing activities using the Capital IQ database and identify 3,884 observations associated with cross-listing firms during our sample period. We exclude all of these observations and rerun our regressions. Panel A of Table 7 reports the results. The coefficients on *Foreign_Ancestry* remain quantitatively and qualitatively similar to those in our main results.

Table 6. Additional analyses

Dep. Var	*AbsFError* (1)	*AbsFError Alt1* (2)	*AbsFError Alt2* (3)
Panel A: African-American and non-African-American analysts			
FA_Africa	0.2108**$^{(1)}$ (0.0267)	2.3842***$^{(3)}$ (0.0038)	0.0550***$^{(5)}$ (0.0090)
FA_NonAfrica	0.0659**$^{(2)}$ (0.0327)	1.0951***$^{(4)}$ (0.0046)	0.0179**$^{(6)}$ (0.0430)
Observations	41,863	41,863	41,863
R-squared	0.5380	0.4696	0.4874
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
F test of equality of coefficients			
Test condition	(1) = (2)	(3) = (4)	(5) = (6)
p-value	0.0028***	0.0956*	0.0653**
Panel B: Geographical distance between analysts' ancestral countries and the US			
FA_Far	0.0866*** (0.0001)	1.3767*** (0.0004)	0.0359*** (0.0070)
FA_Close	−0.0252 (0.5132)	−0.4827 (0.4788)	−0.0096 (0.6893)
Observations	41,863	41,863	41,863
R-squared	0.5380	0.4741	0.2131
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Panel C: The proximity between analysts' and CEOs' ancestral countries			
FA_Non-FACEO	0.1318** (0.0186)	3.1644*** (0.0082)	0.0465*** (0.0052)
Different_Foreign _Ancestry	−0.0732 (0.2191)	−1.9196 (0.1482)	−0.0257 (0.1762)
Same_Foreign_Ancestry	−0.1905** (0.0171)	−2.5729** (0.0387)	−0.0832*** (0.0009)
Observations	41,863	41,863	41,863
R-squared	0.5380	0.4744	0.2132
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Panel D: Common foreign surnames and country favorability			
FA_MoreFavourable	0.0676***$^{(1)}$ (0.0098)	1.1219**$^{(3)}$ (0.0161)	0.0293*$^{(5)}$ (0.0682)
FA_LessFavourable	0.1075**$^{(2)}$ (0.0166)	1.3908*$^{(4)}$ (0.0835)	0.0143$^{(6)}$ (0.6044)
Observations	28,658	28,658	28,658
R-squared	0.5506	0.4892	0.2472
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
F test of equality of coefficients			
Test condition	(1) = (2)	(3) = (4)	(5) = (6)
p-value	0.3592	0.7335	0.5855

Note(s): This table presents the regression results of additional analyses partitioning analysts with common foreign surnames based on (1) whether they are African-American analysts (Panel A), (2) whether the geographical distance between the analyst's ancestral country and the USA is high (Panel B), (3) whether the relation between analysts with common foreign surnames and analyst forecast accuracy varies with the CEOs' ancestral countries inferred from their surnames. (Panel C), and (4) whether the lower forecast accuracy by analysts with common foreign surnames is affected by the perceived favorability of the analysts' ancestral countries inferred by their surnames (Panel D)

In Panel A, *FA_Africa* (*FA_NonAfrica*) is an indicator variable that equals 1 if analyst *i* is (not) an African-American, and 0 otherwise

In Panel B, *FA_Far* (*FA_Close*) is an indicator variable that equals 1 if the geographical distance between an analyst's ancestral country and the USA is above (equal to or below) the sample average and 0 otherwise

In Panel C, *FA_Non-FACEO* is an indicator variable that equals 1 if an analyst with a common foreign surname follows a firm whose CEO has a common surname in the USA/Canada, and 0 otherwise. *Same_Foreign_Ancestry* is an indicator variable that equals 1 if an analyst and the CEO of the firm that the analyst follows both have common foreign surnames pointing to the same ancestral country and 0 otherwise. *Different_Foreign_Ancestry* is an indicator variable that equals 1 if an analyst and the CEO of the firm that the analyst follows both have common foreign surnames but their ancestral countries are different and 0 otherwise

In Panel D, *FA_MoreFavorable* (*FA_LessFavorable*) is an indicator variable that equals 1 if the perceived favorability of the analysts' ancestral countries is above (equal to or below) the mean favorability of all countries with available data, and zero otherwise. Number of observations is reduced because only 32 ancestral countries examined in our study have favorability rating. A country's perceived favorability is measured by the average American favorability rating (ranging from 0–100) for a country based on the responses to Gallup surveys regarding the question, "Is your overall opinion of the following country very favorable, mostly favorable, mostly unfavorable, or very unfavorable?"

p-values (two-tailed) based on robust standard errors clustered by firm and year are reported in parentheses. All control variables are included but not reported for brevity. See Table A2 for variable definitions. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively

Dep. Var	*AbsFError* (1)	*AbsFError Alt1* (2)	*AbsFError Alt2* (3)
Panel A: Excluding all firms with cross-listed securities			
Foreign_Ancestry	0.0639*** (0.0049)	1.0431*** (0.0081)	0.0365** (0.0108)
Observations	37,979	37,979	37,979
R-squared	0.5441	0.4744	0.2221
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Panel B: Excluding all firms with foreign institutional ownership			
Foreign_Ancestry	0.1676** (0.0268)	4.5912*** (0.0003)	0.0748 (0.1270)
Observations	6,239	6,239	6,239
R-squared	0.6104	0.5465	0.2624
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Panel C: Excluding all firms with analysts identified as located in foreign locations			
Foreign_Ancestry	0.0765*** (0.0003)	1.2086*** (0.0018)	0.0304** (0.0211)
Observations	41,249	41,249	41,249
R-squared	0.5399	0.4759	0.2159
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Panel D: The influence of power distance			
FA_HighPDI	0.0680**$^{(1)}$ (0.0175)	0.9386*$^{(3)}$ (0.0675)	0.0308*$^{(5)}$ (0.0779)
FA_LowPDI	0.0693***$^{(2)}$ (0.0097)	1.0198** (0.0404)	0.0377**$^{(6)}$ (0.0217)
Observations	31,849	31,849	31,849
R-squared	0.5496	0.4835	0.2378
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
F test of equality of coefficients			
Test condition	(1) = (2)	(3) = (4)	(5) = (6)
p-value	0.9631	0.8792	0.6904
Panel E: The influence of language			
FA_English	0.0649**$^{(1)}$ (0.0366)	1.5414***$^{(3)}$ (0.0065)	0.0196$^{(5)}$ (0.3106)
FA_NonEnglish	0.0774***$^{(2)}$ (0.0004)	1.1027***$^{(4)}$ (0.0050)	0.0339**$^{(6)}$ (0.0127)
Observations	41,863	41,863	41,863
R-squared	0.5379	0.4742	0.2131
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
F test of equality of coefficients			
Test condition	(1) = (2)	(3) = (4)	(5) = (6)
p-value	0.6565	0.3858	0.4184

Note(s): This table presents the regression results of additional robustness tests to address the concern that the observed positive relation between analysts with common foreign surnames and analyst forecast errors may be driven by (1) foreign analysts (Panel A, B and C); (2) whether the cultural distance between the analyst's ancestral country and the USA is high (Panel D), and (3) whether the primary language of the analyst's ancestral countries is English (Panel E). In Panel D, cultural distance is measured by Hofstede's power distance scores. In Panel E, language distance is measured by whether a country's official language is English. p-values (two-tailed) based on robust standard errors clustered by firm and year are reported in parentheses. All control variables are included but not reported for brevity. See Table A2 for variable definitions. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively

Table 7. Additional tests for alternative explanations

Next, we exclude all firms with foreign institutional ownership (FIO), as foreign institutional investors may create demand for foreign analysts to cover the firms in which they invest (Huang & Shiu, 2009). We obtain FIO data from the FactSet database. As most of the firms in our sample have FIO, we are left with only 6,239 observations after excluding the firms with greater than zero FIO. Albeit with a much smaller sample size, we continue to find that analysts with foreign ancestry make greater forecast errors. Panel B of Table 7 shows that the magnitudes of the coefficients on *Foreign_Ancestry* are more than double those in the main tests.

Finally, we directly exclude analysts working outside of the USA from our sample and rerun our analysis. To this end, we identify whether an analyst with foreign ancestry is actually an analyst residing outside of the USA by manually checking their demographic information using Capital IQ. By classifying analysts as those who are residing outside of the USA using the area codes of their phone number (i.e. if the area codes of their telephone numbers do not belong to the USA), we identify 93 such analysts who contribute 398 earnings forecasts to our sample. Our results remain very similar to the main results after excluding these forecasts (Panel C of Table 7).

4.6.3 The influence of power distance. It is possible that other potentially inherited cultural characteristics of analysts with foreign ancestry can also affect analysts' earnings forecast accuracy. For example, it is likely that certain inherited cultural characteristics such as power distance can have an impact on analysts' own incentives to approach managers. In other words, it is conceivable that analysts themselves would find it harder to initiate and maintain constant communication with CEOs if their cultural heritage indicates greater power distance. This conjecture thus suggests an alternative explanation for the greater level of earnings forecast errors associated with financial analysts with common foreign surnames.

To address this concern, we use Hofstede's power distance scores to measure power distance and partition analysts with foreign ancestry into two groups: high (*FA_HighPDI*) and low power distance (*FA_LowPDI*). *FA_HighPDI* (*FA_LowPDI*) is an indicator variable equal to 1 if an analyst's ancestral country is characterized with a greater (lower) level of power distance relative to that in the USA. Results from Panel D of Table 7 show that there is no significant difference in earnings forecast errors between analysts associated with countries with different levels of power distance.

4.6.4 The influence of language. The difference in language can also have a significant impact on analysts' information costs (Reiter, 2021) because analysts with foreign ancestry can differ in their incentives to approach managers because of the difference in their ability to communicate with executives. As a result, we partition analysts with foreign ancestry based on whether English is the primary language (*FA_English*) or not (*FA_NonEnglish*) in their ancestral countries. We do not find a significant difference in earnings forecast errors between these two groups of financial analysts (Panel E of Table 7). In summary, the results indicate that the greater earnings forecast errors of analysts with foreign ancestry are unlikely driven by language-related characteristics of analysts.

4.6.5 The influence of brokerage house. While findings from previous sections lend support to our conjecture that analysts with foreign surnames tend to face a greater level of difficulty in accessing to managements' private information, we acknowledge that it is also possible that analysts' earnings forecast performance varies with analysts' ability to access to the management privately. Research shows that analysts working in different brokerage houses may have different earnings forecasts performance (Hong & Kubik, 2003). Thus, another possible alternative explanation for higher earnings forecast errors of analysts with foreign ancestry is the difference in the brokerage houses that analysts are working for. To rule out this alternative possibility, in an additional test (untabulated), we separate analysts with foreign ancestry into those who are currently working for large vs small brokerage houses (defined using the number of analysts working for a brokerage house). Presumably, analysts working for larger brokerage houses can have greater access to executives of the firms that they are following. Yet, our result indicates that analysts with foreign ancestry tend to have higher earnings forecast errors regardless of the size of their brokerage houses.

4.6.6 Analysts with uncommon surnames in all countries. In our study, we match each analyst's surname with the common surname database (covering 195 countries) we constructed. For analysts with uncommon surnames in any of these countries, we exclude them for better comparison between analysts with common US/Canadian surnames and those with common foreign surnames. In this section, we examine the earnings forecast errors for analysts without common surnames in any of these 195 countries included in the surname database. Specifically, in our model (1), in addition to the variable of interest (*Foreign_Ancestry*), we include another indicator variable, *Unidentifiable_Ancestry* (an indicator variable that equals 1 if the surname of analyst *i* is not a common surname in any of the countries covered in the surname database, and 0 otherwise). As a result of the inclusion of more analysts, we have a much larger sample size for this test.

The untabulated result exhibits a positive and significant coefficient for *Unidentifiable_Ancestry* (with a magnitude of the coefficient similar to the coefficient for *Foreign_Ancestry*), suggesting higher earnings forecast errors for analysts with uncommon surnames as well. More importantly, the significantly positive association between *Foreign_Ancestry* and earnings forecast errors continues to hold. Taken together, this finding suggests that analysts with uncommon surnames likely encounter informational barriers that are similar to analysts with common foreign surnames due to the presence of unconscious bias of the managers.

4.6.7 The influence of analysts' self-selection. A potential concern about our analysis of the influence of analysts' foreign ancestry on firms' information environment is that analysts with foreign ancestry may self-select themselves into certain firms that happen to have weak information environment. To address this concern, we conduct an additional analysis by restricting our sample to firm-years that are covered by both analysts with foreign ancestry and analysts without foreign ancestry. This approach allows us to compare the average earnings forecast errors associated with analysts with foreign ancestry with the average earnings forecast errors associated with analysts without foreign ancestry for the same firm during the same year. For each firm-year observation, we calculate the average earnings forecast errors for analysts with and without foreign ancestry separately. That is, we split each firm-year observation into two firm-year observations, with one for the analysts with foreign ancestry and one without [22]. We then reexamine whether *Foreign_Ancestry* is associated with lower earnings forecast accuracy while keeping firms followed by both types of analysts constant.

Table 8 reports the results. The dependent variable is the average analysts' earnings forecast error for a firm-year associated with either analysts with foreign ancestry or analysts without foreign ancestry. Lending further support to our prediction, we continue to find a significantly positive coefficient on *Foreign_Ancestry* across all three measures of earnings forecast errors. This finding indicates that analysts with foreign ancestry have higher earnings forecast errors on average than analysts without foreign ancestry even when they provide earnings forecasts for the same firm.

5. Conclusion

By inferring analysts' ancestral countries based on their surnames, we examine whether analysts' surnames affect their earnings forecast errors. Using multiple measures of analyst forecast errors, we find strong evidence that relative to analysts with common surnames in America (the USA and Canada), analysts with common foreign surnames tend to provide earnings forecasts with greater forecast errors. The results of various cross-sectional

Table 8.
Difference in earnings forecast errors for the same firm

Dep. Var	*AbsFError_Avg* (1)	*AbsFError Alt1_Avg* (2)	*AbsFError Alt2_Avg* (3)
Foreign_Ancestry	0.0482** (0.0390)	0.7898* (0.0756)	0.0433** (0.0267)
Horizon	−0.1437 (0.2032)	−2.7458 (0.2084)	0.0135 (0.7709)
AnalystFollowing	−0.1745** (0.0414)	9.3975*** (0.0000)	0.0201 (0.5399)
FirmSize	0.4730** (0.0136)	5.4287 (0.1167)	−0.1083* (0.0955)
Book-to-Market	−0.2850 (0.3296)	−17.9018*** (0.0002)	0.1370 (0.2445)
IntangibleAssets	0.0268 (0.4217)	1.3705** (0.0103)	−0.0035 (0.7853)
StockTurnover	0.0385*** (0.0000)	0.7876*** (0.0000)	0.0004 (0.9046)
ReturnVolatility	0.0817*** (0.0000)	0.0753 (0.6890)	0.0056 (0.1960)
StockReturn	0.8025*** (0.0000)	13.2542*** (0.0000)	0.0011 (0.9795)
Loss	0.1703*** (0.0034)	0.9184 (0.3728)	−0.0146 (0.5147)
EarningsVolatility	−0.0041 (0.7175)	−0.0516 (0.8141)	−0.0073* (0.0852)
AbnormalAccruals	−0.1074 (0.3002)	−0.3912 (0.8448)	0.0381 (0.3773)
InstitutionalOwner	0.2349 (0.1753)	2.8831 (0.3382)	0.0831 (0.2314)
Big4	−0.3449 (0.6581)	−109.8446*** (0.0000)	−1.6192*** (0.0000)
NFirm	−0.1437 (0.2032)	−2.7458 (0.2084)	0.0135 (0.7709)
NIndus	−0.1745** (0.0414)	9.3975*** (0.0000)	0.0201 (0.5399)
FirmExp	0.4730** (0.0136)	5.4287 (0.1167)	−0.1083* (0.0955)
Constant	−0.2850 (0.3296)	−17.9018*** (0.0002)	0.1370 (0.2445)
Observations	10,694	10,694	10,694
R-squared	0.6307	0.5507	0.2240
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes

Note(s): This table presents the regression results examining the difference in earnings forecast errors between analysts with common foreign surnames and analysts with common US/Canadian surnames when they cover the same firms. The sample is restricted to firm-years that are covered by both analysts with foreign ancestry and analysts without foreign ancestry. We split each firm-year observation into two firm-year observations, with one for the analysts with foreign ancestry and one without, and then calculate the average earnings forecast errors for the firm-year by each of the two groups of analysts separately. *NFirm*, *NIndus* and *FirmExp* are the average values based on all sample analysts covering the firm in a given year. *p*-values (two-tailed) based on robust standard errors clustered by firm and year are reported in parentheses. See Table A2 for variable definitions. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively

analyses support our conjecture that our finding is likely attributable to the disadvantage of financial analysts with foreign ancestry in establishing social and informational networks with executives in corporate America.

Further supporting our conjecture, we find that the earnings forecast errors of analysts with foreign ancestry tend to increase with the distance in geographical, social, ethnical or racial dimensions between their ancestral country and the USA. In contrast, we find that when analysts' foreign countries of ancestry are aligned with that of the CEOs, analysts exhibit lower earnings forecast errors relative to analysts with common surnames in America. Additional results further show that firms are likely to exhibit greater earnings forecast errors on average when the percentage of analysts with common foreign surnames following the firm or the industry is high. Taken together, our findings suggest that the presence of unconscious bias of managers to financial analysts with foreign ancestry can significantly affect not only analysts' earnings forecast performance but also firms' information environment.

Notes

1. The Securities and Exchange Commission passed Regulation FD in October 2000, with the stated objective of eliminating the practice of selectively disclosing information to preferred analysts and institutional investors.

2. As Page (2009) note, "people are often both unaware of their biases and, more importantly, how their biases affect their decision making."
3. Mayew (2008, p. 629) echoes this view, stating that "it is conceivable that some managers are not intentionally trying to put unfavorable analysts at a competitive disadvantage. Managers might view favorable analysts as having a better understanding of the firm and believe that discussions with such analysts will better communicate the firm's prospects to the market."
4. For example, according to the statistics provided by DataUSA for 2014–2018, more than 73% of financial analysts in the USA are white, with African-Americans and Asians constituting approximately 11% (https://datausa.io/profile/soc/financial-analysts#employment).
5. We use the terms, analysts with foreign ancestry and analysts with common foreign surnames interchangeably in this study.
6. In addition, we control for the perceived favorability of an analyst's ancestral country (Jung *et al.*, 2019) in our examination of the earnings forecast accuracy of analysts with foreign ancestry. This is because as analysts with common surnames from more favorable foreign countries are likely to be more socially accepted, thereby reducing managers' unconscious bias. Our result indicates a greater level of earnings forecast errors for analysts with foreign ancestry regardless of the perceived favorability of their countries.
7. For example, Liu (2016) finds that corporate corruption inferred from insiders' ancestral country is an important factor predicting corporate misconduct. By identifying executives' ethnicities based on their forenames and surnames, Ellahie *et al.* (2017) report an ethnicity effect in CEO variable pay, and Brochet *et al.* (2019) show that managers' ethnicity affects their communication with investors. Kumar *et al.* (2015) find that investors are less likely to invest in mutual funds that are managed by mutual fund managers with foreign-sounding names.
8. According to Brown *et al.* (2015, p. 19), one analyst described the information he/she discussed with managers via private phone call as follows: "It's not nonpublic material information; it's clarification of points. They help you digest the information a little bit better."
9. Indeed, analysts expend significant efforts to obtain such relations. For example, Solomon and Soltes (2015) present survey evidence that 97% of CEOs tend to meet on average 46 times with investors privately, and many of these meetings are arranged by sell-side analysts.
10. Due to concerns surrounding regulatory compliance, the I/B/E/S has stopped disclosing analysts' names in their detailed estimates files since 2008. Our analysts' name data were downloaded beforehand.
11. One caveat of identifying analysts' ancestral country based on their surnames is that female analysts may change their surname after marriage in some of the countries, thereby creating noise in our identification. However, studies suggest that female analysts represent only a relatively small fraction (approximately 12%) of the entire analyst population (Fang & Huang, 2017). Thus, we follow prior surname studies and do not consider this to be a major issue.
12. Forebears collects more than 27 million surnames from 195 countries and lists up to 200 of the most common surnames from each country.
13. Using the first earnings forecast issued by each analyst, or the average of all earnings forecasts does not change our inferences.
14. In all of our regressions, we include firm- and year-fixed effects and cluster the standard errors by firm and year. All of the continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers.
15. Our results are robust to excluding firms from the food industry.
16. For example, Jung *et al.* (2019) find a mean of 1.3% for the same forecast error measure during the sample period of 1996–2014.
17. See *Wall Street is still a "white man's world" with a "veneer of diversity"*: https://www.cnbc.com/2018/03/13/wall-street-diversity-efforts-have-a-long-way-to-go-commentary.html.

18. In this test, the benchmark sample is earnings forecasts by analysts without foreign ancestry (11,250 observations, 26.87%). *FA_Non-FACEO* = 1 accounts for 20,648 observations (49.32%), *Different_Foreign_Ancestry* = 1 accounts for 8,179 observations (19.54%), and *Same_Foreign_Ancestry* = 1 accounts for 1,786 observations (4.27%).

19. For robustness, we also follow prior studies and use several alternative measures of the information environment, such as analyst forecast dispersion (e.g. Li & Zaiats, 2017), analyst coverage (e.g. Lang *et al.*, 2012), and Amihud's (2002) stock illiquidity (e.g. Li & Zaiats, 2017). We find our inferences are unchanged. For brevity, we do not tabulate our results.

20. Following Jung *et al.* (2019), a country's perceived favorability is measured as Americans' attitudes toward other countries using the response to a Gallup survey regarding the question, "Is your overall opinion of the following country very favorable, mostly favorable, mostly unfavorable, or very unfavorable?" We then measure the level of favorability toward an analyst's ancestral country using the favorability score obtained from this survey.

21. As a robustness check, we control for the level of surname favorability of each analyst's country of ancestry in the regression analysis and find our inference remains unchanged.

22. There are 5,347 firm-years that are covered by both analysts with foreign ancestry and analysts without foreign ancestry. Splitting each firm-year into two firm-year observations leads to a sample of 10,694 observations for this analysis.

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Appendix

Table A1. Distribution of analysts with common foreign surnames by country

	Origin country	No. analyst-years	% Of analyst-years	*AbsFError*	*AbsFError Alt1*	*AbsFError Alt2*
1	United Kingdom	4,350	10.39	1.119	0.240	−0.003
2	Ireland	3,826	9.14	1.212	0.222	0.000
3	Germany	3,302	7.89	1.232	0.248	0.028
4	China	1,649	3.94	1.538	0.235	−0.065
5	Italy	1,541	3.68	0.963	0.306	0.051
6	Israel	1,506	3.60	0.938	0.219	0.007
7	India	721	1.72	1.305	0.208	−0.014
8	Switzerland	714	1.71	1.361	0.199	−0.035
9	Tanzania	657	1.57	0.843	0.256	−0.002
10	Austria	653	1.56	0.822	0.194	−0.044
11	Haiti	453	1.08	1.759	0.175	−0.035
12	Papua New Guinea	444	1.06	1.596	0.233	0.039
13	Bangladesh	436	1.04	1.014	0.267	−0.041
14	Mexico	423	1.01	1.101	0.279	0.020
15	France	404	0.97	1.492	0.238	−0.030
16	Denmark	384	0.92	0.901	0.311	0.048
17	Jamaica	375	0.90	1.038	0.251	−0.110
18	Poland	374	0.89	0.834	0.214	0.030
19	Pakistan	360	0.86	1.339	0.234	−0.151
20	Malaysia	322	0.77	1.959	0.273	0.174
21	Turkey	322	0.77	1.632	0.376	−0.033
22	Bahamas	321	0.77	0.865	0.369	0.006
23	Norway	281	0.67	1.547	0.216	0.047
24	Luxembourg	245	0.59	0.638	0.321	−0.082
25	Puerto Rico	237	0.57	1.573	0.198	−0.016
26	Guinea	236	0.56	1.261	0.300	−0.046
27	Netherlands	232	0.55	0.869	0.231	−0.039

(*continued*)

	Origin country	No. analyst-years	% Of analyst-years	*AbsFError*	*AbsFError Alt1*	*AbsFError Alt2*
28	United Arab Emirates	228	0.54	0.956	0.219	−0.019
29	Brazil	195	0.47	1.737	0.183	0.030
30	Hong Kong	193	0.46	1.661	0.232	−0.161
31	Guyana	192	0.46	1.278	0.402	−0.114
32	Argentina	183	0.44	0.803	0.242	0.006
33	Egypt	180	0.43	1.012	0.158	0.029
34	Malta	177	0.42	0.581	0.202	−0.007
35	South Korea	173	0.41	1.455	0.130	−0.107
36	Vietnam	173	0.41	0.968	0.353	0.098
37	Romania	166	0.40	0.317	0.201	−0.045
38	Iran	163	0.39	1.186	0.096	−0.087
39	Philippines	162	0.39	0.727	0.305	−0.010
40	Falkland Islands	158	0.38	1.038	0.133	0.076
41	Nigeria	153	0.37	2.309	0.269	0.216
42	British Virgin Islands	142	0.34	1.821	0.337	0.133
43	Angola	137	0.33	0.723	0.246	0.022
44	Ghana	137	0.33	0.849	0.215	−0.125
45	Myanmar	132	0.32	1.168	0.155	−0.060
46	Venezuela	130	0.31	1.301	0.268	0.066
47	Singapore	121	0.29	2.216	0.142	0.074
48	South Africa	119	0.28	0.896	0.297	−0.032
49	Isle of Man	115	0.27	0.726	0.185	0.026
50	Hungary	112	0.27	2.361	0.105	−0.001
51	Ecuador	110	0.26	1.635	0.354	0.029
52	Dominica	107	0.26	0.902	0.279	−0.012
53	Greece	107	0.26	1.312	0.173	−0.027
54	Belize	105	0.25	0.878	0.226	0.011
55	Bermuda	103	0.25	0.670	0.203	−0.003
56	Australia	101	0.24	1.021	0.152	0.023
57	Iraq	93	0.22	0.548	0.215	−0.130
58	Moldova	92	0.22	0.817	0.145	0.014
59	Macau	90	0.21	2.080	0.184	0.321
60	Somalia	87	0.21	2.039	0.335	−0.007
61	Sweden	87	0.21	1.688	0.273	0.137
62	Finland	86	0.21	1.979	0.327	0.135
63	Zambia	80	0.19	0.858	0.449	−0.088
64	Maldives	71	0.17	2.064	0.138	−0.042
65	Belgium	68	0.16	0.860	0.305	−0.068
66	Samoa	65	0.16	1.994	0.124	0.116
67	Anguilla	62	0.15	1.011	0.632	−0.176
68	Cambodia	60	0.14	1.177	0.185	−0.128
69	Ukraine	57	0.14	1.473	0.187	0.154
70	Liberia	56	0.13	1.077	0.202	−0.073
71	Cayman Islands	44	0.11	0.953	0.096	−0.002
72	Nepal	41	0.10	1.561	0.174	0.099
73	Spain	36	0.09	1.249	0.186	−0.009
74	New Zealand	29	0.07	2.960	0.202	0.047
75	Togo	29	0.07	0.496	0.417	−0.002
76	Trinidad and Tobago	25	0.06	0.368	0.191	0.025
77	Senegal	21	0.05	2.715	0.089	0.355

Table A1.

(*continued*)

	Origin country	No. analyst-years	% Of analyst-years	*AbsFError*	*AbsFError Alt1*	*AbsFError Alt2*
78	Czech Republic	20	0.05	1.070	0.407	0.369
79	Latvia	20	0.05	2.087	0.425	−0.292
80	Slovenia	20	0.05	2.459	0.200	0.439
81	Niger	18	0.04	2.380	0.548	0.223
82	Cameroon	16	0.04	3.728	0.236	−0.036
83	Colombia	15	0.04	0.958	0.159	0.085
84	Ivory Coast	15	0.04	1.892	0.391	0.381
85	Malawi	14	0.03	0.169	0.355	−0.004
86	Estonia	11	0.03	2.338	0.131	0.592
87	Zimbabwe	11	0.03	1.907	0.324	0.907
88	Ethiopia	10	0.02	0.540	0.339	0.263
89	Lesotho	10	0.02	0.273	0.140	−0.015
90	Portugal	10	0.02	0.793	0.081	0.387
91	Guatemala	9	0.02	1.268	0.298	0.529
92	Bulgaria	8	0.02	0.739	0.199	0.121
93	Cyprus	8	0.02	8.339	0.194	1.654
94	Antigua and Barbuda	7	0.02	2.084	0.453	0.226
95	Djibouti	7	0.02	0.604	0.439	0.019
96	Honduras	6	0.01	0.405	0.127	−0.609
97	Costa Rica	5	0.01	5.588	0.137	1.802
98	Cuba	5	0.01	0.985	0.485	0.069
99	Liechtenstein	5	0.01	0.213	0.721	−0.014
100	Bolivia	4	0.01	3.224	0.069	0.905
101	Georgia	4	0.01	1.085	0.244	0.252
102	Kenya	4	0.01	0.327	0.136	0.068
103	Peru	4	0.01	0.366	0.046	−0.904
104	Uzbekistan	4	0.01	1.604	0.018	0.699
105	Algeria	3	0.01	0.084	0.170	−0.033
106	Greenland	3	0.01	0.472	0.035	0.246
107	Lebanon	3	0.01	2.167	0.175	0.258
108	North Korea	3	0.01	0.023	0.133	−0.118
109	Dominican Republic	2	0.00	0.156	0.005	−0.068
110	Mauritania	2	0.00	1.201	0.060	−0.275
111	Russia	2	0.00	0.414	0.095	−0.695
112	South Sudan	2	0.00	1.465	0.075	0.448
113	Indonesia	1	0.00	1.818	0.540	0.000
114	Saint Lucia	1	0.00	0.482	0.160	0.157
	Total	30,613	73.13	1.203	0.240	0.001

Table A1.

Variable	Definition	Data source
Dependent variables		
AbsFError	Scaled absolute forecast error, defined as the absolute value of the difference between the actual annual EPS and the last annual EPS forecast issued by analyst *i* for the firm scaled by the opening share price (in %)	I/B/E/S
AbsFError_Alt1	Unscaled absolute forecast error, defined as the absolute value of the difference between the actual annual EPS and the last annual EPS forecast issued by analyst *i* for the firm. In regression analyses, we further multiply the value by 100 for a better reporting of the estimated coefficients	I/B/E/S
AbsFError_Alt2	Demeaned absolute forecast error, defined as is defined as the absolute price-scaled annual EPS forecast error of an analyst minus the average absolute price-scaled annual EPS forecast error of all of the analysts for the firm (in %)	I/B/E/S
AbsFError_Avg	Average scaled absolute forecast error (*AbsFError*) of either analysts with foreign ancestry or analysts without for the firm-year	I/B/E/S
AbsFError_Alt1_Avg	Average unscaled absolute forecast error (*AbsFError_Alt1*) of either analysts with foreign ancestry or analysts without for the firm-year	I/B/E/S
AbsFError_Alt2_Avg	Average demeaned absolute forecast error (*AbsFError_Alt2*) of either analysts with foreign ancestry or analysts without for the firm-year	I/B/E/S
Variables of interest		
Foreign_Ancestry	An indicator variable that equals 1 if analyst *i* has a common foreign surname, and 0 otherwise	Forebears
FA_Distance	The geographical distance (in thousands of km) between an analyst's ancestral country and the USA	Distancefromto.net
FA_Far (*FA_Close*)	An indicator variable that equals 1 if the geographical distance between an analyst's ancestral country and the USA is above (equal to or below) the sample average and 0 otherwise	Distancefromto.net
FARatio_Firm	The ratio of the number of analysts with foreign ancestry over the total number of analysts following the same firm	I/B/E/S, Forebears
FARatio_Indus	The ratio of the number of analysts with foreign ancestry over the total number of analysts following the same industry defined based on 2-digit SIC	I/B/E/S, Forebears
FA_HighFirmRatio (*FA_LowFirmRatio*)	An indicator variable that equals 1 if the proportion of analysts with foreign ancestry for a firm is above (equal to or below) the sample mean, and 0 otherwise	I/B/E/S, Forebears
FA_HighIndRatio (*FA_LowIndRatio*)	An indicator variable that equals 1 if the proportion of analysts with foreign ancestry for an industry is above (equal to or below) the sample mean, and 0 otherwise	I/B/E/S, Forebears
FA_Non-FACEO	An indicator variable that equals 1 if an analyst with foreign ancestry follows a firm whose CEO does not have foreign ancestry	
FA_Africa (*FA_NonAfrica*)	An indicator variable that equals 1 if analyst *i* is (not) an African-American, and 0 otherwise	

Table A2.
Variable definitions

(*continued*)

Variable	Definition	Data source
FA_HighPD (*FA_LowPDI*)	An indicator variable that equals 1 if the power distance between an analyst's ancestral country and the USA is above the sample average and 0 otherwise. Power distance is measured by Hofstede's power distance scores	I/B/E/S, Forebears Hofstede Centre's website
FA_English (*FA_NonEnglish*)	An indicator variable that equals 1 if the primary language of analyst i's ancestral country is (not) English	I/B/E/S, Forebears CIA Factbook
Same_Foreign_Ancestry	An indicator variable that equals 1 if an analyst and the CEO of the firm that the analyst follows both have the same ancestral country and 0 otherwise	Forebears
Different_Foregin _Ancestry	An indicator variable that equals 1 if an analyst and the CEO of the firm that the analyst follows both have foreign ancestry, but their ancestral countries are different and 0 otherwise	Forebears
FA_MoreFavorable (*FA_LessFavorable*	An indicator variable that equals 1 if the perceived favorability of the analysts' ancestral countries is above (equal to or below) the mean favorability of all countries with available data, and zero otherwise. A country's perceived favorability is measured by the average American favorability rating (ranging from 0 to 100) for a country based on the responses to Gallup surveys regarding the question, "Is your overall opinion of the following country very favorable, mostly favorable, mostly unfavorable, or very unfavorable?"	Gallup
Control variables		
Horizon	The natural logarithm of the number of days between the forecast date and the corresponding earnings announcement date	I/B/E/S
AnalystFollowing	The natural logarithm of the number of analysts following a firm in a given year	I/B/E/S
FirmSize	The natural logarithm of total assets at the end of the year	Compustat
Book-to-Market	The ratio of the book value of equity to the market value of equity at the end of the year	Compustat
IntangibleAssets	The ratio of intangible assets to total assets at the end of the year	Compustat
StockTurnover	The total number of shares traded in a given year divided by the total number of shares outstanding of a firm	Compustat
ReturnVolatility	The standard deviation of a firm's monthly returns for year $t-1$	Compustat
StockReturn	The average monthly stock returns of a firm for year $t-1$	CRSP
Loss	An indicator variable that equals 1 if a firm reports negative earnings in a given year and 0 otherwise	CRSP
EarningsVolatility	The natural logarithm of the time-series standard deviation of annual EPS, calculated using a rolling window of 10 years before a given year	Compustat

(*continued*)

Table A2.

Variable	Definition	Data source
AbnormalAccruals	The level of abnormal accruals estimated using the performance (return on assets) adjusted modified Jones model based on the 3-digit SIC industry classifications. We require at least 10 observations to be available for each industry-year to calculate abnormal accruals	Compustat
InstitutionalOwner	Institutional ownership, measured as the portion of outstanding shares held by institutional investors	Thomson Reuters 13F
Big4	An indicator variable that equals 1 if the firm is audited by a Big 4 auditor in a given year and 0 otherwise	Compustat
NFirm	The natural logarithm of the number of firms that an analyst covers in a given year	I/B/E/S
NIndus	The natural logarithm of the number of industries that an analyst covers in a given year	I/B/E/S
FirmExp	A measure of the firm-specific experience of an analyst, defined as the number of days/360 between an analyst's first forecast for a firm and the analyst's current forecast	I/B/E/S

Table A2.

Table A3.
Top 10 (in descending order) most common surnames of analysts by continent of analysts' countries of ancestry

	US/CA	Africa	Asia	Europe	Other North America (Excl. CA/US)	Oceania	South America
1	Smith	Mohamed	Wang	Müller	Hernandez	Philip	Da Silva
2	Johnson	Ibrahim	Li	Fernandez	Garcia	Steven	Dos Santos
3	Williams	Diallo	Zhang	Ivanova	Martinez	Jack	Pereira
4	Brown	Ouedraogo	Liu	Ivanov	Lopez	Mark	Alves
5	Jones	Abubakar	Chen	Schmidt	Gonzalez	Rowe	Ferreira
6	Miller	Mahamat	Devi	Kuznetsova	Perez	Douglas	De Oliveira
7	Davis	Tesfaye	Yang	Kuznetsov	Rodriguez	Hogan	Silva
8	Wilson	Tadesse	Singh	Smirnova	Sanchez	Tom	Rodrigues
9	Anderson	Abebe	Huang	Schneider	Ramirez	Bourke	De Souza
10	Taylor	Kebede	Wu	Petrov	Cruz	Dwyer	Gomes

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