CULTURAL PROXIMITY AND THE PROCESSING OF FINANCIAL INFORMATION[*]

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Abstract

This paper examines how culture affects information asymmetry in financial markets. We extract firms traded in the U.S. but headquartered in regions sharing Chinese culture ("Chinese firms"), and manually identify a group of U.S. analysts of Chinese ethnic origin ("Chinese analysts"). We find that Chinese analysts issue more accurate forecasts on Chinese firms than non-Chinese analysts. The effect is stronger among firms with less transparent information environments. Further evidence suggests that cultural proximity can go beyond language commonality and analysts' pre-existing channels for information. Market reaction is stronger when Chinese analysts issue favorable forecast revisions or upgrades about Chinese firms.

Keywords: Culture, Forecast Accuracy, Information Asymmetry, Demographic Economics, Financial Analysts
JEL: G14; G24; F65; J15; J24

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Culture must be one of the foundations for world understanding.

Albert Einstein

1. INTRODUCTION

An emerging literature has documented the significant impact of culture on various economic exchanges and financial outcomes. Cultural distance between countries affects stock market participation (Guiso, Sapienza and Zingales 2008), trade and investment flows (Guiso, Sapienza and Zingales 2009), returns of momentum strategies (Chui, Titman and Wei 2010), cross-border mergers (Ahern, Daminelli and Fracassi 2012), and credit allocations (Fisman, Paravisini and Vig 2012; Giannetti and Yafeh 2012). However, there is little direct evidence in finance on channels through which culture affects interactions between economic agents.

In this paper we explore to what extent culture affects information asymmetry in the financial markets. To emphasize the cultural traits inherited at the individual level, we use ethnicity as a proxy for culture, which can be treated largely as invariant over an individual's life (Guiso, Sapienza and Zingales 2006). We focus on financial analysts, a key participant of financial markets specializing in producing and disseminating firm-specific information. Specifically, we examine the effect of analysts' ethnicity on forecast accuracy regarding the earnings prospects of firms that share the same cultural background.

Whether and how cultural proximity affects analysts' information generation and dissemination can be ambiguous *ex ante*. On the one hand, when foreign firms attempt to access U.S. financial markets, highly skilled immigrants or descendants of recent immigrants, such as those employed as financial analysts, likely have several attributes that help alleviate information asymmetry experienced by firms from their home country. Native language skills may allow immigrants to access firm-specific information quickly. Even if all the foreign firms listed in the

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U.S. are required to publicly disclose information in English, immigrants with the same cultural origin can better interpret the information by "reading between the lines". Well-educated immigrants may possess specialized knowledge and channels to access information about how business is conducted in their home countries. They understand the institutional characteristics and norms of U.S. financial markets better, and can communicate more effectively to investors.

On the other hand, cultural proximity may degrade forecast accuracy, even if forecasts are issued by the immigrants who are perceived as insiders or experts about firms from their home countries. Kahneman and Lovallo (1993) show that an insider focuses more on knowledge about specific cases and is more likely to fall prey to "representativeness heuristic" (Kahneman, Slovic and Tversky 1982), while an outsider is more inclined to take a statistical and comparative view. As a result, an insider tends to produce overly optimistic forecasts. Tetlock (2005) demonstrates that experts performed no better than non-experts when predicting political and economic trends, and in particular, are more likely to be over-confident with their predictions. So it is possible that cultural proximity leads to more optimistic and overconfident predictions, rather than more accurate ones.

To explore the effect of cultural proximity on financial information precision, we design our research around a sample of U.S. analysts that are Chinese immigrants or descendants of recent immigrants, and a sample of firms that are from regions sharing a Chinese culture but are publicly traded in the U.S.—whose culture differs distinctly from that of their home countries. We collect information on 9,788 U.S.-based analysts that provided coverage from 1990 to 2010 on 9,332 U.S. listed firms. Among these firms, 9,137 are headquartered in the U.S. and 195 are headquartered in the "pan-Chinese region", which includes mainland China, Hong Kong, Taiwan,

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and Singapore. We manually screen the 9,788 analysts and identify 333 of them as ethnic Chinese.

To mitigate the concern that different types of firms might attract certain types of analysts, we use a matched sample approach and restrict our sample to the Chinese firms and U.S. firms if they are covered by both Chinese analysts and non-Chinese analysts in a given year. We find that analysts of Chinese ethnicity issue more precise earnings forecasts for firms from the pan-Chinese region than analysts of other ethnicities. When covering Chinese firms, Chinese analysts have an average reduction of forecast errors by about 1/3 of the sample mean, compared to non-Chinese analysts.

To further explore the effect of culture on mitigating information asymmetry, we examine whether a shared cultural background matters more among firms with opaque information environments. The reduction in forecast inaccuracy arising from cultural proximity is indeed more pronounced for firms with weak corporate transparency; that is, firms with high financial reporting opacity (Hutton, Marcus, and Tehranian 2009), with poor readability of annual reports (Li 2008), listed on the OTC market instead of the big three stock exchanges, or with low institutional ownership.

Existing literature identifies that analysts' superior access to the management of firms under their coverage can affect their forecast accuracy. In this respect, we postulate that cultural proximity contributes to the formation of an analyst's social network and communication channels for private information. Nevertheless, superior access to the management may come from sources that are unrelated to culture. In one extension, we restrict our analysis to the period after the implementation of Regulation Fair Disclosure (Reg FD). By prohibiting publicly traded companies to selectively disclose information to certain financial market participants, Reg FD

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has largely eliminated the benefits of private access to management (Koch, Lefanowicz and Robinson 2013). Our findings prevail during the post-Reg FD period.

In addition to regulatory events, we explore firm-specific events such as CEO turnovers that sever the pre-existing ties between analysts and top management. If the superior forecast accuracy arises solely from analysts' prior connections to the CEOs of the Chinese firms, their information advantage, and thus forecast accuracy, should decline once the current management is replaced. Instead, there are no significant changes in forecast accuracy of Chinese analysts surrounding CEO turnovers of Chinese firms. These tests suggest that our results are not driven by any analyst's superior access to management for firm-specific private information, independent of his/her cultural background.

Investors appear to value cultural proximity and recognize the impact of culture on analysts' information advantage. We find that market reaction is stronger when analysts of Chinese ethnicity revise their forecasts upward or upgrade their recommendations for firms from the pan-Chinese region. This suggests that investors believe that Chinese analysts are more informative about Chinese firms than non-Chinese analysts.

Lastly, we recognize that being able to speak the same language may allow analysts to extract more information. Nevertheless, researchers have shown that even with the same information set in the same language, people from different cultures perform differently in cognitive tasks (see Nisbett and Norenzayan 2002 for a review). To check how our results interact with language commonality, we compare between firms from Hong Kong and Singapore where English is the official language, and firms from mainland China and Taiwan, which use Chinese as the official language and face a greater language barrier when communicating to U.S. analysts and investors. Thus, the language advantage of Chinese analysts should be more

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prominent for Chinese-speaking firms. Instead, we find that among firms from the pan-Chinese region, Chinese analysts covering Chinese-speaking firms do not significantly outperform those covering English-speaking firms. This indicates that language alone does not account for our findings, and that cultural proximity can go beyond language commonality.

The potential endogenous matching between analysts and firms is less likely to be a major concern in our setting. We first show that the U.S.-based brokerage firms which cover more foreign firms from the pan-Chinese region do not necessarily employ more analysts with Chinese ethnic background. Given the scarcity of highly skilled immigrants capable of generating information and communicating it across different cultures, not all brokerage firms that would like to hire analysts with such characteristics are able to do so. Conversely, as discussed in Section 3, firms from the pan-Chinese region seek public listing in the U.S. in order to raise capital. The timing and location of their listings are not driven by the desire to secure coverage from analysts of the same cultural origin. In various specifications, we further control for forecast quarter fixed effects, industry fixed effects, broker fixed effects, firm fixed effects, as well as firm-specific and analyst-specific characteristics.

The rest of the paper is organized as follows. Section 2 discusses related literature. Sections 3 and 4 describe our research setting, data sources and sample construction. Sections 5 through 9 present the empirical results. Section 10 concludes the paper. Variable definitions and constructions are in Appendix B. Additional tests are tabulated in the Internet Appendix.

2. RELATED LITERATURE

This paper contributes to the emerging literature exploring the effect of culture on economic outcomes (see, e.g., Guiso, Sapienza and Zingales 2006, for a survey). Most of these

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papers are based on country-level surveys that target all the citizens. By contrast, we study the effect of culture at the firm/individual level and focus exclusively on key participants in the financial markets. In this respect, our paper is related to Fisman, Paravisini and Vig (2012) and Giannetti and Yafeh (2012), who find that the cultural proximity between lenders and borrowers improves credit allocation and loan pricing; to Fisman, Hamao and Wang (2014), who find that cultural aversion affects stock returns; and to Guiso, Sapienza and Zingales (2008), who find individuals' trust affects households' stock market participation. Instead, we explore a specific channel—firm-specific financial information production and dissemination—through which culture may affect economic exchanges.

Our paper is also related to the literature examining information advantage arising from geographic proximity. For instance, researchers have documented the information advantage of local mutual fund managers (Coval and Moskowitz 2001), retail investors (Ivković and Weisbenner 2005), analysts (Malloy 2005; Bae, Stulz and Tan 2008), and commercial and investment banks (Bulter 2008; Agarwal and Hauswald 2010). Monitoring is more effective among local regulators (Kedia and Rajgopal 2011) and institutional investors (Ayers, Ramalingegowda and Yeung 2011). By focusing on firms that are traded in the U.S. and covered by analysts based in the U.S., geographic distance between analysts and such firms is mostly similar regardless of analysts' ethnic background. By contrast, cultural distance is significant between China, an archetypical Eastern culture, and the U.S., a modern Western one. Our research setting thus allows us to focus on an information advantage arising from cultural proximity rather than from geographic proximity.

Lastly, our paper is related to the literature documenting the effect of an individual's social network on decision-making process and the scope of information set (e.g., Cohen,

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Frazzini and Malloy 2008, 2010). More recently, researchers argue that social network itself is endogenous and that cultural proximity contributes to the formation of social ties and network (e.g., Pachucki and Breiger 2010). In this respect, we postulate that cultural proximity helps form an analyst's social network, and highlight culture as an important factor contributing to how an individual's information set is shaped and evolves.

In what follows, we label a U.S. analyst of Chinese ethnic origin as a "Chinese analyst" and a U.S. analyst of another ethnic origin as a "non-Chinese analyst". We label a firm as a "Chinese firm" if it is publicly traded in the U.S. but is headquartered in the pan-Chinese region.

3. RESEARCH DESIGN

3.1 China and U.S. as a Research Setting

China as a research setting offers several unique advantages. First, there are significantly distinct and well-recognized differences between China and the Western world in key aspects of culture, such as language, preferences, beliefs, virtue, and religion. Since the culture of the headquarters' country affects organizational culture (Greif 1994; Bloom, Sadun and van Reenen 2012), these cultural dissimilarities are ideal for our purpose (as in an economic experiment) when examining the impact of culture on information production and communication surrounding Chinese firms listed in the U.S. Second, as discussed in Section 3.2 below, the nature of the Chinese culture allows us to identify the ethnic origin of an individual by surname with significantly less ambiguity relatively to other cultural groups. Third, the influence of Chinese culture spreads historically (and thus exogenously in our current time) beyond China. As discussed later in Section 9, this provides a setting that allows us to explore to what extent cultural proximity affects information precision beyond language commonality.

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China also provides a unique environment to address the potential selection issues associated with analyst coverage. China is the largest emerging market and has experienced spectacular economic growth since the late 1970s, when it initiated an overhaul of its economic system. The long-lasting high growth and sharp rise in entrepreneurial activities have created a large demand for capital in a capital market where the supply of funds has been confined by the under-development of domestic stock market, the regulated and constrained going-public activities, the lack of active participation by foreign investors due to the government's capital and currency controls, and an ineffectively run banking system (Chang et al., 2014). Many Chinese firms are forced to seek financing outside mainland China, from foreign markets that often do not share the same cultural and institutional environment. Consequently, the purpose, timing, and location of international listing by Chinese firms are driven by their desire to raise capital, instead of the need to secure coverage by analysts of the same cultural origin.

Furthermore, the cultural distance between China and Western countries limits the supply of highly skilled knowledge workers who are capable of both understanding and effectively communicating between the two distinctly different cultural environments. Since individuals with such ability are scarce, not all brokerage firms with a similarly high demand for Chinese analysts are able to attract them in order to cover Chinese firms.

The United States, as part of the research setting, also offers unique advantages. It is the largest immigrant country in the world, with immigrants coming from various countries and ethnicities, including a significant portion of Chinese immigrants. These Chinese immigrants may later become financial analysts hired by brokerage firms operating in the U.S., and provide coverage on Chinese firms listed in the U.S. With non-Chinese analysts coming from various ethnic origins, the comparison of forecast precision between Chinese and non-Chinese analysts is

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not driven by the cultural difference between China and a specific ethnic group. More importantly, the United States is the largest and most free capital market. With a very few exceptions, any foreign firms can raise capital from this market as long as they meet the listing requirements. Unlike some well-developed financial markets such as Japan and the United Kingdom, the listing standards and policies in the U.S. do not discriminate significantly between domestic firms and foreign firms.

To focus on information precision arising from cultural proximity rather than from geographic proximity, we focus exclusively on analysts affiliated with brokerage firms operating in the U.S., who provide research coverage on companies traded in the U.S. and who communicate with the U.S. clients of their brokerage firms. Since these analysts are based in the U.S., the geographic distance between analysts and any given firm is relatively similar regardless of analysts' ethnic background.[2]

3.2 Measuring Cultural Proximity and Information Precision

Guiso, Sapienza and Zingales (2006) define culture as "those customary beliefs and values that ethnic, religious, and social groups transmit fairly unchanged from generation to generation." They emphasize key cultural aspects such as "religion and ethnic background that largely can be treated as invariant over an individual's lifetime." Bisin and Verdier (2000) highlight the dynamics of the distribution of ethnic and religious traits which converges to a culturally heterogeneous stationary population. In this paper, our proxy for culture is ethnicity. Individuals belonging to an ethnic group are often identified through a common trait, which can, but does not have to, include an idea of common heritage, a common culture, and a shared

[2] In practice, investment banking and analyst coverage are highly segmented. U.S.-based analysts cover firms traded in the U.S., whereas analysts residing in foreign countries tend to cover local firms. The time zone difference also makes it unlikely for analysts based in the pan-Chinese region to consistently cover firms traded in the U.S.

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language or dialect. The group's ethos or ideology may also stress common ancestry and religion, as opposed to an ethnic minority group which refers to race.

We identify the Chinese ethnic origin of a U.S. analyst based on surname.[3] The unique nature of Chinese culture allows such an identification process to be less noisy compared with other ethnic origins. First, the distribution of Chinese surnames is highly skewed. The 100 most common surnames, which together account for less than 5% of Chinese family names, are shared by over 85% of the population. Second, a great majority of commonly occurring Chinese surnames contain one character and pronounce with one syllable. While about twenty double-character surnames also exist, they are far less common and are easy to recognize for their Chinese origin. Lastly, surnames are usually not changed upon marriage in modern times. Even in places with a Western influence such as Hong Kong, women may adopt their spouse's surname but continue to reserve her own. The surname change due to marriage is especially rare among women pursuing a professional career, such as financial analysts.

Our primary measure for information precision is the analyst forecast error, calculated as the absolute value of the difference between forecasted and actual earnings, scaled by the average share price in the previous year. We also used the score measure developed by Hong and Kubik (2003) as an alternative way to measure forecast precision. Our main results are not affected by the choice of precision measure.

4. DATA SOURCES AND SAMPLE CONSTRUCTION

4.1 Identifying the Chinese Ethnicity of U.S. Analysts

[3] See also Fisman, Paravisini and Vig (2012) and Iyer and Puri (2012) for discussions on using surnames to identify ethnic groups in India.

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We compile a sample of firms under analyst coverage between 1990 and 2010 from the Institutional Brokers' Estimate System (I/B/E/S) database. Analyst coverage is based on the availability of quarterly earnings per share (EPS) estimates, which is the most common estimate provided by analysts. Following our research design, we restrict to firms headquartered either in the U.S. or in the pan-Chinese region, and traded on stock exchanges in the U.S., whose quarterly earnings forecasts are issued by sell-side analysts based in the U.S.

To identify U.S.-based analysts, we manually verify whether a brokerage firm has a branch or is headquartered in the U.S. through I/B/E/S, its own websites and internet searches. An analyst is U.S.-based if he or she is affiliated with the domestic branch of a U.S brokerage firm or with the U.S. branch of a foreign brokerage firm.

Since our research setting involves individual analysts' ethnic backgrounds, we next exclude earnings forecasts issued by analyst groups, whose performance cannot be evaluated individually. In order to compare forecast accuracy among analysts, we require at least two analysts issuing forecasts for a given firm in a given quarter. We focus on the last forecast issued by the analyst before the earnings announcement made by the firm.[4] This filtering process yields a total of 9,332 firms traded at U.S. stock exchanges, with 1,651,985 quarterly forecasts issued by 9,788 analysts that are affiliated with 588 brokerage firms.

Among the 9,332 firms, 9,137 are headquartered in the U.S., and 195 are headquartered in the pan-Chinese region.[5] We collect headquarter information from Compustat, and manually verify through internet searches that the 195 firms are indeed headquartered in the pan-Chinese

[4] Similar results are obtained if the first forecast of an analyst is used.

[5] Our Chinese firm sample size differs from the number of Chinese firms listed in the U.S., as our sample filtering criteria require each firm from the pan-Chinese region to be both publicly listed in the U.S. and covered by at least two analysts based in the U.S.

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region, regardless in which countries they are registered. Among these firms, 156 are from mainland China, 17 from Hong Kong, 11 from Singapore, and 11 from Taiwan.

For each individual analyst, I/B/E/S provides information on surname, the initial of the first name, and the affiliated brokerage firm(s). The 9,788 analysts are associated with 6,241 unique surnames. We first screen each of the 6,241 surnames for potential Chinese ethnic origin by manually searching the following websites: www.houseofnames.com, www.ancestry.com, www.behindthename.com, and www.wikipedia.org. This process yields 77 unique surnames as possibly of Chinese ethnic origin. Second, we screen each last name based on its pronunciation. A surname is defined as of Chinese origin if it contains one syllable.[6] This approach generates 253 unique surnames for potential Chinese origin.

We then manually check for consistency for surnames identified by the above two classification approaches. In case there is a discrepancy between the two, we check the geographical distribution of people with such a surname by searching www.lastnames.myheritage.cn, the Chinese branch of www.myheritage.com, a renowned genealogy website. With currently 864 million users worldwide, the website allows users to discover their heritage and build family trees. Specifically, we classify a surname of Chinese origin if a significant fraction of people with such a surname reside in mainland China, Hong Kong, Taiwan, or Singapore. We exclude surnames that are ambiguous in terms of Chinese origin if this heritage site cannot help remove the ambiguity.

[6] Potential misclassification arises from the first approach when a commonly used Chinese surname is classified by these websites as of a non-Chinese origin. The second approach allows a common surname among multiple ethnicities. While a common surname does carry common cultural heritage, to ensure the conservativeness of our analysis we exclude these that are associated with multiple ethnical groups or whose ethnicity cannot be identified (for example, surnames such as Lee and Park).

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Out of the 9,788 U.S.-based analysts, we identify 333 analysts with 129 unique Chinese surnames. These analysts are affiliated with 148 brokerage firms. In Appendix A, we provide a list of Chinese surnames and describe the distribution of analysts with Chinese surnames.

As Table A1 of the Internet Appendix reveals, it is possible that Chinese firms and U.S. firms listed on U.S. exchanges are very different and may not be readily comparable. To account for the concern that different types of firms might attract different types of analysts, we construct a matched sample to conduct our main tests instead of using the full sample of forecasts for all the U.S. firms and Chinese firms covered by all of the U.S.-based analysts.[7] Specifically, we restrict our sample to the Chinese firms and U.S. firms if they are covered by both Chinese analysts and non-Chinese analysts in a year. For each Chinese firm in a given year, we screen for U.S. firms operating within the same industry (measured by the one-digit SIC code), sharing the same CRSP share type code, and having the same size coverage (measured by the number of analysts in terciles). If multiple U.S. candidates are available, we select the one with the closest size coverage or market-to-book ratio, in order to find a U.S. firm as similar as possible to its Chinese counterpart. As a result, each Chinese firm-year observation is matched to a unique US firm-year observation.

4.2 Descriptive Statistics

Table 1 presents the descriptive statistics of analysts and sample firms based on the matched sample. There are a total of 560 unique analysts — with 98 being ethnic Chinese analysts. There are 1,040 forecasts issued by Chinese analysts and 2,490 forecasts issued by non-Chinese analysts. After the matching, there are no significant differences in forecasting experience regarding Chinese firms and forecast errors between Chinese analysts and non-Chinese analysts.

[7] We thank our referee for the suggestion on using matched sample as the basis of analysis.

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The matched sample includes 115 unique firms with 46 being headquartered in the pan-Chinese region. After the matching, there is no significant difference in the number of forecasts received by firms and forecast errors between Chinese firms and U.S. firms, except that the analysts covering Chinese firms have significantly more experience with forecasting earnings of Chinese firms.

In the Internet Appendix, we present the descriptive statistics of analysts and firms for the full sample. When comparing analyst characteristics, Chinese analysts on average cover significantly fewer firms and issue fewer forecasts than non-Chinese analysts. They are also less experienced and less accurate in their forecasts than non-Chinese analysts. When comparing firm characteristics, U. S. firms on average receive more analyst coverage than Chinese firms. The forecast errors regarding Chinese firms are significantly larger than with those regarding U.S. firms. Chinese firms are on average smaller (in terms of assets and market capitalization) and have lower leverage than U.S. firms. Furthermore, there is evidence that brokerage firms, especially the large ones, do not purposely employ Chinese analysts to exclusively cover Chinese firms. Even if a similar brokerage firm wishes to hire such analysts, it might be not be able to do so due to the limited supply. This suggests that endogenous matching between Chinese analysts and Chinese firms traded in the U.S. is less a concern in our setting.

5. CULTURAL PROXIMITY AND FORECAST ACCURACY

In this section, we examine the impact of common cultural background on information precision in the context of forecast accuracy. Table 2 reports the regression results. The unit of analysis is analyst-firm-quarter observation. Robust standard errors are double clustered at the firm and analyst level and reported in parentheses. In column 1, we regress forecast error on

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"Chinese Analyst", a dummy variable that takes value of one if the forecast for a given firm in a given quarter is issued by a Chinese analyst, and zero if it is issued by a non-Chinese analyst; "Chinese Firm", a dummy that takes a value of one if a quarterly forecast is issued by an analyst for a firm from the pan-Chinese region, and zero for a U.S. firm; and the interaction term between the two: "Chinese Firm" × "Chinese Analyst". In addition, we include quarter fixed effects to absorb effects from time-varying trend and industry fixed effects to account for unobserved time-invariant industrial characteristics that might affect forecast accuracy. Industry classification is based on the two-digit SIC codes.

Column 1 reveals that the coefficient for the interaction term is negative and significant at the 1% level. This suggests that an earnings forecast for a Chinese firm is more accurate if it is issued by a Chinese analyst than by a non-Chinese analyst. By contrast, none of the dummies for "Chinese Analyst" and "Chinese Firm" is significant, indicating that for non-Chinese firms, forecasts issued by Chinese analysts are not significantly different from non-Chinese analysts.

In column 2, we further control for a set of analyst characteristics that potentially explain forecast accuracy. We include an analyst's experience of covering Chinese firms, which is measured by the natural logarithm of one plus the number of months between the first month when an analyst initiates coverage of any Chinese firm in I/B/E/S and current month when a forecast is issued. We also include forecast horizon, size of coverage, and number of revisions. In column 3, we add firm-specific characteristics that can affect analyst forecast accuracy (Hope 2003): firm size, earnings changes, and leverage. We compute firm size as the natural logarithm of total assets, earnings change as the absolute value of the change in earnings from the previous quarter, scaled by the realized earnings of the previous quarter, and leverage as the total liabilities divided by total assets. In column 4, we control additionally brokerage fixed effects.

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We continue to observe that Chinese analysts outperform non-Chinese analysts when forecasting earnings of Chinese firms, as the interaction term “Chinese Firm” × “Chinese Analyst” remains negative, and is statistically significant at the 1% and 5% levels, respectively.

The effect of culture proximity is not only statistically significant, but also economically sizable. For instance, the coefficient for the interaction term in column 4 suggests that when covering Chinese firms, forecast errors from Chinese analysts are on average 0.26 smaller than for non-Chinese analysts; this is equivalent to about 1/3 of the mean forecast errors of the matched sample.

Lastly, as a sensitivity test, we replace the dummy for Chinese firm with firm fixed effects in column 5. The interaction term between the dummy for Chinese firm and the dummy for Chinese analyst remains negative and is significant at the 10% level. It suggests that, among all the earnings forecasts issued for the same firm, those from Chinese analysts are more precise than those originating from non-Chinese analysts.

6. INFORMATION ENVIRONMENT AND THE EFFECT OF CULTURAL PROXIMITY

We now further explore the impact of a shared cultural background in mitigating information asymmetry. Specifically, we examine how the effect of cultural proximity varies among firms with different information environments and poise that the effect should be more prominent for less transparent firms. We employ two groups of proxies to assess a firm’s information environment: financial-statement-based and capital-market-based proxies.

6.1 Financial-statement-based Proxies

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We start with financial-statement-based proxies, which capture the transparency of a firm's financial statements. First, we split the sample based on the opacity of a firm's financial reports, derived from an indicator of earnings management and developed by Hutton, Marcus, and Tehranian (2009). This indicator is computed as a firm's prior three year moving sum of the absolute value of discretionary accruals. The intuition is that firms are more likely to be managing earnings if they have consistently large absolute values of discretionary accruals—a common proxy for earnings management (e.g., Dechow, Sloan, and Sweeney 1996). Consequently, less firm-specific information is revealed to investors. A higher value of this opacity measure thus indicates a less transparent information environment. A firm is classified as having a less (more) opaque information environment if its opacity level is below (above) the median of the Chinese firms. We expect the impact of cultural proximity to be more pronounced for firms that are more informationally opaque.

Alternatively, we divide our sample based on a firm's disclosure quality—i.e., the readability of its financial report. An emerging accounting literature has used measures that capture the narrative quality of texts in annual reports, such as the Fog index (Li, 2008). Developed from the computational linguistics literature, a fog index is higher if an annual report is "foggier"—i.e., if it is more difficult and complicated to read. Less readable annual reports thus increase the information-processing costs and possess a lower quality of disclosure. We classify a firm as having more (less) foggy financial reports if its Fog index is above (below) the median Fog level of Chinese firms. Again, we expect the impact of cultural proximity to be more pronounced for firms with more "foggy" annual reports.

We re-estimate our baseline regression in Table 2 column 4 for these four sets of subsamples and report the results in columns 1 through 4 of Table 3. The coefficients for

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"Chinese Analyst" × "Chinese Firm" are negative and significant for firms with more earnings management (column 1) or more foggy financial reports (column 3) but are insignificant for those with less earnings management (column 2) or less foggy financial reports (column 4).

6.2 Capital-market-based Proxies

Our second set of proxies for a firm's information environment is capital-market-based. First, we take advantage of the differences in listing and disclosure standards across stock exchanges, and compare firms listed on the major stock exchanges (i.e., NYSE, NASDAQ, or AMEX) with firms listed on the OTC market. We expect that the effect of cultural proximity is more pronounced for firms listed on the OTC, which imposes less stringent disclosure requirements than the major stock exchanges.

Next, a large literature has established that the presence of institutional investors contributes to a more transparent information environment (e.g., El-Gazzar 1998, Jiambalvo, Rajgopal, and Venkatacklana 2002, Amihud and Li, 2006, and Boehmer and Kelley 2009). We collect the institutional ownership data from the Thomson Financials Spectrum database, and compute a firm's quarterly institutional holding as the number of shares held by all institutional investors scaled by the total number of shares outstanding. In the same spirit of Hutton, Marcus, and Tehranian (2009), we classify a firm as having higher (lower) institutional ownership if its institutional holding averaged over the previous three years (i.e. 12 quarters) is above (below) the sample median of Chinese firms.[8]

We repeat our baseline regression in Table 2 column 4 for these four sets of subsamples and report the results in columns (5)-(8) of Table 3. While the coefficient associated with "Chinese Analyst" × "Chinese Firm" is negative and significant for both the OTC (column 5)

[8] If no institutional ownership information is available, we treat the value of the observation as missing. Alternatively, we replace missing institutional ownership with zero. Our findings are robust.

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and NYSE/AMEX/NASDAQ subsamples (column 6), it is economically larger for the OTC firms: a shared cultural background allows a Chinese analyst to trim his/her forecast error regarding a Chinese firm by 1.11 if it is listed on the OTC, nearly 4 times bigger than the 0.26 reduction if it is listed on one of the big three stock exchanges. Furthermore, columns 7 and 8 reveal that the coefficient for "Chinese Analyst" × "Chinese Firm" is negative and significant only for firms with low institutional holdings. For the firms with high institutional ownership, the estimate is negative but statistically insignificant.

The evidence suggests that the effect of cultural proximity does vary among firms with differing degrees of information asymmetry. The reduction in forecast errors due to a shared cultural background is most prominent among firms with a more opaque information environment and weak corporate transparency. These findings shed light on culture as a potential mechanism to help mitigate information asymmetry that adversely affects foreign firms, especially those from emerging markets.

7. SUPERIOR ACCESS TO MANAGEMENT

One common explanation for analysts' forecast skills is their superior access to the management of firms under their coverage. In reality, analysts both emphasize and pledge significant resources to achieve interactions with firm managements, such as private meetings with the management, visits to firm's headquarters, and broker-hosted conferences (Green et al. 2014; Solomon and Soltes 2015). In particular, Green et al. (2014) provide direct evidence that access to management constitutes a crucial source of analysts' information advantage.

It is possible that Chinese analysts' superior forecast precision on Chinese firms comes from their unique access to management and thus private information of these firms. Existing

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literature has shown that an individual's social networks, through professional and personal background similarities such as family, school ties, and work relationship, affect decision-making process and the scope of information set (e.g., Cohen, Frazzini and Malloy 2008, 2010). More recently, researchers argue that social network itself is endogenous and cultural proximity contributes to the formation of social ties and network (e.g., Pachucki and Breiger 2010).[9] In this respect, we postulate that cultural proximity helps form an analyst's social network and communication channels for private information, and highlight cultural similarity as an important factor contributing to how an individual's information set is shaped and evolves.

However, an analyst's superior access to management can come from sources unrelated to culture. To explore whether an analyst's superior access to management accounts for our finding, we restrict our sample to the period after the implementation of Regulation Fair Disclosure (Reg FD). Reg FD is a regulation promulgated by the U.S. Securities and Exchange Commission (SEC) in August 2000, mandating that all publicly traded companies must disclose material information to all investors at the same time. The regulation sought to stamp out selective disclosure, in which some market professionals received market moving information before others. By fundamentally changing how companies communicate with investors, Reg FD significantly reduces an analyst's private channel to firm-specific information (e.g., Cohen, Frazzini and Malloy 2010). In a survey of the related literature, Koch, Lefanowicz and Robinson (2013) conclude that Reg FD has largely eliminated the benefits of private access to management.

Since Reg FD applies to all analysts based in the U.S., its implementation severs an analyst's superior access to management, regardless of his or her cultural background. If it is just

[9] For example, many Asian students in the U.S. schools are much more socially connected to other students from the same country, despite the fact that they do not know each other prior to their arrival in the U.S.

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that any analyst—being a Chinese or a non-Chinese—that has superior access to management explains our findings, then our results should diminish during the post-Reg FD period.

Columns 1 through 3 of Table 4 reveal that our main finding holds during the post-Reg FD period. In particular, the interaction term for "Chinese Analyst" × "Chinese Firm" remains negative and significant at least at the 5% level for all regression specifications. This indicates that it is not just any analyst with superior access to management for firm-specific private information (independent of his or her cultural background) that can explain our findings.

Another plausible concern is that despite that we restrict sample firms to those listed in the U.S. and analysts to those residing in the U.S., Chinese analysts may have (unobserved) connections with the management prior to their move to the U.S. Instead of regulatory events that may apply to all the sample firms, we explore firm-specific events such as management turnovers that sever pre-existing ties between analysts and top management. If the superior forecast accuracy arises solely from Chinese analysts' personal connections to the existing management of Chinese firms, then we should observe a decline in their forecast accuracy once the current management is replaced.

To test for the impact of management turnover on Chinese analysts' relative advantage in covering Chinese firms, we manually collect information on CEO turnovers occurred within Chinese firms during the sample period through news and internet searches and identified 31 Chinese firms with turnovers. For this part of the analysis, we focus on forecasts issued to Chinese firms. "Turnover" is a dummy variable equal to one if a Chinese firm changed its CEO during the sample period and zero otherwise. We then interact "Turnover" with the dummy for Chinese analyst. If the forecast accuracy of a Chinese analyst hinges on personal ties with the

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CEO, then we should expect larger forecast errors after the departure of the CEO and a positive and significant coefficient associated with "Turnover" × "Chinese Analyst".

Columns 4 of Table 4 reveals that the coefficient for "Turnover" is negative and insignificant. Analysts' forecast errors do not increase for firms with CEO turnovers. In addition, column 5 of Table 4 shows that the coefficient for the interaction term "Turnover" × "Chinese Analyst" is insignificant. In fact, the sum of the coefficients for "Chinese Analyst" and "Turnover" × "Chinese Analyst" is 0. This implies that Chinese analysts' forecast accuracy is not significantly affected once their ties with the current management of these Chinese firms are severed. Overall, the results suggest that cultural proximity goes beyond analysts' private channels for information.

8. VALUING CULTURAL PROXIMITY

So far we document evidence consistent with that cultural proximity allows analysts to better access and infer financial information of firms sharing the same cultural origin. In this section we explore whether and how investors take into account the effect of cultural proximity.

We examine the impact of cultural proximity in the context of market reactions to forecast revisions. The market reaction is captured by "CAR", the abnormal return computed as the difference between the stock return and the CRSP value-weighted market return on the day when a revision to forecast occurs.

To construct the sample of forecast revisions, we require our sample analysts to issue at least two forecasts for each firm-quarter-analyst observation. We define "Revision" as the difference between the current EPS forecast and the previous one, scaled by last year's average price. Upward revision occurs if "Revision" is positive, whereas downward revision occurs when

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"Revision" is negative or unchanged. As we use all the forecast revisions, the sample is larger than the one used in earlier tests, which only contains the last forecasts by analysts.

Next, we partition the sample into four subgroups based on both the direction of revisions (upward versus downward revisions) and the cultural origin of sample firms (Chinese versus U.S. firms). We conduct regressions for each of the four subsamples, focusing on the interaction term ("Chinese Analyst" × "Revision") to identify how investors react to revisions made by analysts of different cultural backgrounds.

Panel A of Table 5 report the regression results for forecast revisions. For the subsample of upward revisions for Chinese firms, the coefficient for "Chinese Analyst" × "Revision" is positive and significant at the 5% level. This suggests that among all the analysts revising upwards their EPS forecasts on Chinese firms, Chinese analysts generate stronger market reactions than non-Chinese analysts. Columns 2 through 4 reveal that the coefficient for this interaction term is statistically insignificant for the remaining three subsamples. Untabulated regressions yield similar results when "CAR" is measured over a three-day event window instead of one-day window.

Besides earnings forecasts, analysts often issue stock recommendations. Compared to forecasts, stock recommendations are less directly mapped to analyst information precision; they also occur less frequently. Nevertheless, we repeat the same set of market reaction tests for recommendation revisions. To construct the sample of recommendation revisions, we require our sample analysts to issue at least two recommendations to the same firm they cover. "Revision" is the change of the current recommendation (on a 1 to 5 scale, with strong buy as 5 and strong sell as 1) from the previous recommendation by the same analyst. "Upgrade" is when "Revision" is positive, and "Downgrade" is when "Revision" is negative or unchanged. We then split the

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sample of recommendation revisions into four groups: upgrades and downgrades for sample Chinese firms, as well as upgrades and downgrades for sample U.S. firms.

Panel B of Table 5 reports the regression results on analyst recommendation revisions. Similar to Panel A on forecast revisions, market reaction to an upgrade for a Chinese firm is significantly stronger if it is issued by a Chinese analyst than by a non-Chinese analyst.

Overall, the results from Table 5 indicate that the market recognizes the impact of culture on analysts' information advantage. Price reaction is stronger when Chinese analysts revise their forecasts upwards or issue an upgrade for Chinese firms than non-Chinese analysts.

9. ROBUSTNESS CHECKS

9.1 Language Commonality versus Cultural Proximity

While language, a key component of culture, plays an important role in extracting and disseminating information, prior literature has suggested that the scope of cultural proximity can go beyond language commonality (e.g., Nisbett and Norenzayan 2002).[10] It is empirically challenging to directly assess and quantify language proficiency of individuals. Instead, we explore the robustness of our findings to language commonality by distinguishing between Chinese-speaking and English-speaking Chinese firms.

In mainland China and Taiwan, Chinese is the official language, whereas the language environment of Hong Kong and Singapore is more similar to the U.S. Once publicly listed in the U.S., firms from these two regions face a much smaller language barrier to communicate with U.S. analysts and investors than firms from mainland China and Taiwan. This implies that the

[10] For example, even though all the communications are conducted via English during analysts' interactions with management of firms under coverage, analysts that share the same cultural background with the firm may be better at gathering firm-specific information from management's facial expression, body language, or vocal cues (Mayew and Venkatachalam 2012) than other analysts.

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language advantage of an analyst on extracting firm-specific information relative to other analysts diminishes if the later can also communicate effectively with these firms themselves.

In the first set of tests, we restrict to the quarterly forecasts issued by Chinese analysts regarding earnings of Chinese firms, and distinguish between Chinese-speaking firms (from Chinese mainland and Taiwan) versus English-speaking firms (from Hong Kong and Singapore). If our finding is driven *exclusively* by a Chinese analyst's ability to speak the same language, then the forecasts of Chinese analysts should be more precise when they cover Chinese-speaking firms. Instead, we find no significant difference in Chinese analysts' forecasts accuracy between Chinese-speaking and English-speaking firms.

Alternatively, we conduct a set of tests in a setting similar to those in Table 3, separating Chinese firms into Chinese-speaking and English-speaking firms and together with the matched U.S. firms. If language commonality accounts for our main findings, the coefficient for the interaction term "Chinese Analyst" × "Chinese Firm" should be much larger for the Chinese-speaking subsample than the English-speaking subsample. We find, instead, that the coefficient for the interaction term is -0.24 for the Chinese-speaking subsample and is -0.26 for the English-speaking subsample. Furthermore, the difference in the effect of culture proximity between the two subsamples is statistically insignificant.

Our tests for language commonality suggest that Chinese analysts are not more accurate when covering Chinese-speaking Chinese firms. The results thus indicate that language alone may not explain our findings, and that cultural proximity can go beyond language commonality. In this respect, our findings are consistent with the evidence from the psychology literature that people from different cultures can perform significantly differently in cognitive tasks even with

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the same set of information in the same language (see, e.g., Nisbett and Norenzayan 2002, for a review).[11]

9.2 Other Robustness

In the Internet Appendix, we replicate our main findings using the full sample of 1,651,985 forecasts and obtain consistent results. We also conduct a number of tests to explore other aspects of cultural proximity.

First, are non-Chinese analysts covering Chinese firms less competent than non-Chinese analysts only covering U.S. firms? If this is true, our finding of superior forecasting accuracy of Chinese analysts regarding Chinese firms is confounded by selecting a poor benchmark of non-Chinese analysts. In unreported test, we find that among all the non-Chinese analysts who cover the same U.S. firms, analysts that also cover Chinese firms do not underperform those who exclusively cover U.S. firms. We further show that culture cannot be easily spilled over to those with different cultural backgrounds. For non-Chinese analysts covering the same Chinese firms, those with Chinese colleagues in their brokerage house (our proxy for culture spillover) do not significantly outperform others without Chinese colleagues.

Second, we check whether Chinese analysts suffer from over-optimism when covering Chinese firms. It is possible that our main results in Table 2 are driven by analysts of Chinese ethnic origin being biased – more optimistic about earnings prospective of firms from their home country, concurrent with the higher growth experienced by these firms during the same time. In unreported tests, we find that Chinese analysts are not subject to optimism regarding Chinese firms, so familiarity does not lead to optimism or rosy recommendations.

[11] For example, people from Eastern cultures are more likely to view the world in terms of relationships, to explain events situationally, and to rely on knowledge-based reasoning. By contrast, people from Western cultures are more likely to view the world in terms of rule-based categories, to explain events dispositionally, and to rely on formal, decontextualized reasoning (Nisbett et al. 2001).

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Third, we conduct a change analysis to provide more direct evidence of the impact of cultural proximity. We identify a total of 537 replacement events in the full sample for which a broker replaces an analyst with another analyst for covering the *same Chinese firm*. We find that forecast errors significantly reduce when a Chinese analyst replaces a non-Chinese analyst forecasting the same Chinese firm, after controlling for the analyst and forecast characteristics. But we do not observe significant changes in forecast errors for the other types of replacement events.

10. CONCLUSIONS

In this paper we examine the effect of cultural proximity on the processing of financial information and mitigating information asymmetry. Using the last names of financial analysts to code their ethnicity, we identify a group of Chinese analysts, and compare their forecasts with their non-Chinese peers. We document that Chinese analysts make more accurate forecasts for Chinese firms, after controlling for observed and unobserved industry-specific, time-specific, brokerage-specific, and firm-specific characteristics, as well as analysts' professional experience. Furthermore, the effect of cultural proximity is stronger among firms with less transparent information environment. Financial markets appear to be aware of the effect of cultural proximity on information precision: stock prices respond more strongly when Chinese analysts revise their forecasts upward or issue upgrades on Chinese firms than non-Chinese analysts.

Our study indicates that cultural proximity mitigates information asymmetry which adversely affects foreign firms, especially those with more information asymmetry. In addition, it sheds light on culture as an important component of human capital, and as a venue for shaping the information set of individuals and the formation of networks to access private information.

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A common challenge for empirical studies on the subject of culture is that it is difficult to directly pinpoint the channels through which culture affects economic outcome. We perform a battery of tests to rule out selections arising from other analyst attributes instead of culture, such as an individual's ability, specialization, analyst optimism, superior access to management for information, and conflicted interest in analyst research. Future work, perhaps through controlled experiments, may help shed more lights on the specific channels through which cultural proximity affects information flows between analysts and firms.

Lastly, we wish to point out that our study explores the effect of culture on the accuracy of earnings forecast, one of the main functions provided by financial analysts. Brokerage firms may assign analyst coverage based on other traits and roles played by individuals. It remains to be explored to what extent culture affects the other dimensions that analysts may function, as well as the development of analysts' human capital over time. We consider this an exciting area for future research.

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Appendix A: Surnames of Chinese Ethnic Origin

This table reports the surnames of analysts classified as a Chinese ethnic origin and the distribution of U.S. analysts with such surnames based on the full sample. The sample period is 1990-2010.

Surname	Frequency	Surname	Frequency	Surname	Frequency	Surname	Frequency
WANG	13	KANG	3	CHING	1	PENG	1
CHEN	12	PANG	3	CHIU	1	POON	1
LIU	12	TAI	3	CHOU	1	QIU	1
LU	10	TAM	3	CHU	1	QUEK	1
CHANG	8	TAN	3	CHUA	1	RO	1
HO	8	TING	3	DING	1	SHAO	1
HUANG	8	WEI	3	DONG	1	SHEN	1
LAU	8	YEE	3	FENG	1	SHU	1
CHENG	7	YEUNG	3	FOO	1	SIT	1
LEUNG	7	YU	3	FU	1	SIU	1
LI	7	CHOW	2	FUNG	1	SONG	1
LIN	7	CHUN	2	HA	1	SU	1
WONG	7	DU	2	HAO	1	SUE	1
TANG	6	FAN	2	HE	1	TEO	1
ZHANG	6	HSU	2	HOU	1	TIAN	1
CHAN	5	HU	2	HSUEH	1	TSAO	1
HONG	5	KOH	2	JU	1	TSE	1
TONG	5	LAI	2	JUE	1	WEN	1
WU	5	LIANG	2	KEUNG	1	WUH	1
YIN	5	LIM	2	KIANG	1	YAP	1
ZHAO	5	LOH	2	KUAN	1	YE	1
CHAO	4	SHI	2	KWAN	1	YEH	1
JIANG	4	SUN	2	LIAN	1	YIP	1
LAM	4	TAO	2	LO	1	YUAN	1
MA	4	TSAI	2	LUI	1	YUE	1
NG	4	WOO	2	LUK	1	YUEN	1
PAN	4	XU	2	LUO	1	ZENG	1
YANG	4	AI	1	MAO	1	ZHONG	1
ZHOU	4	AU	1	MENG	1	ZHU	1
CHIANG	3	BAO	1	MIN	1	ZOU	1
CHUNG	3	CAI	1	MOK	1		
FONG	3	CHAI	1	MOU	1		
JI	3	CHEUNG	1	ONG	1		

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Appendix B: Variable Definition and Construction

Variables	Definition
Analyst Forecast Error	The percentage of absolute value of the difference between forecasted and actual earnings scaled by the average share price in the previous year.
CAR	Abnormal announcement day return when an analyst revises a forecast. Computed as the difference between the stock return and the value-weighted CRSP index on the announcement day, and multiple by 100%.
Turnover	A dummy variable to indicate whether a Chinese firm changed its CEO during the sample period.
Chinese Analyst	A dummy variable equal to one if the surname of a U.S.-based analyst is of Chinese ethnic origin, and zero otherwise.
Chinese Firm	A dummy variable equal to one if a firm that is publicly traded on the stock exchange in the U.S. and is headquartered in mainland China, Hong Kong, Singapore, or Taiwan, and is zero if it is headquartered in the U.S.
Earnings Change	The absolute value of the change in earnings over the previous quarter, scaled by the previous quarter's earnings. (Hope 2003)
Leverage of Firm	Total liabilities divided by total assets.
Log # of Firms Covered	The natural logarithm of one plus the number of firms covered by an analyst in the year when he or she issues a forecast.
Log # of Revisions	The natural logarithm of one plus the number of forecast revisions made by an analyst regarding the same firm in the same forecasting quarter, prior to his/her current forecast.
Log Chinese Firm Experience	The natural logarithm of one plus the number of months between the date when an analyst initiates the coverage of any Chinese firm in I/B/E/S, and the current forecast date.
Log Forecast Horizon	The natural logarithm of the number of days between an analyst issues earnings forecast and the corporate earnings announcement date.
Market Value of Equity	Market capitalization measured at the end of the year in millions of dollars.
Order of Revision	The order of a forecast based on when it is issued by an analyst regarding the quarterly earnings of a firm.
Revision	For forecast revision, this variable is defined as the difference between the current EPS forecast and the previous forecast issued by the same analyst, scaled by the average share price of the previous year. For recommendation revision, this variable is the difference between the current recommendation (on a 1 to 5 scale, with strong buy as 5 and strong sell as 1) and the previous recommendation issued by the same analyst.
Size of Coverage	Number of analysts covering a given firm in a given quarter.
Size of Firm	The natural logarithm of total assets.
Total Assets	Book value of total assets measured in millions of dollars.
Total Experience	The number of months between the date when an analyst initiates the coverage of any firm in I/B/E/S, and the current forecast date.

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Table 1: Descriptive Statistics

The sample period is 1990-2010. We reports descriptive statistics based on the matched sample. T-statistics testing the difference in means between Chinese analysts and non-Chinese analysts, and between Chinese firms and U.S. firms, respectively, are based on uneven variance. Variables are defined in the Appendix B. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Analyst Characteristics

	Total	Mean	Chinese Analyst	Non-Chinese Analyst	T-statistics
# of Analysts	560		98	462	
# of Forecasts	3,530		1,040	2,490	
Chinese Firm Experience (in months)		18.04	18.45	17.87	-0.71
Analyst Forecast Error (%)		0.73	0.74	0.73	-0.06

Firm Characteristics

	Total	Mean	Chinese Firm	U.S. Firm	T-statistics
# of Firms	115		46	69	
# of Forecasts	3,530		1,801	1,729	
Chinese Firm Experience (in months)		18.04	28.15	7.50	-23.89***
Analyst Forecast Error (%)		0.73	0.73	0.74	0.12

Forecast Characteristics

	Total	Mean	Chinese Firm	U.S. Firm	T-statistics
# of Forecasts Issued					
By Chinese Analysts	1,040		752	288	
By Non-Chinese Analysts	2,490		1,049	1,441	
Analyst Forecast Error (%)					
Chinese Analysts		0.74	0.66	0.93	2.93***
Non-Chinese Analysts		0.73	0.78	0.70	-1.83*

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Table 2: Cultural Proximity and Forecast Accuracy

This table relates analyst forecast accuracy to analyst's Chinese ethnic background based on the matched sample. The sample period is 1990-2010. The dependent variable is analyst forecast error, calculated as the percentage of absolute value of the difference between forecasted and actual earnings, scaled by the average share price in the previous year. The other variables are defined in the Appendix B. Robust standard errors are double clustered at the firm and analyst levels and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Chinese Analyst	0.13	0.09	0.14	0.13	0.14
	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)
Chinese Firm	0.12	0.05	0.04	0.00	
	(0.16)	(0.17)	(0.13)	(0.13)	
Chinese Analyst × Chinese Firm	-0.40***	-0.32***	-0.35***	-0.26**	-0.20*
	(0.11)	(0.10)	(0.10)	(0.10)	(0.12)
Log Chinese Firm Experience		0.02	-0.00	0.01	0.01
		(0.02)	(0.02)	(0.02)	(0.01)
Log Forecast Horizon		0.14***	0.10***	0.10***	0.11***
		(0.03)	(0.03)	(0.03)	(0.03)
Log # of Firms Covered		0.03	0.04	-0.02	0.05
		(0.07)	(0.06)	(0.06)	(0.07)
Log # of Revisions		-0.06	-0.06	-0.09	-0.15**
		(0.04)	(0.05)	(0.07)	(0.06)
Size of Coverage		-0.03*	-0.01	-0.01	-0.02
		(0.02)	(0.02)	(0.02)	(0.02)
Earnings Change			0.06*	0.06*	0.07*
			(0.04)	(0.04)	(0.04)
Size of Firm			-0.14**	-0.13*	-0.47
			(0.06)	(0.07)	(0.33)
Leverage of Firm			1.51***	1.35***	-0.22
			(0.29)	(0.29)	(0.76)
Industry Fixed Effects	Yes	Yes	Yes	Yes	No
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Broker Fixed Effects	No	No	No	Yes	Yes
Firm Fixed Effects	No	No	No	No	Yes
Observations	3,530	3,530	3,295	3,247	3,247
R-squared	0.218	0.238	0.236	0.295	0.489

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Table 3: Information Environment and the Effect of Cultural Proximity

This table examines the effect of cultural proximity for firms with different information environment. The dependent variable is analyst forecast error. Columns 1 and 2 report regression results for firms in more and less opaque information environment respectively, where a firm is classified as of more opaque information environment if its Hutton-Marcus-Tehranian (2009) measure of financial reporting opacity is above the sample median of Chinese firms. In columns 3 and 4, a firm is classified as "more foggy" if its Fog index (Li, 2008) is above the sample median of Chinese firms. Column 5 and 6 report the results based on a firm's listing exchange (OTC versus the big three—NYSE, NASDAQ and AMEX). In columns 7 and 8, a firm is classified as having high institutional holding if its previous three years' moving average of institutional holding is above the sample median of Chinese firms. Other variables are defined in the Appendix B. Standard errors double clustered at the firm and analyst levels are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Earnings Management		Fog Index		Exchange Listing Standards		Institutional Holding	
	More Opaque	Less Opaque	More Foggy	Less Foggy	OTC	NYSE/AMEX/ NASDAQ	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chinese Analyst	-0.03	0.18	0.05	0.08	1.14***	0.10	0.11	-0.02
	(0.12)	(0.16)	(0.05)	(0.33)	(0.24)	(0.09)	(0.17)	(0.09)
Chinese Firm	0.02	-0.13	0.31	-0.32	0.14	0.14	-0.52	0.39
	(0.20)	(0.21)	(0.20)	(0.50)	(0.30)	(0.12)	(0.44)	(0.29)
Chinese Analyst × Chinese Firm	-0.17*	-0.13	-0.22**	-0.24	-1.11***	-0.26**	-0.39**	-0.12
	(0.09)	(0.17)	(0.10)	(0.35)	(0.24)	(0.10)	(0.17)	(0.19)
Log Chinese Firm Experience	-0.01	0.04	-0.01	-0.02	0.07	0.01	0.03	-0.01
	(0.04)	(0.05)	(0.02)	(0.07)	(0.07)	(0.02)	(0.02)	(0.02)
Log Forecast Horizon	0.12***	0.12***	0.09*	0.12***	0.08*	0.10***	0.12***	0.09
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)	(0.06)
Log # of Firms Covered	-0.03	0.01	0.04	0.08	0.02	-0.01	-0.03	-0.02
	(0.11)	(0.07)	(0.06)	(0.07)	(0.10)	(0.07)	(0.09)	(0.08)
Log # of Revisions	-0.10	-0.16**	-0.14*	-0.04	-0.06	-0.08	-0.03	-0.15**
	(0.09)	(0.07)	(0.07)	(0.08)	(0.09)	(0.07)	(0.06)	(0.07)
Size of Coverage	-0.06**	0.06*	0.01	0.01	0.05	-0.01	-0.14**	0.02
	(0.03)	(0.03)	(0.02)	(0.05)	(0.09)	(0.02)	(0.07)	(0.02)
Earnings Change	0.08	0.04	0.05	0.02	0.20**	0.06*	-0.11	0.02

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	(0.06)	(0.04)	(0.04)	(0.04)	(0.08)	(0.04)	(0.18)	(0.04)
Size of Firm	-0.19	-0.38***	-0.29***	-0.17	0.69***	-0.14*	0.40	-0.40***
	(0.12)	(0.09)	(0.08)	(0.23)	(0.21)	(0.07)	(0.45)	(0.08)
Leverage of Firm	0.22	2.73***	1.83***	1.75**	1.53***	1.17***	-0.57	1.89***
	(0.53)	(0.59)	(0.47)	(0.79)	(0.53)	(0.27)	(0.61)	(0.47)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,201	1,218	1,942	855	400	2,847	594	1,581
R-squared	0.407	0.552	0.404	0.553	0.797	0.300	0.530	0.450

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Table 4: Superior Access to Management

The sample period for columns 1 through 3 is the post Reg FD Period of 2001-2010, and for columns 4 and 5 is 1990-2010. The dependent variable is analyst forecast error. In columns 1 through 3, we repeat the regression analysis of Table 2 Panel A for the post Reg FD period. For columns 4 and 5, the sample consists of all analysts' forecasts regarding Chinese firms. "Turnover" is a dummy variable to indicate whether a Chinese firm changed its CEO in the sample period. Other variables are defined in the Appendix B. Robust standard errors are double clustered at the firm and analyst levels and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Post Reg FD			CEO Turnover	
	(1)	(2)	(3)	(4)	(5)
Chinese Analyst	0.13	0.09	0.13		-0.09
	(0.09)	(0.09)	(0.09)		(0.07)
Chinese Firm	0.12	0.04	-0.06		
	(0.17)	(0.18)	(0.13)		
Chinese Analyst × Chinese Firm	-0.41***	-0.32***	-0.23**		
	(0.12)	(0.11)	(0.11)		
Turnover				-0.09	-0.14
				(0.14)	(0.13)
Chinese Analyst × Turnover					0.09
					(0.06)
Log Chinese Firm Experience		0.02	0.02	0.03	0.03
		(0.02)	(0.02)	(0.02)	(0.02)
Log Forecast Horizon		0.14***	0.10***	0.12***	0.12***
		(0.04)	(0.03)	(0.04)	(0.04)
Log # of Firms Covered		0.02	-0.04	-0.04	-0.05
		(0.07)	(0.07)	(0.08)	(0.09)
Log # of Revisions		-0.06	-0.08	-0.16	-0.16
		(0.04)	(0.06)	(0.10)	(0.10)
Size of Coverage		-0.03*	-0.01	-0.02*	-0.02*
		(0.02)	(0.02)	(0.01)	(0.01)
Earnings Change			0.07*	0.18***	0.18***
			(0.04)	(0.05)	(0.05)
Size of Firm			-0.13*	0.17	0.17
			(0.07)	(0.17)	(0.18)
Leverage of Firm			1.35***	-0.43	-0.42
			(0.30)	(0.40)	(0.40)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Broker Fixed Effects	No	No	Yes	Yes	Yes
Observations	3,330	3,330	3,047	1,666	1,666
R-squared	0.209	0.228	0.291	0.423	0.423

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Table 5: Market Reactions to Forecast and Recommendation Revisions

This table relates market reactions to forecast and recommendation revisions by Chinese analysts. The sample period is 1990-2010. The dependent variable is "CAR", computed as the difference between the stock return and the CRSP value-weighted index return on the day when an analyst revises his/her earnings forecast or stock recommendation. In Panel A, "Revision" is the difference between the current and previous EPS forecasts by the same analyst, scaled by the average share price of the firm in the previous year. "Upward Revision" occurs if "Revision" is positive, and "Downward Revision" occurs when "Revision" is negative or unchanged. In Panel B, "Revision" is the difference between the current and previous stock recommendations (on a 1 to 5 scale with strong buy as 5 and strong sell as 1) issued by the same analyst. "Upgrade" occurs if "Revision" is positive, and "Downgrade" occurs when "Revision" is negative or unchanged. Other variables are defined in the Appendix B. Industry classification is based on the one-digit SIC code. Robust standard errors double-clustered at the firm and analyst level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: EPS Forecast Revisions

	Chinese Firms	Chinese Firms	U.S. Firms	U.S. Firms
	Upward Revision	Downward Revision	Upward Revision	Downward Revision
	(1)	(2)	(3)	(4)
Chinese Analyst × Revision	0.01**	-0.00	0.00	0.00
	(0.01)	(0.00)	(0.01)	(0.01)
Chinese Analyst	-0.01	0.01	0.01	0.01
	(0.00)	(0.00)	(0.01)	(0.01)
Revision	0.00	0.02**	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Log Chinese Firm Experience	-0.00	-0.01*	0.00**	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Log Forecast Horizon	0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Size of Coverage	-0.00	-0.00	0.00	-0.01**
	(0.00)	(0.00)	(0.00)	(0.00)
Log # of Firms Covered	-0.00	0.00	-0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Order of Revision	-0.00***	-0.00**	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,852	3,407	1,469	2,718
R-squared	0.241	0.148	0.333	0.240

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Table 5 Continued.

Panel B: Recommendation Revisions

	Chinese Firms	Chinese Firms	U.S. Firms	U.S. Firms
	Upgrade	Downgrade	Upgrade	Downgrade
	(1)	(2)	(3)	(4)
Chinese Analyst × Revision	0.10*	-0.01	-0.14	-0.11*
	(0.06)	(0.02)	(0.21)	(0.06)
Chinese Analyst	-0.07	0.01	0.29	-0.09*
	(0.09)	(0.03)	(0.18)	(0.06)
Revision	-0.03	0.03**	0.08	0.02**
	(0.03)	(0.01)	(0.07)	(0.01)
Log Chinese Firm Experience	-0.00	0.02*	-0.02	0.00
	(0.02)	(0.01)	(0.03)	(0.01)
Size of Coverage	0.00	-0.00	-0.01	0.01*
	(0.00)	(0.00)	(0.01)	(0.00)
Log # of Firms Covered	0.05**	-0.01	0.01	-0.02
	(0.02)	(0.01)	(0.08)	(0.03)
Order of Revision	-0.00	-0.01**	-0.01	0.01
	(0.01)	(0.00)	(0.06)	(0.01)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	102	186	58	115
R-squared	0.661	0.425	0.970	0.773

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