Accounting & Taxation
Vol. 11, No. 1, 2019, pp. 35-46
ISSN: 1944-592X (print)
ISSN: 2157-0175 (online)

www.theIBFR.com

EFFECTS OF ANALYSTS' COUNTRY FAMILIARITY ON FORECAST BEHAVIOR: EVIDENCE FROM CHINESE CROSS-LISTED FIRMS IN THE UNITED STATES

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ABSTRACT

This study provides empirical evidence regarding the effect of analysts' country familiarity on their forecast behavior. Prior research has generally agreed that local analysts outperform their nonlocal counterparts due to information advantage or local familiarity. However, the effect of country familiarity on analysts' earnings forecast abilities for foreign firms cross-listed in the United States is unclear. Using a hand-collected sample of Chinese cross-listed firms, I examine whether analysts who are familiar with these Chinese firms are associated with better performance in forecast accuracy, forecast dispersion, and information precision. Results indicate that country familiarity has a positive effect on analysts' earnings forecasts. Specifically, analysts who are familiar with Chinese cross-listed firms have higher accuracy and lower dispersion. Additional analysis suggests that the superior performance can be attributed to analysts' private information precision rather than public information precision.

JEL: F23, F37

KEYWORDS: Analyst Forecast Behavior, Local Analyst Advantage, Country Familiarity

INTRODUCTION

Prior empirical studies find that local analysts produce better forecasts than their nonlocal counterparts due to an information advantage or local familiarity (Malloy 2005, Bae et al. 2008, Green et al. 2014, O'Brien and Tan 2015). However, little is known about the effect of country familiarity on analysts' earnings forecast abilities for foreign firms cross-listed in the United States. Using a hand-collected sample of Chinese cross-listed firms, I examine whether analysts familiar with these Chinese firms (Chinese familiarity CFML) are associated with better performance, such as forecast accuracy, forecast dispersion, and information precision. To test the effect of analysts' country familiarity, I split all analysts who follow cross-listed Chinese firms into two groups, analysts with Chinese familiarity (CFML) and analysts without Chinese familiarity (NCFML). An analyst is classified into CFML group if he/she meets one of the following criteria: (1) the analyst has a Chinese last name, 2.) the analyst's brokerage office/branch is located in China mainland, Hong Kong, or Taiwan, 3.) the analyst travels to China frequently, or 4.) the analyst's research is focused on Chinese or Asian firms/markets. If an analyst does not meet any one of the four criteria, he/she is classified as NCFML.

The criteria are based on assumptions that analysts will enjoy country/local informational advantage via the same culture/language (Du et al. 2017), geographic proximity (Malloy 2005), or focused research area. Therefore, it is possible that analysts with Chinese familiarity might outperform their non-familiarity counterparts. However, behavior studies (Chen and Tan 2013) find that U.S. investors are more willing to buy or rely on services provided by U.S. analysts (the majority are analysts without Chinese familiarity) since investors are more familiar with these analysts. High demands from U.S. domestic investors may motivate U.S. analysts to produce more accurate forecasts with low dispersion and high information precision.

Given the competing arguments, the effect of Chinese familiarity on analysts' earnings forecasts is an empirical question. Using a hand-collected sample of Chinese cross-listed firms from 2008 to 2015, I examine whether analysts who are familiar with Chinese cross-listed firms are associated with better performance in forecast accuracy, forecast dispersion, and information precision. Regression results show that analysts with Chinese familiarity outperform their non-familiarity counterparts by providing forecasts with higher accuracy and lower dispersion. Furthermore, I investigate the source of this superior performance. The difference reflected in forecast accuracy and forecast dispersion between the CFML group and the NCFML group can be attributed to analysts' public information precision or analysts' private information precision. Using Barron et al. (1998) model (BKLS model), I measure unobservable information precision with observable forecast accuracy and dispersion. Additional analysis reveals that analysts' Chinese familiarity advantage is mainly driven by analysts' higher private information precision rather than by the public information precision.

This study is related to the work of Comiran and Siriviriyakul (2019) paper and Du et al. (2017). Using foreign cross-listed stocks from 41 foreign countries, Comiran and Siriviriyakul (2019) demonstrate the local advantage vanishes for cross-listed stocks and nonlocal analysts can provide more accurate forecasts. The current paper is different from theirs in three respects. First, I only examine Chinese cross-listed firms to avoid institutional differences problems from various home countries, a concern usually found in international studies. Second, my analysts' Chinese familiarity (CFML) is hand collected and can provide more direct and more accurate practical implications. Third, I extend previous studies studies by testing dispersion and information precision to identify the possible source for the observed analyst forecast accuracy differences. Du et al. (2017) examines how culture affects analysts' forecasts and finds that for Chinese cross-listed firms, analysts with Chinese ethnic origin issue more accurate forecasts as they share the same culture with these Chinese firms. My study is different in two respects. While their paper relies only on cultural proximity, my paper uses a broader definition of Chinese familiarity, which includes both cultural measure (CFML criterion 1) and non-cultural measures (CFML criterion 2/3/4). I argue that although culture plays an essential role in analysts' behavior, non-cultural factors, such as analyst's office location, travel destination/frequency and research focus, can also benefit analysts with critical information collection. In addition, I extend their paper by testing dispersion and information precision to investigate the channels for different forecast accuracy.

This paper makes two main contributions. First, it provides direct evidence regarding analysts' Chinese familiarity on their forecast behavior. Prior literature has investigated local informational advantage in the U.S and other countries (Orpurt 2004, Chang 2010). However, studies on country advantage for cross-listed firms are limited. This paper uses hand-collected data to provide more accurate evidence on the effect of Chinese country familiarity. Secondly, although prior studies have found that local/culture proximity can improve analysts' forecast accuracy, this paper is the first paper that examines the effect of country familiarity on analyst information precision using Chinese cross-listed firms as the sample. Venkataraman (2001) argues that "it is not possible to unambiguously characterize changes in the precision of common information and idiosyncratic information based on measures such as dispersion or squared error in the mean forecast" (Venkataraman 2001, page 2). My paper extends prior studies by showing that the superior performance for analysts with Chinese familiarity results mainly from their more precise private information rather than from different public information precision. The results support the hypothesis that analysts with Chinese familiarity can use their advantage to gain valuable private information about these cross-listed firms, which in turn increases their forecast accuracy and decreases their forecast dispersion.

The remainder of the paper is structured as follows. The next part reviews literature and develops the hypothesis. The following section presents the methodology, data and sample. The paper continues by providing the results and analysis. The paper closes with some concluding comments.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

A large body of literature examines the effect of geographic proximity on analysts' forecasting performance. Evidence from U.S. studies generally finds a positive association. Local analysts can directly inspect local firms, arrange personal contacts with firm management, or acquire information about local firms' operations. Analysts may also receive valuable information from other local channels (for example, customers, suppliers, and competitors) in a cheaper and faster manner. The informational advantage enables analysts with local familiarity to provide more accurate forecasts. For example, Malloy (2005) compares local analysts' performance with distant analysts' performance. They argue that local analysts can obtain important private information by meeting with suppliers, managers, and employees. They also know the local market/economy better. These advantages will help them issue more accurate forecasts.

However, results from international cross-country studies are inconclusive on the effect of geographic proximity. Although Bae et al. (2008) document local analyst advantage in 32 countries by showing that forecasts from analysts who stay in the same country as firms are more accurate than non-resident analysts, Comiran and Sirlviriyakul (2019) find that local advantage disappears for firms cross-listed in the U.S. market. In fact, nonlocal analysts outperform local analysts for these firms. They argue that when foreign firms are cross-listed in the U.S., U.S. domestic investors are more interested in these firms than non-cross-listed firms. As a result, investors demand service for these firms when they make investment decisions. Therefore, nonlocal (predominantly U.S.) analysts might spend more time and devote more effort to produce more accurate forecasts.

My study focuses on Chinese firms that are cross-listed in the U.S. Analysts with Chinese familiarity (CFML) may have better performance than analysts without Chinese familiarity (NCFML) for several reasons. First, these analysts share the same cultural and language background with these cross-listed firms (criterion 1). Du et al. (2017) find that analysts of Chinese ethnic origin (with Chinese last names) issue more accurate forecasts due to their language and cultural advantage. Although Chinese firms file their reports in English, analysts with the same cultural background can "read between the lines" and have better interpretation. Second, analysts with Chinese familiarity are usually geographically closer to the Chinese market (criterion 2), travel to China frequently (criterion 3), or focusing on Chinese firms (criterion 4). Therefore, they have better access to valuable private information via personal connections, communication with local employees, customers, and competitors. They can collect first-hand information, which is usually not available from firms' public announcements or reports. Following this argument, analysts with Chinese familiarity might have better forecasting performance than analysts without Chinese familiarity.

U.S. investors generally prefer U.S. analysts (predominantly analysts without Chinese familiarity). The high demand for U.S. analysts may motivate analysts to generate more accurate forecasts. Chen and Tan (2013) find that when investors are more exposed to an analyst's name *per se*, investors' reliance on that analyst's forecast reports will be increased. This experimental study suggests that participants subconsciously associate the analyst with higher credibility when his/her name is shown more times than other analysts. More importantly, the study indicates that once participants are familiar with the analyst's name, participants ignore the analyst's prior performance records. In other words, when participants form their own earnings forecasts to a company, they would rely more on the analyst's reports whose name is more familiar, no matter if the analyst's prior performance is good or bad. The mere exposure effect from the Chen and Tan (2013) study is consistent with the Bonner et al. (2007) empirical research. Using analysts' celebrity status as a measure of familiarity, they find that investors have stronger reactions to forecast revision from celebrity analysts. They explain the finding as "the celebrity status of analysts will affect investor reaction to forecast revisions…because these analysts' names are more familiar" (page 482). Investors treat forecasts from familiar analysts as more accurate and precise because analysts with more familiar names are perceived to have higher credibility. If this is the case, then U.S. analysts (predominantly analysts without Chinese familiarity) will be in high demand, which in turn will motivate U.S. analysts to produce earnings forecasts with higher accuracy and lower dispersion, consistent with the finding of Comiran and Sirlviriyakul (2019. Given the competing arguments discussed above and mixed evidence, I form the hypothesis as non-directional:

Hypothesis 1: For Chinese cross-listed firms in the U.S., there is no difference in analyst forecast accuracy and dispersion between Chinese familiarity analysts (CFML) and non-Chinese familiarity analysts (NCFML)

RESEARCH METHODOLOGY

Following (Srinivasan et al. 2015), I identify foreign cross-listed firms using the variable "LOC" in Compustat. This variable shows the country of a firm's headquarters. I retain only foreign firms that are headquartered in China (LOC=CHN) and are listed on NYSE, NASDAQ, and AMEX from 2008 to 2015. These firms are merged with the I/B/E/S Recommendation file to collect analysts' last names and respective brokerage firms, which are used to discover analysts' LinkedIn information. Variables for forecast accuracy, dispersion, and information precision are calculated based on I/B/E/S Detail file. Data for all other variables are retrieved from Compustat and CRSP. Analyst forecast accuracy (*Accuracy*) is calculated as the opposite of forecast errors (-100 times forecast error, which is the absolute difference between actual EPS and the mean consensus EPS forecasts, scaled by the stock price of the prior year). Analyst forecast dispersion (*Dispersion*) is 100 times the standard deviation of forecasts, scaled by the stock price from the previous year. An analyst is classified as Chinese familiarity (CFML) if he/she meets one of the following criteria: 1.) the analyst has a Chinese last name, 2.) the analyst brokerage office/branch is located in China mainland, Hong Kong, or Taiwan, 3.) the analyst travels to China frequently, or 4.) the analyst's research is focused on Chinese/Asian firms or markets.

If an analyst does not meet any one of the four criteria, he/she is classified as NCFML. The criteria are based on assumptions that analysts will enjoy country/local informational advantage via the same culture/language (Du et al. 2017), the geographic proximity (Malloy 2005), or the focused research area. OLS regression models are used to test the hypothesis:

$$Accuracy\ (Dispersion) = \beta_0 + \beta_1 CFML + \beta_2 Size + \beta_3 ROA + \beta_4 Sale\_change + \beta_5 Volatility + \beta_6 Earn\_change + \beta_7 Horizon + \beta_8 Loss + \beta_9 Big4 + \beta_{10} Coverage + Year\ Dummies + Industry\ Dummies + error\ term \quad (1)$$

The main variable of interest is the dummy variable $CFML$, which equals one if the analyst is defined as with Chinese familiarity. Several additional control variables are included following prior studies (Bhushan 1989, Brennan and Hughes 1991, Lang and Lundholm 1996, Clement 1999, Barth et al. 2001, Lehavy et al. 2011, Jiraporn et al. 2012, Du et al. 2017, Comiran and Siriviriyakyl 2019). I also include year fixed effect and industry fixed effect to control for unobservable factors over the years and among different industries. All variables are defined in the Appendix. Table 1 shows the sample distribution by Year (Panel A) and Industry (Panel B). The observations are generally even over the years, but are concentrated on Service (SIC 7000-7999) and Manufacturing (SIC 2000-3999) industries.

Table 1: Sample Distribution by Year & Industry

Panel A			Panel B		
Year	**Frequency**	**Percent**	**SIC Industry**	**Frequency**	**Percent**
2008	70	12.028	2000-2999	56	9.622
2009	83	14.261	3000-3999	159	27.320
2010	89	15.292	4000-4999	31	5.327
2011	96	16.495	5000-5999	27	4.639
2012	86	14.777	6000-6999	37	6.357
2013	63	10.825	70000-7999	214	36.770
2014	53	9.107	8000-8999	58	9.9660
2015	42	7.217			
Total	582	100%	Total	582	100%

Table 1 presents the sample distribution by year (Panel A) and by industry based on SIC classification (Panel B) for the full sample with 582 firm-year observations from 2008 to 2015.

Table 2 displays descriptive statistics for the CFML group (Column 1), NCFML group (Column 2), and comparison (t-statistic) of the mean difference between these two groups (Column 3). The CFML group has significantly higher (lower) forecast accuracy (dispersion) relative to the NCFML group. In addition, the CFML group has lower *ROA* and more analysts' coverage (*coverage*).

Table2: Descriptive Statistics

	Column 1				Column 2				Column 3
Variable	**Analysts with Chinese Familiarity (CFML)**				**Analysts without Chinese Familiarity (NCFML)**				**t-statistic for**
	N	**Mean**	**Median**	**Std Dev**	**N**	**Mean**	**Median**	**Std Dev**	**Mean Difference**
Accuracy	405	-2.867	-0.716	9.143	177	-5.100	-0.693	18.755	-1.93 *
Dispersion	405	2.315	0.889	4.832	177	4.489	0.733	18.763	2.17 **
Size	405	6.760	6.544	1.802	177	6.785	6.642	1.745	0.15
ROA	405	0.070	0.058	0.141	177	0.096	0.086	0.149	1.96 *
Sale_change	405	2.488	1.653	2.622	177	2.572	1.602	3.030	0.34
Volatility	405	0.166	0.153	0.073	177	0.174	0.164	0.073	1.26
Earn_change	405	-0.300	0.006	3.652	177	0.055	0.065	3.863	1.06
Horizon	405	4.861	4.905	0.404	177	4.899	4.920	0.434	1.02
Loss	405	0.242	0.000	0.429	177	0.215	0.000	0.412	-0.71
Big4	405	0.901	1.000	0.299	177	0.864	1.000	0.343	-1.31
Coverage	405	1.939	1.792	0.687	177	1.583	1.386	0.516	-6.17 ***

*Table 2 displays the descriptive statistics for the CFML group (Column 1), NCFML group (Column 2), and comparison (t-statistic) between the two groups' means (Column 3). ***, **, * indicate significance at the 1, 5 and 10 percent levels respectively. All variables are defined in the Appendix.*

Table 3 reports the Pearson correlation matrix of all variables. For brevity, I use *Var1-Var12* to refer to the following variables: *CFML, Accuracy, Dispersion, Size, ROA, Sale_change, Volatility, Earn_change, Horizon, Loss, Big4, and Coverage*. *Accuracy (Var2)* and *Dispersion (Var3)* are positively (negatively) correlated with *CFML (Var1)*, suggesting that analysts with Chinese familiarity issue more accurate (lower dispersion) forecasts.

Table 3: Pearson Correlation Matrix

	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var8	Var9	Var10	Var11	Var12
Var1	1											
Var2	0.0800 *	1										
Var3	-0.0899 **	-0.8487 ***	1									
Var4	-0.006	0.193 ***	-0.136 ***	1								
Var5	-0.081 *	0.3169 ***	-0.244 ***	0.3020 ***	1							
Var6	-0.014	0.1413 ***	-0.126 ***	0.3661 ***	0.4811 ***	1						
Var7	-0.052	-0.150 ***	0.070 *	-0.362 ***	-0.080 *	-0.051	1					
Var8	-0.044	0.036	0.001	0.071 *	0.136 ***	0.062	-0.086 **	1				
Var9	-0.042	-0.132 ***	0.105 **	-0.334 ***	-0.156 ***	-0.088 **	0.018	-0.055	1			
Var10	0.030	-0.328 ***	0.269 ***	-0.297 ***	-0.660 ***	-0.183 ***	0.201 ***	-0.082 **	0.172 ***	1		
Var11	0.054	-0.044	0.059	0.241 ***	-0.082 **	0.047	-0.101 **	-0.005	0.031	0.077 *	1	
Var12	0.248 ***	0.040	0.020	0.242 ***	0.218 ***	0.287 ***	-0.033	-0.013	-0.027	-0.033	0.223 ***	1

*Table 3 reports the Pearson correlation matrix of all variables. Var1-Var12 refer to the following variables: CFML, Accuracy, Dispersion, Size, ROA, Sale_change, Volatility, Earn_change, Horizon, Loss, Big4, and Coverage. ***, **, * indicate significance at the 1, 5 and 10 percent levels respectively. All variables are defined in the Appendix.*

RESULTS AND DISCUSSION

Table 4 presents the main results for regression tests. Model 1 shows the results for analyst forecast accuracy (*Accuracy).* The coefficient on *CFML* is positive and significant at the 10% level, indicating that, on average, analysts with Chinese familiarity issue more accurate forecasts. As discussed earlier, analysts with Chinese familiarity usually have an information advantage via the same culture/language, the geographic proximity, or the focused research area. Each factor can benefit analysts' forecast accuracy. The finding is consistent with prior studies using U.S. domestic analysts as the sample, but differs from Comiran and Siriviriyakyl (2019) study of cross-listed firms. It also supports Du et al.'s (2017) findings that analysts with Chinese culture provide more accurate forecasts. In addition, the results indicate that non-cultural factors, as well as the cultural factor, have a positive effect on analysts' forecast accuracy. For the control variables, the results show that on average, firms with larger size (*Size*), higher profitability (*ROA*), lower sales growth (*Sale_change*), and no loss (*Loss*) have higher forecast accuracy.

Model 2 shows the test results for analyst forecast dispersion (*Dispersion*). Analyst forecast dispersion is widely used as a proxy of analysts' uncertainty and disagreement (Barron and Stuerke 1998). The coefficient on *CFML* is significantly negative at the 1% level. Analysts with Chinese familiarity share the same cultural background and speak the same language. They also have more private information about Chinese cross-listed firms. As their offices are located close to the China market, they travel to China frequently, or their research is focused on China. Therefore, Chinese familiarity can decrease analysts' uncertainty to Chinese cross-listed firms and increase agreement among these analysts, which is reflected in lower forecast dispersion. Results also suggest that firms with a smaller size (*Size*), loss (*Loss*), and more coverage (*Coverage*) have higher forecast dispersion.

Table 4: Regression Results

	Model 1 (*Accuracy*)	**Model 2 (*Dispersion*)**
Variable	Coefficient	Coefficient
CFML	2.201*	-2.898***
	(1.817)	(-2.676)
Size	1.910***	-1.866***
	(2.822)	(-3.082)
ROA	12.180**	-3.092
	(2.051)	(-0.582)
Sale_change	-0.607**	0.306
	(-2.281)	(1.287)
Volatility	-0.058	-10.871
	(-0.007)	(-1.493)
Earn_change	-0.094	0.166
	(-0.691)	(1.360)
Horizon	-1.961	0.925
	(-1.441)	(0.760)
Loss	-4.788***	4.376***
	(-2.825)	(2.887)
Big4	-1.963	1.345
	(-1.016)	(0.778)
Coverage	-1.425	2.485***
	(-1.396)	(2.722)
Constant	-2.807	5.245
	(-0.316)	(0.659)
Year Dummies	YES	YES
Industry Dummies	YES	YES
Observations	582	582
R-squared	0.246	0.193
Adj R-squared	0.186	0.129

Table 4 presents the results for regression model (1), which tests the effect of Chinses familiarity (CFML) on analysts forecast accuracy (Model 1) and dispersion (Model 2). The estimated equations equals: $Accuracy\ (Dispersion) = \beta_0 + \beta_1 CFML + \beta_2 Size + \beta_3 ROA + \beta_4 Sale\_change + \beta_5 Volatility + \beta_6 Earn\_change + \beta_7 Horizon + \beta_8 Loss + \beta_9 Big4 + \beta_{10} Coverage + Year\ Dummies + \ Industry\ Dummies + error\ term$ *T-statistics are shown in parentheses. ***, **, * indicate significance at the 1, 5 and 10 percent levels respectively. All variables are defined in the Appendix.*

Regression results suggest that analysts with Chinese familiarity outperform analysts without Chinese familiarity by issuing more accurate and less dispersed forecasts for Chinese cross-listed firms. This superior performance can be attributed to either more precise public information or more precise private information. Public information refers to the information that is available to all analysts, while private information only belongs to that specific analyst by his/her private information acquisition. Previous studies have shown that "it is not possible to unambiguously characterize changes in the precision of common information and idiosyncratic information based on measures such as dispersion or squared error in the mean forecast" (Venkataraman 2001, page 2). To better understand the source for the observed differences between CFML analysts and NCFML analysts, I test analysts' total, public and private information precision with Barron et al. (1998) model (BKLS model) which is widely used by other studies (Byard et al. 2011, Kim and Shi 2012). Information precision variables are measured as follows:

Public information precision (*Public*) = $\frac{SE-\frac{D}{N}}{\left[\left(1-\frac{1}{N}\right)D+SE\right]^2}$

Private information precision (*Private*) = $\frac{\mathrm{D}}{\left[\left(1-\frac{1}{\mathrm{N}}\right)\mathrm{D}+\mathrm{SE}\right]^2}$

Total information precision (*Total*) = *Public* + *Private*

Where *D* is the variance of analysts' earnings forecasts, *SE* is the squared error in mean forecasts, and *N* is the number of earnings forecasts.

The results are presented in Table 5. Analysts with Chinese familiarity have significantly more accurate total information precision (*Total*), reflected in the positive coefficient on the variable "*CFML*" in Model 1. I then test the public and private information separately. The results suggest that better total precision for CFML analysts is achieved by more accurate private information precision rather than differences in public information precision. While the coefficient on *CFML* is significantly negative at the 1% level in the private information precision test (Model 3), it is not significant when testing public information precision (Model 2). The findings suggest that analysts with Chinese familiarity are enabled to search and gather important private information, which might come from their "reading between the lines" or personal communication with management. In contrast, Chinese familiarity does not play a critical role for analysts' public information precision since all analysts receive the same public disclosures or reports.

Table 5: Additional Analysis

Variable	**Model 1 (*Total*) Coefficient**	**Model 2 (*Public*) Coefficient**	**Model 3 (*Private*) Coefficient**
CFML	0.440*	0.189	1.809***
	(1.853)	(0.399)	(4.014)
Size	-0.189	-0.533**	-0.134
	(-1.466)	(-2.083)	(-0.548)
ROA	1.479	-0.704	3.931*
	(1.335)	(-0.320)	(1.871)
Sale_change	0.004	0.168*	0.024
	(0.088)	(1.691)	(0.253)
Volatility	-1.244	-5.005	-4.521
	(-0.792)	(-1.603)	(-1.517)
Earn_change	-0.030	-0.021	-0.033
	(-1.124)	(-0.390)	(-0.656)
Horizon	-1.161***	-1.372**	-0.029
	(-4.290)	(-2.552)	(-0.056)
Loss	-1.370***	-1.408**	-1.300**
	(-4.340)	(-2.246)	(-2.173)
Big4	-0.540	2.531***	0.274
	(-1.461)	(3.446)	(0.392)
Coverage	-1.011***	-0.287	-0.054
	(-5.159)	(-0.736)	(-0.144)
Constant	10.833***	11.996***	1.648
	(6.369)	(3.550)	(0.511)
Year Dummies	YES	YES	YES
Industry Dummies	YES	YES	YES
Observations	435	435	435
R-squared	0.447	0.202	0.178
Adj R-squared	0.389	0.118	0.092

Table 5 presents the results of the test that examines the effect of Chinses familiarity (CFML) on analysts forecast information precision. Model 1 (Model 2/ Model 3) shows result for Total (Public/ Private) information precision. The estimated model equals: $Precision = \beta_0 + \beta_1 CFML + \beta_2 Size + \beta_3 ROA + \beta_4 Sale\_change + \beta_5 Volatility + \beta_6 Earn\_change + \beta_7 Horizon + \beta_8 Loss + \beta_9 Big4 + \beta_{10} Coverage + Year\ Dummies + Industry\ Dummies + error\ term.$ *T-statistics are shown in parentheses. ***, **, * indicate significance at the 1, 5 and 10 percent levels respectively. All variables are defined in the Appendix.*

CONCLUSION

Prior studies using U.S. samples have generally agreed that local analysts outperform their nonlocal counterparts due to an information advantage or local familiarity. However, will this phenomenon still hold for foreign firms cross-listed in the U.S.? While Du et al. (2017) show that analysts with Chinese ethnic origin share the same cultural background with Chinese cross-listed firms and therefore issue more accurate forecasts, Comiran and Siriviriyakyl (2019) find conflicting evidence that nonlocal analysts provide more accurate forecasts than local analysts for cross-listed firms from 41 foreign countries. Given the inconclusive results, I examine whether analysts with Chinese familiarity (CFML) behave differently from analysts without Chinese familiarity (NCFML) using a hand-collected sample of Chinese cross-listed firms from 2008 to 2015. An analyst is classified as with CFML if he/she meets one of the following criteria: the analyst has a Chinese last name; or the analyst's brokerage office/branch is located in China mainland, Hong Kong or Taiwan; or the analyst travels to China frequently; or the analyst's research is focused on Chinese or Asian firms/markets. The broader definition includes not only the cultural factor as used by Du et al. (2017), but also non-cultural factors as used by geographic proximity studies (Malloy 2005).

Results indicate that analysts with Chinese familiarity have higher accuracy forecasts with lower dispersion. The difference reflected in forecast accuracy and forecast dispersion between analysts with and without Chinese familiarity can be attributed to analysts' public information precision or analysts' private information precision. Using Barron et al. (1998) model (BKLS model), I measure the unobservable information precision with observable forecast accuracy and dispersion. Additional analysis reveals that analysts' Chinese familiarity advantage is mainly driven by analysts' higher private information precision rather than by the public information precision. Overall, the results indicate that analysts with Chinese familiarity can acquire and collect private information of Chinese cross-listed firms by sharing the same culture/language, locating close to firms' headquarters, visiting firms frequently, or focusing on the China market. Each of these activities benefits analysts with Chinese familiarity to possess more accurate private information, which leads to more accurate forecasts with lower dispersion.

The findings from this study are a useful resource for investors who are interested in trading in Chinese cross-listed firms and stocks. As noted by Hirst et al. (1995), investors perceive analysts' services as one of the most noteworthy tools for investment decisions (SRI International, 1987). Analysts who act as the middleman between firms and investors process information within their respective specialties and then transform that information into earnings forecasts. When investors trade in Chinese cross-listed firms, they usually face severe information asymmetry due to language barriers or cultural differences. In this situation, investors might rely more on analysts' services. Analysts with Chinese familiarity have an advantage when it comes to Chinese cross-listed firms and information, and they have the upper hand at extracting firms' private information. With firm-specific private information, these analysts can outperform their counterparts without Chinese familiarity by issuing forecasts with higher accuracy, lower dispersion, and better information precision. All these favorable properties can benefit investors by making better investment decisions.

One limitation of this study is that it uses analysts' last names as an indicator of Chinese familiarity. This method can be problematic, especially under two circumstances. Firstly, some female analysts may change their last names upon marriage, so use of last names falls short of expectations. Secondly, some Chinese immigrants, such as the second or third generation, although may still carry their Chinese last names, they might rarely speak Mandarin or maintain even their Chinese cultural heritage. They are usually Chinese in name only. When they become analysts, they are less likely to demonstrate Chinese familiarity. Future research should explore other proxies to measure Chinese familiarity more accurately.

APPENDIX

All variables are defined as follows:

Accuracy= -100 * [(|Actual EPS-Consensus EPS|) / Stock price of prior year]

Dispersion=100 * Standard deviation accrual EPS / Stock price of prior year

Public= natural logarithm of public information precision calculated with BKLS (1998) model

Private= natural logarithm of private information precision calculated with BKLS (1998) model

Total=sum of public information precision and private information precision

Size=market value of the firm

ROA= net income before extraordinary items / total assets

Sale change=change of sales from prior year to current year

Volatility= standard deviation of monthly stock returns

Earn change= change of earnings from prior year to current year

Horizon= forecast horizon

Loss=dummy variable equals to one if net income is negative, and zero otherwise

Big4= dummy variable equals to one if firms' financial statements are audited by Big 4 CPA firms, and zero otherwise

Coverage=number of analysts following the firm

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