JOURNAL OF INTERNATIONAL ACCOUNTING RESEARCH American Accounting Association
Vol. 9, No. 1 DOI: 10.2308/jiar.2010.9.1.23
2010
pp. 23–38

The Effect of a Change in Analyst Composition on Analyst Forecast Accuracy: Evidence from U.S. Cross-Listings

John Nowland and Andreas Simon

ABSTRACT: Prior research has shown improvements in analysts' forecast accuracy around various events (e.g., new disclosure regulations or cross-listings), but these studies do not consider a change in the composition and ability of the analysts providing forecasts over time. By studying foreign firms cross-listing on U.S. stock exchanges, we find that analyst composition changes by more than 50 percent during the three-year period around cross-listing. We show that cross-listing is associated with a shift away from analysts who are less accurate forecasters and toward analysts who are more accurate forecasters. This shift in analyst composition accounts for a significant improvement, of 9.5 percent, in analyst forecast accuracy. In addition, we document that changes in both analyst ability and public information disclosure affect analyst forecast accuracy around cross-listing. Our results indicate that researchers should control for changes in analyst composition and ability when measuring the impact of specific events on analyst forecast accuracy.

Keywords: analyst composition; analyst following; analyst forecast accuracy; cross-listing; disclosure.

Data Availability: Data are available upon request.

JEL Classifications: G14; G15; G34.

I. INTRODUCTION

Since Lang and Lundholm (1996) established a link between firm disclosure practices and analyst behavior, various studies have examined the effect of new disclosure regulations and other events (e.g., cross-listings) on the properties of analysts' forecasts. For example, researchers have investigated how analyst forecast accuracy has been affected by IFRS adoption (Ashbaugh and Pincus 2001), the introduction of Regulation FD in the U.S. (Bailey et al. 2003; Heflin et al. 2003; Irani and Karamanou 2003), and the introduction of corporate governance codes

John Nowland is an Assistant Professor at City University of Hong Kong and Andreas Simon is an Assistant Professor at California Polytechnic State University, San Luis Obispo.

Thanks to the editor for helpful comments and to two anonymous referees, Erv Black, Tony Cavoli, Howard Chan, John Chen, Jia-Chi Cheng, Stephen Crawford, Fang-Chi Lin, Ali Mutasowifin, Daniel Smith, Ethan Ming-Sian Syue, Jeng-Nien Yuan, and participants at the Asian FA Conference 2009.

Published Online: March 2010

and continuous disclosure requirements in non-U.S. markets (Brown et al. 1999; Chang et al. 2007; Nowland 2008). In the cross-listing literature, Baker et al. (2002) and Lang et al. (2003) show that analyst following and analyst forecast accuracy increase when foreign firms cross-list on U.S. markets. The increase in analyst forecast accuracy has been attributed to the commitment by firms to the improved disclosure practices required by U.S. markets.[1]

While these studies examine the change in the number of analysts and the change in forecast accuracy around the event of interest, they do not investigate whether there is also a change in the composition and ability of the analysts providing forecasts. In other words, analysts providing forecasts before and after the specific event are assumed to be similar and of equal forecasting ability. This paper questions this assumption, as we propose that the event of interest could lead to a change in the composition and quality of the analysts following a company.

Prior work by Bae et al. (2008), for example, shows that local analysts forecast earnings more accurately than foreign analysts. Mikhail et al. (1997) document a positive relationship between analyst experience and forecast accuracy. Therefore, existing analysts might have an advantage over new analysts (especially nonlocal analysts) who start forecasting the company. Alternatively, McNichols and O'Brien (1997) find a self-selection bias in analyst coverage, i.e., analysts selectively choose to follow companies where they believe they have superior forecasting ability. This self-selection bias in new analyst coverage may result in new analysts producing more accurate forecasts than existing analysts.[2] In either case, failure to control for a change in analyst composition and ability would confound the effect of the event of interest on the accuracy of analysts' forecasts.

To illustrate this confounding effect, we use a sample of foreign firms cross-listing on U.S. markets. We categorize analysts into old, continuing, and new analysts in the seven-year period around cross-listing. Old analysts are those who only follow the company prior to listing. New analysts only follow the company after it cross-lists. Continuing analysts follow the company throughout the period. We find that over the three-year period around cross-listing, more than 50 percent of the analyst composition changes from old to new analysts. This represents a substantial shift in the composition of analysts around cross-listing.

We then test for differences in forecasting accuracy between these groups of analysts. We find that the forecast accuracy of old analysts is significantly lower than that of continuing analysts before cross-listing. In addition, the forecast accuracy of new analysts is significantly higher than that of continuing analysts after cross-listing. This result illustrates that the cross-listing event is associated with a shift in analyst coverage away from a group of analysts who are less accurate forecasters and toward a group of analysts who are more accurate forecasters.

To quantify the effect of this shift on analyst forecast accuracy, we compare the change in the forecast accuracy of all analysts around cross-listing to the change in the forecast accuracy of continuing analysts. We call this difference *composition bias*, as it reflects the direct effect of the change in analyst composition on analyst forecast accuracy.[3] Continuing analysts are used as the benchmark because they represent a consistent group of analysts who forecast the company over the entire period around cross-listing. We find that the *composition bias* reaches 9.5 percent of

[1] An increase in analyst forecast accuracy around cross-listing is seen as an improvement in a firm's information environment, which is shown to have benefits such as lower cost of capital, access to more external financing, and higher stock market valuations (Doidge et al. 2004; Hail and Leuz 2007; Reese and Weisbach 2002).

[2] This is because fewer analysts with poorer forecasting ability choose to start following the company. Therefore, the new group of analysts is comprised of more analysts with better forecasting ability compared with the group of existing analysts.

[3] For example, if the average forecast accuracy of all analysts before and after cross-listing is -0.5 and -0.4 and the average forecast accuracy of continuing analysts before and after cross-listing is -0.45 and -0.45, then the change for all analysts is 0.1 and the change for continuing analysts is 0. Composition bias is then $0.1 - 0 = 0.1$.

average forecast accuracy if we measure the change around cross-listing using the year before and the year after listing. Furthermore, the *composition bias* is positive, which is in favor of finding an improvement in analyst forecast accuracy around cross-listing.

To further understand the change in analyst composition around cross-listing, we investigate the characteristics of the old, continuing, and new analysts. Before cross-listing, we find that old analysts have lower forecasting ability, less experience, and less access to resources; follow a lower percentage of U.S. companies; forecast in fewer markets; and issue less timely forecasts than continuing analysts. This poorer forecasting performance and the relative lack of experience are likely to contribute to the decision of old analysts to stop following the companies when the companies cross-list. After cross-listing, we find that new analysts have higher forecasting ability, less experience, and less access to resources; follow fewer companies; forecast in fewer markets; issue more timely forecasts; and follow companies with higher growth than continuing analysts. This suggests that it is not experience, access to resources, or international expertise that is helping the new analysts accurately forecast the earnings of the newly cross-listed companies. Rather, consistent with the self-selection bias in analyst coverage found by McNichols and O'Brien (1997), it seems that the new analysts are selectively choosing to follow companies with good prospects that they are able to forecast accurately.

Finally, we relate changes in analyst forecast accuracy around cross-listing to changes in analyst ability, analyst following, and public information disclosure. We find that both changes in analyst ability and public information disclosure are positively related to changes in analyst forecast accuracy around cross-listing. An increase in the number of analysts following companies around cross-listing is not found to be directly related to improved analyst forecast accuracy but moderates the effect between increased public disclosure and improved forecast accuracy.

Our study contributes to the literature in two ways. First, we show that analyst composition can change substantially over time, which can bias the results in favor of finding an improvement in analyst forecast accuracy around a specific event of interest. Second, we show that increased public information disclosure and analyst following are not the sole reasons for improved analyst forecast accuracy around events such as cross-listings. We find that analyst ability, i.e., the change to a group of analysts with greater forecasting ability, plays an incremental role. Therefore, our results indicate that researchers should control for changes in analyst composition and ability when measuring the impact of specific events on analyst forecast accuracy.

Our paper proceeds as follows. Section II describes the data and variables. Section III explains the methodology and discusses our results. Section IV concludes the paper.

II. DATA AND VARIABLES

This study examines the extent of analyst following and analyst forecast accuracy of foreign firms from three years before to three years after cross-listing on U.S. exchanges. Cross-listed companies are sourced as American Depositary Receipts (ADRs) from the Bank of New York website.[4] We use data from the Historical I/B/E/S International database to compute our measures of analyst following and accuracy. Firm financial data is from Compustat Global. Firms are included in the sample if they were cross-listed on the New York Stock Exchange (NYSE) or NASDAQ at the end of 2006 and if analyst earnings forecasts are available from I/B/E/S for at least one year before and after cross-listing. I/B/E/S coverage is from 1988 to 2006, so our

[4] We do not include non-exchange listings, because they are not required to meet the same new disclosure requirements as exchange listings. We do not include direct listings, because the sample of ADRs provides us with sufficient data across an adequate number of countries to illustrate our case.

cross-listing dates range from 1989 to 2005. The main sample comprises 1,189 firm-year observations of 191 firms from 31 countries. At the analyst level, this includes 81,924 annual earnings forecasts from 7,790 analysts.

Analyst forecast accuracy is the negative of the absolute value of average forecast earnings per share less actual earnings per share all divided by actual earnings per share (see, for example, Lang et al. 2003). If analysts have multiple forecasts in an estimation period, we use only the most recent forecast. Analyst forecast accuracy is winsorized at the 1st and 99th percentiles to mitigate the effect of small actual earnings figures. All results are consistent if yearend share price is used as the denominator instead of actual earnings; however, the sample size is significantly reduced. Analyst following is defined as the number of analysts providing annual earnings forecasts for the company during the fiscal year. We perform robustness checks by computing analyst following at various cutoff dates throughout the year, and our results remain unchanged.

Table 1 provides summary statistics for the sample based on a firm's country of domicile. Consistent with Chang et al. (2000), we find wide variation across countries in average analyst following and forecast accuracy. The greatest number of sample firms and firm-year observations are from the United Kingdom (31, 194), Brazil (17, 124), and France (17, 110). The average sample firm has an analyst following of 21.37 analysts and analyst forecast accuracy of −0.3934. There is considerable variation in the sample, with average analyst following ranging from 5.42 in Russia to 41.55 in Germany. Average forecast accuracy ranges from a low of −0.7961 in the Philippines to a high of −0.0533 in Denmark.

III. METHODOLOGY AND RESULTS

Shift in Analyst Composition

The first section of our analysis examines the change in analyst composition around cross-listing. For each firm-year observation, we categorize analysts into old, continuing, and new analysts. Old analysts are those who forecast the earnings of the company at least once before the date of cross-listing and then do not forecast again after cross-listing. New analysts provide earnings forecasts of the company at least once after cross-listing, but not before cross-listing. Continuing analysts forecast company earnings at least once before and after cross-listing.

Table 2 shows average analyst following across the seven-year period around cross-listing. We see that overall analyst following steadily increases from before to after cross-listing. In the year before cross-listing, analyst following is 19.93. In the year after cross-listing, analyst following is 22.39. This is consistent with the findings of previous research that cross-listing is associated with increased analyst coverage (Baker et al. 2002; Lang et al. 2003). However, the breakdown between old, continuing, and new analysts (also displayed in Figure 1) shows that there is a considerable change in analyst composition around cross-listing. A large number of analysts following the companies before cross-listing drop out in the year of cross-listing. In the years after cross-listing, more and more of the analyst following is comprised of new analysts. On average, over the three-year period around cross-listing, more than 50 percent of the analyst composition changes from old to new analysts.[5] This represents a substantial change in analyst composition from old to new analysts around cross-listing.

Effect on Forecast Accuracy

A change in analyst composition, however, will only have implications for analyst forecast accuracy if the relative forecasting abilities of the old, continuing, and new analysts are

[5] Here is another way to describe the shift: Of the 19.93 analysts who follow companies in the year before cross-listing, only 7.01 (35 percent) and 4.93 (25 percent) remain as continuing analysts in the two and three years after cross-listing, respectively.

TABLE 1
Descriptive Statistics

Country	No. Firms	No. Firm-Years	Average Forecast Accuracy	Average Analyst Following
Argentina	4	24	−0.7416	6.04
Australia	6	31	−0.3301	9.32
Belgium	1	7	−0.5259	31.71
Brazil	17	124	−0.4735	16.44
Chile	6	34	−0.3705	16.24
China	4	23	−0.3197	24.30
Colombia	1	5	−0.5753	6.00
Denmark	1	7	−0.0533	16.71
Finland	3	20	−0.5393	25.75
France	17	110	−0.5049	29.29
Germany	15	96	−0.3308	41.55
Hong Kong	3	17	−0.5186	15.29
Hungary	1	5	−0.1977	14.00
India	10	55	−0.2410	15.91
Ireland	4	26	−0.4537	7.62
Italy	1	6	−0.0537	12.50
Japan	14	88	−0.3432	12.85
Korea	2	9	−0.1144	21.11
México	10	61	−0.5124	19.75
The Netherlands	11	70	−0.3605	27.27
New Zealand	1	7	−0.3410	22.29
Norway	3	17	−0.5375	11.24
Philippines	1	6	−0.7961	21.83
Russia	2	12	−0.7430	5.42
South Africa	7	38	−0.4460	7.13
Spain	2	14	−0.3389	38.21
Sweden	2	12	−0.2887	26.67
Switzerland	6	41	−0.3171	34.34
Taiwan	4	23	−0.3717	15.04
United Kingdom	31	194	−0.2937	22.14
Venezuela	1	7	−0.6035	14.14
Total	191	1,189	−0.3934	21.37

No. firms is the number of firms. No. firm-years is the number of firm-year observations. Forecast accuracy is the negative of the absolute value of average forecast earnings per share less actual earnings per share all divided by actual earnings per share. Analyst following is the number of analysts providing earnings forecasts of the company during the fiscal year. Analyst forecast accuracy is winsorized at the 1st and 99th percentiles. Data is from I/B/E/S.

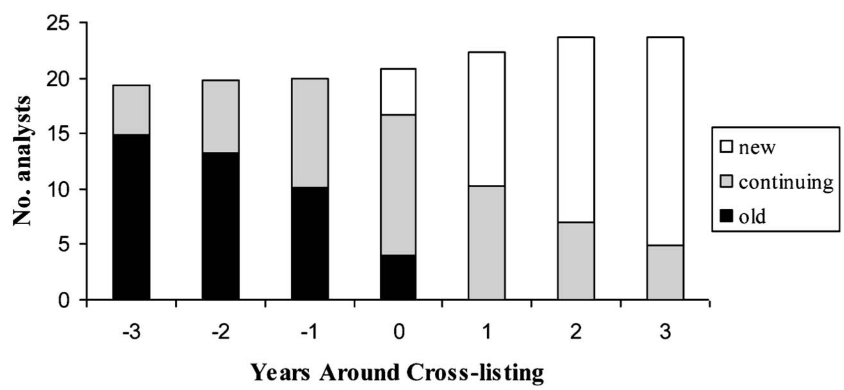
different. We therefore examine the average forecast accuracy of the old, continuing, and new analysts in the seven-year period around cross-listing. Table 3 shows the results of paired sample means tests for two comparisons: between old and continuing analysts before cross-listing, and between new and continuing analysts after cross-listing. We use paired-sample means tests

TABLE 2
Analyst Following around Cross-Listing

	Years around Cross-Listing						
Analysts	**−3**	**−2**	**−1**	**0**	**+1**	**+2**	**+3**
Old	14.92 (77%)	13.23 (67%)	10.05 (51%)	4.03 (19%)			
Continuing	4.41 (23%)	6.62 (33%)	9.88 (49%)	12.64 (61%)	10.23 (46%)	7.01 (30%)	4.93 (21%)
New				4.16 (20%)	12.16 (54%)	16.70 (70%)	18.79 (79%)
All Analysts	19.33 (100%)	19.85 (100%)	19.93 (100%)	20.83 (100%)	22.39 (100%)	23.71 (100%)	23.72 (100%)
No. Firm-Year Observations	155	165	181	183	184	162	150

Analyst following is defined as the number of analysts providing earnings forecasts of the company during the fiscal year. Old analysts are those who forecast the earnings of the company only before cross-listing. Continuing analysts forecast company earnings before and after cross-listing. New analysts provide earnings forecasts of the company only after cross-listing. Data is from I/B/E/S.

FIGURE 1
Analyst Coverage around Cross-Listing



because they provide direct tests between the different analyst groups using the same firm-year observations.[6]

The analysis indicates that old analysts have lower forecast accuracy than continuing analysts in the year before and the year of cross-listing. New analysts have significantly higher forecast accuracy than continuing analysts in the year of and the year after cross-listing. This result illustrates that the event of cross-listing is associated with a shift in analyst coverage away from a

[6] However, as not all firm-year observations have both old and continuing analysts or both new and continuing analysts, the results for the means tests do not directly equate to the differences between the average forecast accuracy numbers.

TABLE 3

Forecast Accuracy of Old, Continuing, and New Analysts

Analysts	Years around Cross-Listing						
	−3	**−2**	**−1**	**0**	**+1**	**+2**	**+3**
Old	−0.3570	−0.4101	−0.3697	−0.4447			
Continuing	−0.3672	−0.4098	−0.3460	−0.3892	−0.4583	−0.3660	−0.2710
New				−0.3840	−0.4229	−0.3542	−0.3013
Old − Continuing	0.0102	−0.0003	−0.0237**	−0.0512***			
New − Continuing				0.0375*	0.0354**	0.0118	−0.0303*
No. Firm-Year Observations	155	165	181	183	184	162	150

*, **, *** Significance of t-tests for paired sample means tests at the 10 percent, 5 percent, and 1 percent levels, respectively.

Analyst forecast accuracy is the negative of the absolute value of average forecast earnings per share less actual earnings per share all divided by actual earnings per share. Old analysts are those who forecast the earnings of the company only before cross-listing. New analysts provide earnings forecasts of the company only after cross-listing. Continuing analysts forecast company earnings before and after cross-listing. Old − Continuing represents the paired sample difference between old and continuing analysts. New − Continuing represents the paired sample difference between new and continuing analysts. As not all firm-year observations have both old and continuing analysts or both new and continuing analysts, the results for the means tests do not directly equate to the differences between the average forecast accuracy numbers. Data is from I/B/E/S.

group of analysts (old analysts) who are less accurate forecasters and toward a group of analysts (new analysts) who are more accurate forecasters. This shift by itself results in an improvement in analyst forecast accuracy around cross-listing that is unrelated to the direct effect of cross-listing (i.e., improved public disclosure) on analyst forecast accuracy.

Three years after cross-listing, there is also a significant difference between new and continuing analysts. In this case, new analysts have lower forecast accuracy than continuing analysts. This is most likely due to the superior forecasting ability of a small number of continuing analysts who have been following the company for a long time (Mikhail et al. 1997).

To quantify the effect of the shift in analyst composition on analyst forecast accuracy, we compare the change in the forecast accuracy of all analysts around cross-listing to the change in the forecast accuracy of continuing analysts. Continuing analysts are used as the benchmark as they represent a consistent group of analysts who forecast the company over the entire period around cross-listing. We first measure the difference between the forecast accuracy of all analysts and the forecast accuracy of continuing analysts in each firm-year observation. This means we are measuring the relative forecasting performance of the two groups for the same firm in the same period and do not need to control for firm- or period-specific differences. Composition bias is then defined as the difference between the forecast accuracy of all analysts and that of continuing analysts after cross-listing, minus the difference before cross-listing—in other words, the bias introduced if the forecast accuracy of all analysts is used to measure the change around cross-listing, rather than the forecasts of a consistent group of continuing analysts.

Table 4 presents estimates of composition bias over a number of periods around cross-listing. Note that we are not measuring the change in analyst forecast accuracy from before to after cross-listing, as per Lang et al. (2003); rather, we are measuring the difference between the change for all analysts and the change for continuing analysts. Because the previous section documents significant differences in the forecast accuracy of old, continuing, and new analysts in the three-year period around cross-listing, we expect the composition bias to be highest in this period. We find that the composition bias is highest at 0.0372, or 9.5 percent of average forecast accuracy, if we measure the change around cross-listing using just the year before and the year after listing. Furthermore, the composition bias is positive, i.e., in favor of finding an improvement in analyst forecast accuracy around cross-listing.

TABLE 4

Composition Bias

Years around Cross-Listing	No. Firm-Years	Difference in Forecast Accuracy (All − Continuing Analysts): Before		After		Composition Bias (After − Before)
		Mean	Std	Mean	Std	
−1, +1	341	−0.0061	0.0145	0.0311	0.0130	0.0372***
−1 to +1	519	−0.0061	0.0145	0.0234	0.0209	0.0295***
−2 to +2	819	−0.0015	0.0356	0.0229	0.0198	0.0244**
−3 to +3	1078	0.0017	0.0292	0.0107	0.0256	0.0090

*, **, *** Significance of t-tests for differences in means at the 10 percent, 5 percent, and 1 percent levels, respectively.

Composition bias is the difference between the forecast accuracy of all analysts and continuing analysts after cross-listing minus the difference before cross-listing. Analyst forecast accuracy is the negative of the absolute value of average forecast earnings per share less actual earnings per share all divided by actual earnings per share. Data is from I/B/E/S.

Using the three-year period around cross-listing (−1 to +1), the composition bias is 0.0295, or 7.5 percent of average forecast accuracy. This is slightly lower because the year of cross-listing has both positive effects (difference between new and continuing analysts) and negative effects (difference between old and continuing analysts) on the bias, and both of these effects are included in the after-cross-listing data.[7] The five-year period around cross-listing (−2 to +2) has a composition bias of 0.0244, or 6.2 percent of average forecast accuracy. This is smaller than the three-year period because the bias is now averaged over a longer period of time. The composition bias over the seven-year period is insignificant at 0.0090, or 2.3 percent of average forecast accuracy. This suggests that the magnitude of the bias is reduced as the event window around cross-listing grows longer.

Overall, these results show that there is a significant bias in the measurement of analyst forecast accuracy around cross-listing if the forecast accuracy of all analysts is used instead of just the forecast accuracy of continuing analysts. Therefore, researchers need to be careful when making conclusions about the effect of cross-listing on analyst forecast accuracy (or the effect of any event of interest on analyst forecast accuracy) without taking the bias from the change in analyst composition into consideration.

Differences in Analyst Characteristics

The results presented in the previous sections indicate that cross-listing has two effects on analyst coverage: (1) old analysts who have lower forecast accuracy stop following the company at cross-listing, and (2) new analysts provide better forecasts after the company cross-lists in the U.S. This section explores explanations for these effects by examining differences between the characteristics of old, continuing, and new analysts. For example, the new analysts may have more experience and resources, or they may be selectively following companies, which would give them an edge over continuing analysts. Old analysts may be busier, have fewer resources, and provide less timely forecasts, which would result in less accurate forecasts than those of continuing analysts.

We examine eight analyst characteristics related to forecasting ability, experience, access to resources, busyness, international forecasting expertise, and the timeliness of forecasts. The first measure is a standardized score of analyst forecasting ability (analyst ability) from Clement (1999). Analyst ability is calculated by averaging the mean absolute forecast error of each analyst's forecasts across all companies they forecast each year. Mean absolute forecast error is calculated as the negative of the analyst's forecast error minus the average forecast error of all analysts covering the firm divided by the average forecast error of all analysts covering the firm.

As Mikhail et al. (1997) document a relationship between analyst experience and forecast accuracy, we examine two measures of analyst experience: a broad measure of experience (analyst experience), which is the number of years since the analyst had their first forecast recorded on I/B/E/S, and a company-specific measure of experience (company experience), which is the number of years the analyst has been forecasting the company. If analysts work at brokerages with more resources, they are more likely to be able to access more information and provide more accurate forecasts. Consistent with Michaely and Womack (1999), we include brokerage size, which proxies for the resources available to analysts. If analysts are busy (i.e., if they follow more companies), they may produce less accurate forecasts as they have less time to devote to each forecasted company. Following Clement (1999), we measure busyness as the number of companies the analyst forecasts during the same year.

[7] It is not possible to separate the observations for the year of cross-listing into pre- and post-cross-listing periods, because continuing analysts can provide multiple forecasts both before and after the cross-listing date. This would result in double counting of these analyst-firm-year observations.

The next two characteristics measure the international expertise of analysts. As the cross-listed companies are now part of both their home market and U.S. markets, we measure the expertise of analysts in following both U.S. companies and companies from other foreign markets. The percentage of U.S. companies followed measures the number of U.S. companies forecasted divided by all companies forecasted. The number of markets measures the number of different markets (represented by different forecasting currencies) in which the analyst forecasts companies. The final analyst characteristic is the timeliness of analyst forecasts, measured as the number of days between the date of the forecast and the release of the actual earnings result.

In addition to analyst characteristics (such as poorer forecasting ability), it is possible that firm characteristics play a role in the decision to start or stop following a company. Bhushan (1989) shows that analysts prefer to follow bigger and more successful companies. Therefore, we also examine two firm characteristics: firm size (total assets in billions of U.S. dollars) and firm growth (one-year sales growth). However, the need to merge analyst forecast data with firm financial data means there is a reduced sample of analyst-firm-year observations (shown in parentheses in Table 5) for the firm characteristics.

Table 5 Panel A presents the differences between old and continuing analysts in the year before cross-listing. Panel B presents the differences between the new and continuing analysts in the year after cross-listing. Only analyst-firm-year observations in these two years are examined as this is where the greatest differences between the groups were found in the previous analysis.[8]

Before cross-listing, we find that old analysts have lower forecasting ability, less experience (broad and company-specific), and less access to resources (lower brokerage size); follow a lower percentage of U.S. companies; forecast in fewer markets; and issue less timely forecasts than continuing analysts. There is no significant difference in the busyness (number of companies followed) of old and continuing analysts. The firm characteristics indicate that old analysts follow companies that are smaller and have lower growth than continuing analysts. These results show that old analysts are poor forecasters not just of the cross-listing company, but also more generally across all companies they follow. If the old analysts foresee that the company will be followed by a new group of analysts with greater experience or ability than themselves, then it is logical that they would decide to stop following the company.

After cross-listing, we find that new analysts have higher forecasting ability, less experience, and less access to resources (lower brokerage size); follow fewer companies; forecast in fewer markets; and issue more timely forecasts than continuing analysts. There is no significant difference in the percentage of U.S. companies followed by new and continuing analysts. The firm characteristics show that new analysts follow companies that are smaller and have higher growth than continuing analysts. This suggests that it is not experience, access to resources, and international expertise that are helping the new analysts accurately forecast the earnings of the newly cross-listed companies. Rather, it seems that the new analysts are generally more accurate forecasters, and because they follow fewer companies, it is likely that the new analysts are selectively choosing to follow companies with good prospects that they are able to forecast accurately. This is consistent with the self-selection bias in analyst coverage found by McNichols and O'Brien (1997).

Forecast Accuracy, Analyst Ability, and Public Disclosure

Lang et al. (2003) document a difference in forecast accuracy between cross-listed and non-cross-listed firms and an improvement in analyst forecast accuracy around cross-listing, which

[8] We do not include the year of cross-listing, because the timeliness of forecasts by old and new analysts, by definition, will be different. Old analysts only forecast in the period before cross-listing, whereas new analysts only forecast after the cross-listing date.

TABLE 5
Analysts Characteristics

Panel A: Old versus Continuing Analysts (year = −1)

	Old		**Continuing**		**Difference (Old − Continuing)**
	Mean	**Std.**	**Mean**	**Std.**	
Analyst Characteristics					
Analyst Ability	−0.05	0.39	0.03	0.25	−0.08***
Analyst Experience (years)	3.13	2.98	3.52	3.25	−0.40***
Company Experience (years)	1.51	1.90	1.73	2.17	−0.22***
Brokerage Size	104.81	116.69	109.80	114.69	−4.99*
No. Companies Followed	17.88	62.37	18.27	28.34	−0.39
% of U.S. Companies	9.78	26.28	13.46	28.89	−3.67***
Number of Markets	2.27	3.25	2.61	2.81	−0.34***
Timeliness (days)	171.88	77.27	146.56	66.83	25.32***
Firm Characteristics					
Firm Size (U.S.$ billions)	55.30	146.21	68.79	164.92	−13.49**
Firm Growth (%)	25.11	115.34	42.65	156.92	−17.54***
No. of Analyst-Firm-Years	1904 (1546)		1998 (1517)		

Panel B: New versus Continuing Analysts (year = +1)

	New		**Continuing**		**Difference (New − Continuing)**
	Mean	**Std.**	**Mean**	**Std.**	
Analyst Characteristics					
Analyst Ability	0.01	0.34	−0.05	0.35	0.06***
Analyst Experience (years)	2.22	2.76	5.00	3.23	−2.78***
Company Experience (years)	0.41	0.91	3.05	2.24	−2.64***
Brokerage Size	104.72	113.11	116.64	112.97	−11.93***
No. Companies Followed	13.68	26.40	15.17	22.55	−1.49**
% of U.S. Companies	13.76	30.81	12.86	27.71	0.89

(continued on next page)

Panel B: New versus Continuing Analysts (year = +1)

	New		Continuing		Difference (New − Continuing)
	Mean	**Std.**	**Mean**	**Std.**	
Number of Markets	2.17	1.95	2.47	2.35	−0.30***
Timeliness (days)	139.16	73.41	177.43	66.10	−38.27***
Firm Characteristics					
Firm Size (U.S.$ billions)	67.10	178.19	88.03	201.92	−20.93***
Firm Growth (%)	15.56	127.62	−1.38	71.16	16.94***
No. of Analyst-Firm-Years	2383 (1816)		2091 (1418)		

*, **, *** Significance of t-tests for differences in means at the 10 percent, 5 percent, and 1 percent levels, respectively.

Analyst characteristics in the year before (t–1) and after (t+1) cross-listing. Analyst ability is a standardized score of analyst forecasting ability across all forecasted firms from Clement (1999). Analyst experience is the number of years since the analyst had their first forecast recorded on I/B/E/S. Company experience is the number of years the analyst has been forecasting the company. Brokerage size is the number of analysts who work at the brokerage in the same year. No. companies followed is the number of companies the analyst forecasts during the same year. Percentage of U.S. companies followed measures the number of U.S. companies forecasted divided by all companies forecasted. Number of markets measures the number of different markets (represented by different forecasting currencies) in which the analyst forecasts companies. Timeliness is the number of days between the forecast date and actual earnings date. Firm size is total assets measured in billions of U.S. dollars. Firm growth is measured as one-year sales growth. Old analysts are those who forecast the earnings of the company only before cross-listing. New analysts provide earnings forecasts of the company only after cross-listing. Continuing analysts forecast company earnings before and after cross-listing. The number in parentheses in the no. of analyst-firm-years represents the reduced sample for firm characteristics. Data is from I/B/E/S and Compustat Global.

they attribute to the improved public disclosure of foreign firms once the firms are cross-listed on U.S. markets. Baker et al. (2002) and Lang et al. (2003) also report an increase in analyst following around cross-listing, which may have a direct effect on analyst forecast accuracy. In this paper, we have documented a change in analyst ability around cross-listing that also impacts analyst forecast accuracy. This section therefore examines which one or combination of these factors is related to the change in analyst forecast accuracy around cross-listing.

We relate the change in analyst forecast accuracy from the year before to the year after cross-listing to changes in analyst ability, analyst following, and public information disclosure. Our measure of public information disclosure is from Barron et al. (1998). They separate the information in analysts' forecasts into common and idiosyncratic components. We use their measure of common information as it represents information that is available to all analysts, which is consistent with publicly available information.[9] We also include control variables to eliminate the influence of the timeliness of forecasts on forecast accuracy and to remove the effect of earnings surprise on forecast accuracy. Earnings surprise is measured as the difference between last year's and this year's earnings per share. We do not include changes in firm-specific variables, such as firm size or risk, as these variables are not expected to change significantly around cross-listing.[10] We do include a dummy variable, equal to 1 if the cross-listing also raises capital, to control for the potential impact of this new capital raising on the ability of analysts to forecast the earnings capacity of the firm. As the change model requires data for firms in both the year before and year after cross-listing, the sample is reduced to 157 firms.[11] The inclusion of the earnings surprise variable further reduces the sample, to 134 firms, because two more years of earnings data are required for the analysis. All models are run with robust standard errors.

Table 6 presents these results. In the first regression, we find a significant positive relationship between the change in forecast accuracy and the change in analyst ability around cross-listing. This confirms that a change in the average ability of analysts following firms does have a significant effect on analyst forecast accuracy around cross-listing. In the second regression, we also include analyst following and public information. Again, we find a positive relationship between changes in analyst ability and forecast accuracy. The relationships between analyst following, public information disclosure, and forecast accuracy are insignificant. In the third regression, which includes all control variables, both analyst ability and public information disclosure are significant. The timeliness of forecasts is also found to be negatively related to forecast accuracy, which confirms that forecasts issued closer to the release of earnings results are more accurate.

To compare the economic significance of the two variables (Δ analyst ability and Δ public information), we measure the effect of a one standard deviation change in the variables on the change in analyst accuracy. We find a one-standard-deviation increase in Δ analyst ability results in an increase in analyst accuracy of 0.0771. A one-standard-deviation increase in Δ public information disclosure results in an increase in analyst accuracy of 0.0323. Therefore, in our analysis a change in analyst quality has a greater impact on analyst forecast accuracy.

In the fourth regression, we introduce interaction terms between change in public disclosure and change in analyst quality, and between change in public disclosure and change in analyst

---

9 It is calculated as follows:

$$(SE - \mathrm{D/n})/((1 - 1/\mathrm{n})\mathrm{D} + SE)^2$$

where *SE* is actual earnings minus average analyst forecast, D is the standard deviation of analyst forecasts, and n is the number of analyst forecasts.

10 This is consistent with the change model of Lang et al. (2003).

11 We also exclude the top and bottom 5 percent of observations as their change in forecast accuracy is unrealistic. This means moving from below the fifth percentile of forecast accuracy before listing to above the 95th percentile after listing, or vice versa.

TABLE 6

Forecast Accuracy, Analyst Ability, and Public Disclosure

	Δ Analyst Forecast Accuracy			
	(1)	**(2)**	**(3)**	**(4)**
Intercept	−0.0514	−0.0512	−0.0876	−0.0933
	(0.18)	(0.22)	(0.08)	(0.07)
Δ Analyst Ability	0.5494	0.5934	0.7015	0.7921
	(0.03)	(0.04)	(0.08)	(0.06)
Δ Analyst Following		−0.0014	−0.0032	−0.0014
		(0.77)	(0.56)	(0.81)
Δ Public Information		−0.0001	0.0018	0.0012
		(0.14)	(0.06)	(0.19)
Δ Timeliness			−0.0025	−0.0026
			(0.01)	(0.01)
Δ Earnings Surprise			0.0001	0.0001
			(0.45)	(0.47)
Capital Raising			0.1551	0.1652
			(0.13)	(0.11)
Δ Public Information * Δ Analyst Ability				0.0025
				(0.70)
Δ Public Information * Δ Analyst Following				0.0004
				(0.04)
Adj. R^2	0.02	0.01	0.06	0.05
No. Firm-Year Observations	157	157	134	134

Regressions relate changes in analyst forecast accuracy from the year before to the year after cross-listing to changes in analyst ability, analyst following, public information, and control variables. Analyst forecast accuracy is the negative of the absolute value of average forecast earnings per share less actual earnings per share all divided by actual earnings per share. Analyst ability is a standardized score of analyst forecasting ability across all forecasted firms from Clement (1999). Analyst following is the number of analysts providing earnings forecasts of the company during the fiscal year. Public information is the common information component from analysts' forecasts from Barron et al. (1998). Timeliness is the number of days between the forecast date and actual earnings date. Earnings surprise is the difference between earnings last year and this year. Capital raising is a dummy variable equal to 1 if the company raised new capital at cross-listing. Data is from I/B/E/S. p-values are in parentheses.

following. These interaction terms determine whether increased public disclosure has a greater effect when analyst ability increases, and whether increased public disclosure has a greater effect when analyst following increases. The results show no significant interaction between change in public disclosure and change in analyst quality, but a significant positive interaction between change in public disclosure and change in analyst following. This is not surprising, as it suggests that increased public disclosure has a greater effect on analyst forecast accuracy when there are more analysts analyzing and interpreting the information provided by the firm. The lack of significance of the interaction between change in public disclosure and change in analyst quality suggests that these are independent effects.

In summary, these results show that both changes in analyst ability and changes in public information disclosure have an effect on analyst forecast accuracy around cross-listing. An increase in the number of analysts following companies around cross-listing is not directly related to improved analyst forecast accuracy but moderates the effect between increased public disclosure and improved forecast accuracy.

IV. CONCLUSION

A number of recent studies have investigated how analyst forecast accuracy has been affected by certain events, e.g., IFRS adoption, the introduction of Regulation FD, the adoption of corporate governance codes, and the cross-listing of foreign firms on U.S. exchanges. However, in doing so they have implicitly assumed that the composition and forecasting ability of analysts do not change around the event of interest. We use the example of foreign firms cross-listing on U.S. exchanges to illustrate the effect of a shift in analyst composition on analyst forecast accuracy. We document a substantial change in analyst composition around cross-listing which includes a shift away from a group of analysts who are less accurate forecasters and toward a group of analysts who are more accurate forecasters.

We show that this shift in analyst composition biases the results in favor of finding an improvement in forecast accuracy around cross-listing. This bias can reach a magnitude of 9.5 percent of average forecast accuracy. We then relate changes in analyst forecast accuracy around cross-listing to changes in analyst ability, analyst following, and public information disclosure. We find that changes in both analyst ability and public information disclosure are positively related to changes in analyst forecast accuracy around cross-listing.

Our study contributes to the literature by showing that changes in both analyst composition and analyst ability can have a significant effect on analyst forecast accuracy. We do not expect the effects to be of the same magnitude and significance across studies of different events during different time periods and in different countries, but we hope future studies will take these effects into consideration. To minimize the potential for bias, we suggest researchers use the forecasts of a fixed group of analysts around the event of interest and control for analyst ability in their analysis.

REFERENCES

Ashbaugh, H., and M. Pincus. 2001. Domestic accounting standards, international accounting standards, and the predictability of earnings. *Journal of Accounting Research* 39: 417–434.

Bae, K.-H., M. Stulz, and H. Tan. 2008. Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts. *Journal of Financial Economics* 88: 581–606.

Bailey, W., H. Li, C. X. Mao, and R. Zhong. 2003. Regulation Fair Disclosure and earnings information: Market, analyst, and corporate responses. *The Journal of Finance* 58: 2487–2514.

Baker, H. K., J. Nofsinger, and D. Weaver. 2002. International cross-listing and visibility. *Journal of Financial and Quantitative Analysis* 37: 495–521.

Barron, O. E., O. Kim, S. C. Lim, and D. E. Stevens. 1998. Using analysts' forecasts to measure properties of analysts' information environment. *The Accounting Review* 73: 421–433.

Bhushan, R. 1989. Firm characteristics and analyst following. *Journal of Accounting and Economics* 11: 255–274.

Brown, P., S. L. Taylor, and T. S. Walter. 1999. The impact of statutory sanctions on the level and information content of voluntary corporate disclosure. *Abacus* 35: 138–162.

Chang, J., Y. J. Cho, and H. H. Shin. 2007. The change in corporate transparency of Korean firms after the Asian crisis: An analysis using analysts' forecast data. *Corporate Governance: An International Review* 15 (6): 1144–1167.

Chang, J., T. Khanna, and K. Palepu. 2000. Analyst activity around the world. HBS Strategy Unit Working Paper No. 01–061, Harvard Business School.

Clement, M. B. 1999. Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics* 27 (3): 285–303.

Doidge, C., G. A. Karolyi, and R. Stulz. 2004. Why are foreign firms listed in the U.S. worth more? *Journal of Financial Economics* 71: 205–238.

Hail, L., and C. Leuz. 2007. Cost of capital effects and change in growth expectations around U.S. cross-listings. Working paper, The University of Chicago.

Heflin, F., K. R. Subramanyam, and Y. Zhang. 2003. Regulation FD and the financial information environment: Early evidence. *The Accounting Review* 78: 1–37.

Irani, A. J., and I. Karamanou. 2003. Regulation Fair Disclosure, analyst following, and analyst forecast dispersion. *Accounting Horizons* 17: 15–29.

Lang, M., and R. Lundholm. 1996. Corporate disclosure policy and analyst behaviour. *The Accounting Review* 71: 467–492.

Lang, M., K. Lins, and D. Miller. 2003. ADRs, analysts, and accuracy: Does cross-listing in the U.S. improve a firm's information environment and increase market value? *Journal of Accounting Research* 41: 317–345.

McNichols, M., and P. O'Brien. 1997. Self-selection and analyst coverage. *Journal of Accounting Research* 35: 167–199.

Michaely, R., and K. Womack. 1999. Conflict of interest and the credibility of underwriter analyst recommendations. *Review of Financial Studies* 12 (4): 653–686.

Mikhail, M. B., B. R. Walther, and R. H. Willis. 1997. Do security analysts improve their performance with experience? *Journal of Accounting Research* 35 (3): 131–157.

Nowland, J. 2008. The effect of national governance codes on firm disclosure practices: Evidence from analysts earnings forecasts. *Corporate Governance: An International Review* 16: 475–491.

Reese, W., and M. Weisbach. 2002. Protection of minority shareholder interest, cross-listing in the United States, and subsequent equity offerings. *Journal of Financial Economics* 66: 65–104.