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Local versus foreign analysts' forecast accuracy: does herding matter?

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The aim of this paper is to compare the information and resource endowments possessed by different analyst types, classified by both location and employment within the context of seven emerging Asian markets. Our results show that local analysts are more accurate than expatriate and global analysts when we consider all earnings forecasts. However, when we control for the segregated herding behaviour of analysts, we find that herding local forecasts are one of the least accurate compared to other herding forecasts. By contrast, bold local (that is, non-herding local) forecasts are more accurate than all other bold forecasts. This suggests that the information endowment of bold local analysts is superior to the information and resource endowments of bold expatriate analysts. We show that the superior accuracy of bold local forecasts does not stem from business group affiliations, investment banking relationships, demand for local analysts' services or the specialisation of analysts vis-à-vis countries or sectors. We consistently find that bold local analysts are better at assessing the earnings of the firm they forecast. Our results show that the prior documented advantage of local analysts in terms of forecasting accuracy is driven by the bold local analysts, with herding locals diluting this effect. To the best of our knowledge, this is the first study to explore the segregated herding behaviour of local, expatriate and global analysts, and its impact on relative forecast accuracy across analyst types.

Key words: Local analyst; Forecast accuracy; Herding

JEL classification: G14, G15

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1. Introduction

There is considerable debate regarding the relative quality of earnings forecasts produced by local and foreign analysts (see, e.g., Conroy *et al.*, 1997; Bacmann and Bolliger, 2003; Bolliger, 2004; Orpurt, 2004; Bae *et al.*, 2008b; Comiran and Siriviriyakul, 2019).[1] The majority of studies in the field argue that resident analysts (those located in the same country as the local firm) are more accurate than non-resident analysts. This is driven primarily by their local advantage in terms of their understanding of local customs, cultures, language and the relationship with local firms (the information endowment factor).[2] By contrast, non-resident analysts, especially globally operating analysts such as UBS, Merrill Lynch and JP Morgan Chase, benefit from superior skills at processing and extrapolating pertinent information when forecasting earnings that are enhanced by in-house training programmes and the team/network of professionals they work with (the resource endowment factor). However, to the best of our knowledge, no prior studies in the field have taken into account the fact that a specific earnings forecast can be formed simply by mimicking other forecasts (that is, by herding). The failure to account for this behaviour prevents the researcher from testing the true forecasting abilities of analysts and accurately comparing the information versus resource endowment factors. To address this concern, we control for the segregated herding behaviour of analysts and focus on bold (non-herding) forecasts as they are more likely to reflect the true ability of analysts to collect and process extant information.

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[1]Analyst types are defined differently in prior studies. Some studies such as Orpurt (2004) define analysts according to geographical location, so that local analysts are those employed in a brokerage house located inside a particular country, regardless of the origin of the brokerage house. Other studies, such as Conroy *et al.*, (1997) and Bacmann and Bolliger (2003) for example, define analysts according to the origin of brokerage houses, so that local analysts are those employed in a local brokerage house. In this paper we take into account the location as well as employment effects when categorising analysts. Specifically, as stated in Appendix II of the paper, 'local' analysts are defined as analysts employed in a brokerage house located inside a particular country in which the covered firm's equity is traded. Resident foreign analysts are referred to as 'expatriate' analysts, and are employed in a foreign brokerage house operating in a country where the covered firm's equity is traded. Non-resident foreign analysts are referred to as 'global' analysts who work outside the country in which the firm's equity is traded and forecast earnings for local firms. The term 'resident' analysts refers to local and expatriate analysts, and the term 'foreign' analysts refers to expatriate and global analysts. The terms 'relative quality of earnings forecasts' or 'relative accuracy of earnings forecasts' are used to refer to the difference across analyst types.

[2]For example, using survey data, Hu *et al.*, (2008) show that financial analysts exhibit greater information comprehension when they conduct more company-level surveys such as on-the-spot visits to the company, news conferences and telephone surveys to the company.

There is well-documented evidence that analysts tend to herd when making earnings forecasts or stock recommendations (see, e.g., Welch, 2000; Gleason and Lee, 2003; Clement and Tse, 2005; Jegadeesh and Kim, 2010; Lee and Lee, 2015; Frijns and Huynh, 2018; Lin, 2018), and that such behaviour leads to improvements in the quality of forecasts (see, e.g., Ke and Yu, 2006; Salamouris and Muradoglu, 2010; Mira and Taylor, 2011).[3] However, there are no studies in the field that examine whether the propensity to herd can be explained by the location and employment characteristics of analysts. Also, it is not clear whether this potential herding behaviour affects the accuracy of forecasts made by different analyst types. This knowledge will help investors to make more informed investment decisions by possibly relying on non-herding forecasts produced by a specific analyst type (e.g., Chang, 2010). It will also further assist brokerage houses to make strategically important and capital-intensive decisions on whether to enter new markets and the role of behavioural factors in the forecasting activity of the analysts they employ. Furthermore, this will advance the understanding of the academic community on the determinants of herding when producing forecasts and ultimately the role of different analyst types in disseminating firm-specific information.

This paper first explores whether the propensity to herd is explained by the location and employment characteristics of analysts and then it tests whether the segregated herding behaviour across different analyst types affects the accuracy of earnings forecasts produced by these analysts. We argue that bold forecasts reflect more accurately the information and resource endowments possessed by different analyst types. Hence, in order to perform an accurate comparison on the endowments held by different analyst types, we place greater emphasis on bold forecasts as herding forecasts are formed by mimicking the forecasts of others.

This study focuses on Asian countries as we believe that emerging countries possess a number of distinguishing features that makes them an ideal laboratory to explore the impact of herding behaviour on the accuracy of analysts' forecasts. First, as pointed out by Hsieh *et al.*, (2011), the information environment in emerging markets is relatively opaque mainly due to weak reporting requirements, lower accounting standards, lax enforcement of regulations and costly information acquisition. These factors may force market participants, including financial analysts, to herd on the information of others.[4]

[3]The literature regarding whether (non-herding) bold forecasts are on average more accurate than herding forecasts provides mixed findings. Clement and Tse (2005) and Huang *et al.*, (2017), for example, use US data and find that bold forecasts are more accurate than herding forecasts. However, Salamouris and Muradoglu (2010) and Mira and Taylor (2011) use UK data and show that bold forecasts are less accurate than herding forecasts. To the best of our knowledge, there are no prior studies exploring the impact of boldness on the accuracy of forecasts in an international or Asian setting.

[4]Lin (2018), for example, shows that analysts are more likely to ignore their own beliefs and follow the decisions of others who they perceive to have superior information when producing stock recommendations in times of greater aggregated uncertainty.

Second, prior evidence also suggests the role of financial analysts in terms of explaining stock returns is far more prominent in Asia compared to the US. Covrig and Low (2005), for example, explore the role of financial analysts in equity valuation in Japan and show that the incremental contribution of analysts' forecasts to explain stock returns is 405 percent (in terms of the percentage increase in adjusted-R^2) over the accounting information. This compares to the 41 percent previously reported using US evidence by Amir *et al.*, (1999). This indicates that the skill and expertise of analysts are more valuable in markets with poor financial disclosure, such as Asian markets. Third, Asia is one of the fastest growing economic centres with financial markets representing trillions of dollars (Walsh, 2014). Any market that large will attract the interest of international investors. Therefore, knowledge of the determinants of the relative quality of earnings forecasts produced by different analyst types vis-à-vis their proximity to the forecasted markets is important to investors. And, finally, there is only limited empirical work on herding behaviour in emerging markets – surprising given the greater tendency of investors and analysts to herd in such markets. In a review study on herding behaviour in financial markets, Bikhchandani and Sharma (2001) acknowledge the need for more empirical work exploring the herding behaviour of investors and financial analysts in emerging markets. This concern is also echoed by Dang and Lin (2016) when researching the herding behaviour of investors with heterogeneous information in emerging markets. The lack of attention is particularly surprising given the growing importance of emerging markets in the global economy (e.g., Kaminsky *et al.*, 2001).

The main objective of this paper is to test the relative accuracy of different analyst types by taking into consideration their propensity to herd. We categorise analyst types as local, expatriate and global (see Section 3.2.3 and Appendix II for detailed definitions of each analyst type), and address the following three issues. First, we re-examine the relative accuracy of forecasts produced by the local, expatriate and global analysts (e.g., Bae *et al.*, 2008b). Second, we identify whether some types of analysts are more likely to herd than other analysts. To the best of our knowledge, very few attempts have been made, if any, to explore the segregated herding behaviour of local, expatriate and global analysts. Indeed, while previous evidence suggests that analysts herd (see, e.g., Clement and Tse, 2005; Jegadeesh and Kim, 2010; Huang *et al.*, 2017), it is not clear whether this behaviour tends to vary across different analyst types vis-à-vis their proximity to the forecasted market. Finally, we explore the relative accuracy of analysts but only focusing on bold forecasts as these reflect the true information and resource endowments possessed by the different analyst types.

The findings of this study show that local analysts are the most accurate analyst type in terms of their earnings forecasts, and expatriate analysts in emerging Asian markets are less likely to herd compared to other analysts. However, when the herding behaviour is controlled for, the herding local analysts emerge as one of the least accurate analyst types whereas bold local analysts are the most accurate analyst type. This indicates that bold local analysts have a higher information advantage than even bold expatriate analysts. It also shows that the prior documented advantage of local analysts in terms of forecasting accuracy is driven by the bold local analysts, with herding locals diluting this effect. The informational advantage of bold locals is not explained by the business group affiliations, investment banking relationships, demand for local analysts' services or the specialisation of analysts vis-à-vis countries or sectors. We consistently show that bold local analysts are better at assessing the earnings of the firms they forecast.

To the best of our knowledge this is one of the first studies to explore the relative propensity of analysts to herd by analyst types. Moreover, it is one of the first studies to rationalise the relative accuracy of analysts by taking into account behavioural factors. Analysts' forecasts have a decisive role in the stock market and we believe it is vital to be aware of the propensity of analysts to herd and how this tendency affects the accuracy of their forecasts. This evidence contributes to a better understanding by academics and practitioners of the determinants of the accuracy of the forecasts produced by analysts.

The rest of the paper is organised as follows. Section 2 provides a brief review of the literature and develops the hypotheses. Section 3 describes the data and the models and Section 4 presents the empirical results. Section 5 concludes the paper.

2. Hypotheses

We first examine the relative accuracy of local versus foreign analysts. Prior studies in the field find support for the geographic information asymmetry hypothesis (hereafter GIAH) according to which geographically proximate analysts produce more accurate forecasts due to their geographical advantage. For instance, Orpurt (2004) finds evidence that resident analysts (i.e., local and expatriate in terms of our definition) are more accurate compared to non-resident foreign analysts (i.e., global in terms of our definition) in seven European countries. Also, Conroy *et al*., (1997) examine the relative forecast accuracy of local analysts in Japan (Japanese brokerage houses) compared with expatriate analysts in Japan (Western brokerage houses operating in Japan), and find that local analysts produce more accurate forecasts than expatriate analysts. They argue that Japanese houses have 'a better gauge on year-end information to be announced by the firm they forecast' (p. 30). However, Bacmann and Bolliger (2003) analyse the performance of local analysts for seven Latin American countries and find that foreign analysts outperform local analysts in these markets.

More recently, using an international dataset (32 non-US countries covering the markets that we consider), Bae *et al*., (2008b) find that there is no significant difference in the accuracy of forecasts produced by local and expatriate analysts. Nevertheless, the authors document that resident analysts (i.e., local and expatriate in terms of our definition) produce more accurate forecasts than non-resident forecasters. Sonney (2009) further tests the GIAH and shows that both geographical proximity between analysts and the firm they cover as well as superior knowledge about the country-specific factors are significant determinants of analysts' forecasting accuracy. Hence, there is strong but not unanimous support for the GIAH when exploring analysts' forecasting accuracy.

Before testing our main hypothesis, we re-examine the relative forecast accuracy of different analyst types using Asian markets. Given the mixed evidence in prior studies, the unknown relative advantage between the information and resource endowment factors in Asia, and the highly possible impact of herding behaviour, it is not clear which type of analyst is more accurate. We test the following null hypothesis:

H_0^1: *On average, there is no difference in forecast accuracy between local, expatriate and global analysts.*

Next, in line with the main aim of this study, we focus on the relative forecast accuracy of different analyst types conditional on their herding behaviour. While the herding literature is vast (see, e.g., Devenow and Welch, 1996; Bikhchandani and Sharma, 2001; Hirshleifer and Teoh, 2003, for reviews of the theoretical and empirical issues associated with such behaviour), few, if any, studies have examined this issue within the context of analyst types. This is surprising as local analysts have good incentives to herd. Specifically, their lack of resource endowments may force them to mimic the behaviour of others. In so doing they may be able to produce more accurate forecasts (e.g., Mira and Taylor, 2011). In addition, local analysts in emerging markets are less confident compared to foreign analysts when making earnings forecasts. Orpurt (2004) argues that local analysts are more likely to be penalised for inaccurate earnings forecasts in terms of their career prospects and reputation. A further pressure comes from the market itself. Chang (2010) shows that local institutional traders in Taiwan herd around the expatriate recommendations at all horizons. If the local analysts are aware of this, they might be tempted to mimic the earnings forecasts made by what the market considers to be 'most reliable' and prevent their forecasts from deviating too much from the consensus forecasts. Given the reputational and market pressures, as well as the resource versus information endowments, we expect that the relative accuracy of different analyst types is affected by their herding behaviour, and we need to disentangle these effects.

In the spirit of the reputational principal-agent models of Scharfstein and Stein (1990) and Trueman (1994), we categorise the analysts into two types; those that possess and make use of their information and/or resource endowments and those that do not have these advantages or find it beneficial to ignore their endowments and issue forecasts close to the prevailing consensus forecast.[5] The herding type behaviour is consistent with the information cascade models of Bikhchandani *et al.*, (1992) and Welch (1992), where an economic agent with a small private information endowment imitates the actions of a superior agent (as revealed by the consensus forecast), as they cannot directly observe the private information endowment of the superior agent.

In the context of our study, in order to disentangle the effect of herding behaviour on the relative accuracy of different analyst types, we control for analysts' herding behaviour and focus on bold forecasts as the latter reflect the information and resource endowments possessed by analysts whereas the herding forecasts are formed by simply mimicking the forecasts of others. Our analysis is unique and differs from the traditional rationale for the relative performance of different analyst types. Specifically, previous studies explain the superior performance of resident analysts using the information advantage argument, whereby local analysts have an information advantage due to their familiarity with local languages, customs and cultures, and/or due to cheaper collection of information using their human network (Conroy *et al.*, 1997; Orpurt, 2004; Bae *et al.*, 2008b).[6] In this study, however, we argue that local analysts' information advantage can only be directly compared with other analysts' information and/or resource-based advantage *after* controlling for their herding behaviour – achieved by focusing on bold forecasts that reflect the true endowments possessed by analysts.[7]

Based on our argument that expatriate analysts possess both information and resource endowment factors compared to a single-factor holding of local and global analysts, we expect bold expatriate analysts to produce more accurate forecasts compared to other bold forecasts. However, based on the reputational principal-agent models of Scharfstein and Stein (1990) and Trueman (1994) and the cascade models of Bikhchandani *et al.*, (1992) and Welch (1992), we believe

[5]This categorisation of behaviour can also be made based on the anti-herding and herding behaviour; see Sharma and Bikhchandani (2001) for an overview of the theoretical and empirical issues associated with such behaviour.

[6]The superior performance of local analysts may also be explained by career-concern incentives. This is because, compared to global analysts, local analysts may be penalised more by their employer and investors for inaccurate forecasts. Hence, given the external information advantage of local analysts, their incentive to produce accurate earnings forecasts may be larger in order to secure their job. Orpurt (2004) documents that career-concern incentives, including reputation, compensation and security, may induce local analysts to produce superior earnings forecasts.

[7]In other words, to accurately compare the information and resources endowments possessed by analysts and differentiate analysts' ability in terms of collecting and processing information, we need to focus on bold forecasts only as the herding forecasts are formed by simply mimicking the forecasts of others.

that bold local analysts possess and make use of a greater (private) informational advantage compared to bold expatriate analysts despite the fact that both types are resident analysts. Given the lack of prior evidence in the field and mixed theoretical expectations, we do not predict who is more accurate and instead we test the following null hypothesis:

H_0^2: Analysts' herding behaviour does not condition the relative accuracy of the forecasts of local, expatriate and global analysts.

What factors and theories explain the potential differences in terms of relative forecasting accuracy by analyst types? Past intuition and evidence in the field show that the information advantage of bold local analysts may stem from at least four sources, such as business group affiliations, investment banking relationships, demand for local analysts' services and specialisation of analysts vis-à-vis countries or sectors.

Business group affiliations (chaebols) is a common feature in our sample of Asian countries. According to the information-sharing hypothesis (e.g., Lim and Jung, 2012) affiliated analysts tend to have a better understanding of the firms they produce forecasts for because of their proprietary information, personal ties and working relations with the employees, suppliers and customers of member firms. These closer relations may help local affiliated analysts to assess better firm-specific risks and other firm characteristics resulting in accurate forecasts. Hence, affiliated bold local forecasts may have an information advantage over other bold forecasts because they benefit from private information which is not easily available to non-affiliated bold analysts.[8] It is possible that the differences between the accuracy of bold local forecasts and other bold forecasts is greater in the case of business group affiliations.

Investment banking relationships may be another reason for a greater information endowment possessed by bold locals. Lai and Teo (2008) show that Asian firms usually choose local underwriters when issuing new equity. Bold locals may have better access to firm-specific information to firms with investment banking ties (e.g., Jacob *et al.*, 2008), which ultimately results in more accurate forecasts. Analysts working for lead or co-lead underwriters benefit from better access to management and richer private information.[9] We argue that the differences between the accuracy of bold local forecasts and other bold forecasts are increasing with the investment banking relationships.

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[8]A downside to this argument is that affiliations create incentives that may lead to conflict of interest and ultimately biased forecasts. For example, prior studies found evidence of tunnelling and propping in business groups (e.g., Bae *et al.*, 2008a) as well as risk sharing within business groups (Khanna and Yafeh, 2005).

[9]However, investment banking relationships may also create conflicting incentives for analysts and biased forecasts (e.g., Lai and Teo, 2008).

Next, *the demand for local analysts' services* may result in greater information endowment possessed by local analysts due to greater efforts and funds allocated to their activity. Using an international sample (Asian countries included), Comiran and Siriviriyakul (2019) show that the local advantage in terms of forecasting accuracy disappears in American depositary receipt (ADR) firms. In terms of our hypothesis, this means that bold locals may produce more accurate forecasts for the non-ADR firms. This accuracy advantage may be driven by the greater interest of local investors in the local firms and ultimately higher demand for the services provided by the local analysts. Hence, we expect that the differences between the accuracy of bold local forecasts and other bold forecasts are increasing with the demand for local analysts' services.

Finally, the *specialisation of analysts vis-à-vis countries or sectors* may result in greater relative accuracy of forecasts for certain analyst types. Sonney (2009) shows that the organisational structure of brokerage houses affects the accuracy of the forecasts. He finds that country-specialised analysts are more accurate than sector-specialised analysts and this advantage stems from superior knowledge of country-specific factors, as well as the geographical proximity between analysts and the firms they follow. Hence, the advantage of the bold local forecasts may stem from their country specialisation, because analysts employed by local brokerage houses cover fewer countries and sectors (e.g., Bae *et al*., 2008b). This leaves the possibility that local brokerage houses are country specialists and this specialisation drives the difference between the accuracy of bold local forecasts and other bold forecasts.

All four potential explanations discussed above indicate that if we disentangle the effect of the herding behaviour on the relative accuracy of forecasts by analyst type, we expect bold locals to have a greater information endowment advantage compared to other bold forecasts. However, given the lack of prior evidence in the field and mixed theoretical expectations, this issue still remains an empirical question.

Finally, although it is not formally hypothesised, comparing the relative accuracy of herding forecasts between different analyst types is also of interest. If all herding analysts mimic other forecasts randomly, the accuracy of different analyst types is expected to be the same. However, the different analyst types may refer to different sets of prior earnings forecasts. Anecdotal evidence, for example, indicates that local analysts usually refer to the local databases containing forecasts made only by the analysts employed by the local brokerage houses.[10] If this is the case, the herding local forecasts may be based on a sub-set of prior forecasts made by the local analysts only, whereas the herding expatriate forecasts may be based on a full set of prior forecasts.

[10]A senior analyst employed by a local Korean brokerage house indicated they and other local analysts refer to a local database called Fn-Guide. This database collects information from local brokerage houses only.

This setting is in line with our argument that expatriate analysts benefit from both information and resource endowments, including more comprehensive databases, whereas local analysts benefit from an information advantage only. As a consequence, the accuracy of forecasts may be systematically different for different analyst types with herding expatriates ultimately producing more accurate herding forecasts.

3. Data, variables and models

3.1. Sample selection

The analysis is based on earnings forecasts from the International Edition of the Institutional Brokers Estimate System (I/B/E/S) Detail History files.[11] Specifically, for each forecast we have the name of the company the forecast is made for, the forecast and actual earnings per share (EPS) and, respectively, their forecasting and reported date. We retain in the sample *all* the forecasts made by a particular analyst instead of focusing just on either beginning or end-of-year forecasts made by an individual analyst for a firm (Hong *et al.*, 2000). This will allow us to capture the likely scenario that an individual analyst produces a mixture of bold and herding forecasts throughout the year. A vital requirement for this study is to know the name of the brokerage house an analyst works for in order to classify them into local, expatriate and global analysts. This information is available up to 2006 after which I/B/E/S reviewed their policy whereby, in order to protect the providers of specific forecasts, the name of the providers of forecasts is no longer made public.[12] Hence, given the data availability, we classify all the brokerage houses included in the sample prior to 2006 and then extrapolate this information post-2006.[13]

Bae *et al.*, (2008b) examine a large set of countries (32 non-US countries) and demonstrate that resident analysts are more accurate compared to global analysts and local analysts are as accurate as expatriate analysts. However, such comprehensive studies may overlook the idiosyncratic behaviour of analysts within a particular market environment. This suggests that focusing on a particular geographical region will alleviate some of the (behavioural) inconsistencies encountered in the previous studies. In order to control for the

[11]Analyst-specific characteristics are calculated based on both the International and US I/B/E/S Detail History files in order to fully capture analysts' activity.

[12]I/B/E/S no longer provides the broker and analyst translation files (often referred to as BRAN) which could be used to translate broker and analyst codes to actual names. This issue has been mentioned in other studies in the field (see, e.g., footnote 1 in Mayew *et al.*, 2013 and the sample used by Hilary and Hsu, 2013).

[13]We do a robustness check with the two sub-periods separately to alleviate selection bias concerns. Untabulated results show that we find support for our main findings in both periods.

political, economic and cultural conditions, we purposefully focus on only one (important) economic region such as Asia.

For a country to be included in the sample, and given the restrictions in the data availability, we require it to be an emerging country in Asia with at least 100,000 annual earnings forecasts in the I/B/E/S database until 2006 fiscal year end.[14] This leads to data covering seven countries: Hong Kong, India, Korea, Malaysia, Singapore, Taiwan and Thailand. We then set the sample period from January 1994 to December 2016.[15] These selection criteria resulted in a sample of 1,040,416 forecasts. As noted in Appendix I, the sample of observations is reduced to 981,151 after dropping forecasts with missing control variables, such as forecasting horizon, firm size, number of industries, companies, countries, general and firm experience and brokerage size. From these we remove 10,931 forecasts with a horizon greater than 400 days (see Huang *et al.*, 2017) and another 11,443 forecasts with missing actual EPS, forecasted EPS and/or a mean actual forecast error of all forecasts for firm j in year T equal to zero.[16] As a result of these restrictions, the number of observations in the sample drops to 958,777.

We use boldness as our measure of non-herding (see details in Section 3.2.2). Forecasts are regarded as bold if they deviate by a large margin from the consensus forecast immediately prior to the analyst's forecast. In order to calculate the consensus forecast for an observation, we need at least two forecasts by different analysts in the 90 days prior to an analyst's forecast. Applying this criterion leads to 120,560 forecasts dropping out of the sample. Next, we classify the brokerage house into local, expatriate or global. Appendix I reports the sample composition separately for the 1994 to 2006 and 2007 to 2016 sub-periods to account for the changes in the disclosure

[14]China is not included in our sample for three main reasons. First, the number of forecasts for Chinese firms as of 2006 is less than 100,000. This requirement represents our first sample selection criterion. Second, although the contribution of private sector companies to the Chinese economy is growing, the Chinese economy largely relies on state-owned enterprises, which are controlled by the government (Guluzade, 2019). Finally, as most of the brokerage houses in China are also state-owned, the characteristics of analysts' activity and the resulting earnings forecasts may be different from those of other emerging countries in Asia (He and Ma, 2019).

[15]Though we have data going back to 1986, we truncate the beginning of the sample period to avoid the problem of time lags between submitting the forecasts to I/B/E/S and subsequent inclusion in the I/B/E/S database. See Cooper *et al.*, (2001) for further explanation.

[16]The forecasting horizon is defined as the time period (in days) between the date of the forecast made by an analyst and reported date of the actual earnings. Our analysis involves the calculation of the proportional mean forecast error. As detailed in Section 3.2.1, the denominator used to calculate this measure of forecast accuracy is the mean forecast error for firm j in year T; hence the imposition of the non-zero value restriction.

related to the providers of forecasts by I/B/E/S. We have lost only 260 forecasts due to insufficient information regarding the classification of the brokerage houses as local, expatriate or global in the sub-sample of forecasts made between 1994 and 2006. Yet, as expected, the attrition rate is much higher in the 2007–2016 sub-period resulting in a drop of 115,685 observations. Finally, the three continuous variables (the forecast accuracy measure, the boldness measure and firm size) are winsorised at one percent each in the top and bottom tails.[17] The final sample comprises 722,272 observations.[18]

3.2. Variables

We test the validity of our hypotheses using forecast accuracy as the dependent variable. Analyst-type variables, boldness and the respective interaction terms between analyst-type variables and boldness represent our test variables, or independent variables of interest. In all the regressions we also control for forecast-specific characteristics (horizon), firm-specific characteristics (market value of the firm), and analyst-specific characteristics (forecasting frequency, number of industries, companies and countries followed by an analyst each year, firm and general experience of an analyst as well as the size of the brokerage house an analyst works for). We further examine the validity of our second hypothesis by controlling for the implementation of the country-specific Regulation Fair Disclosure, affiliation of the brokerage houses with the firms, the demand for local analysts' services and specialisation of analysts. Next, we confine attention to the forecast accuracy, boldness and analyst-type variables, with a description of the control variables provided in Appendix II.

3.2.1. Forecast accuracy

The forecast accuracy measure is given by the proportional mean absolute forecast error ($PMAFE_{ijt}$). This is defined as the ratio of the difference between the absolute forecast error made by analyst i for firm j at time t (AFE_{ijt}) and the mean absolute forecast error of all forecasts for firm j in year T ($MAFE_{jT}$), to the mean absolute forecast error. That is,

$$PMAFE_{ijt} = \frac{AFE_{ijt} - MAFE_{jT}}{MAFE_{jT}}, \tag{1}$$

[17]We perform a robustness check by using trimming at one percent each in the bottom and top tails of the three variables; untabulated results show that our main findings are qualitatively similar for both sample selection techniques.

[18]We find support for our main findings using the sub-samples of firms followed by all three analyst types and when we retain just the last forecast made by an analyst in a particular firm-year.

where

$$AFE_{ijt} = \left|F_{ijt} - A_{jT}\right|, \; and MAFE_{jT} = \frac{1}{n_{jT}} \sum_{i=1}^{n_{jT}} AFE_{ijt} \tag{2}$$

Here A_{jT} is the actual earnings reported by firm j at the fiscal year end T. Following Bae *et al.*, (2008b), in order to facilitate the interpretation of the calculated variable, we multiply it by minus one. Thus, the larger $PMAFE_{ijt}$ is, the more accurate the forecast.

3.2.2. Boldness

We use boldness ($BOLD_{ijt}$), which is the proportional mean deviation from the consensus, as our measure of herding. $BOLD_{ijt}$ is defined as the difference between the deviation of a forecast made by analyst i for firm j at time t from the consensus forecast (DC_{ijt}) and the mean deviation of all forecasts for firm j in the fiscal year T (MDC_{jT}), divided by the mean deviation. That is,

$$BOLD_{ijt} = \frac{DC_{ijt} - MDC_{jT}}{MDC_{jT}}, \tag{3}$$

where

$$DC_{ijt} = \left|F_{ijt} - C_{jt}\right|, \text{ and} \, MDC_{jT} = \frac{1}{n_{jT}} \sum_{i=1}^{n_{jT}} DC_{ijt} \tag{4}$$

Here F_{ijt} is the earnings forecast produced by analyst i for firm j at time t, whereas C_{jt} is the consensus forecast calculated using forecasts by different analysts for firm j within 90 days of the forecast date t. n_{jT} is the number of forecasts within firm j and fiscal year T. Note that we use the deviation from the consensus *proportional* to the mean deviation in order to ensure comparability across different countries and companies. Country indices are suppressed in all the above equations.

In practical terms, boldness is calculated as follows. First, the consensus forecast at time t when an analyst produces the forecast is calculated as the average of all forecasts made by other analysts in the 90 days prior to the forecast. Second, the forecast deviation from the consensus is then taken as the absolute value of the difference between the forecast and the consensus. Finally, after calculating the deviations for all the forecasts made for firm j in a fiscal year T, its mean is computed and then used to calculate the proportional mean deviation from the consensus ($BOLD_{ijt}$). This measure of boldness is motivated by Hong *et al.*,'s (2000) boldness score measure and by the definition of herding.[19] Higher values of $BOLD_{ijt}$ correspond to more deviation from the consensus (bolder forecasts). In order to make a clear distinction between bold and herding forecasts, we generate three dummy variables such as $DBOLD_{md}$, $DBOLD_{t1t3}$ and $DBOLD_{q1q4}$. These variables equal one if $BOLD_{ijt}$ is greater than its median, the third tertile, and the fourth quartile respectively. These variables are equal to zero if $BOLD_{ijt}$ is equal to or smaller than its median, the first tertile, and the first quartile respectively. A forecast is defined as bold if $DBOLD_{md}$, $DBOLD_{t1t3}$ and $DBOLD_{q1q4}$, respectively, equal one and a herding forecast otherwise.[20] If our boldness measure is related to forecast accuracy, the expectation is that if we compare the top and bottom of the $BOLD_{ijt}$ distribution only, we should observe more pronounced results compared to the more conservative approach when using the median as a cut-off point.

3.2.3. Analyst types

Following Bae *et al.*, (2008b) and Chang (2010), we take into account both location and employment effects when categorising analysts. Specifically, local analysts are defined as analysts employed by a local brokerage house located inside a particular country in which the covered firm's equity is traded. Expatriate analysts are those working for a foreign brokerage house operating in a country where the covered firm's equity is traded. Finally, global analysts are defined as analysts who work outside the country in which the firm's equity is traded. We categorise each brokerage house in the sample into local, expatriate or global using at least one of the following methods: (i) screening the information on the brokerage houses' websites, (ii) emailing each country's relevant authorities/regulators that possess information about the relevant brokerage houses, and (iii) asking various professional acquaintances working in the financial industry in one of the countries in the sample to classify the brokerage houses.[21] In most cases, a particular classification is cross-verified

[19]Our measure of boldness is a forecast-specific measure rather than an analyst-specific measure as in Hong *et al.*, (2000). We believe that a firm-year forecast-specific boldness measure is more appropriate for our paper as we do not need to assume that a specific analyst produces only bold forecasts (or only herding forecasts) on average. The same analyst can produce bold as well as herding forecasts.

[20]We perform a robustness check by using Hong *et al.*,'s (2000) boldness score measure (and indicator variables generated from the boldness score measure); untabulated results show that our main findings are qualitatively similar for both boldness measures.

[21]We contacted via email the following relevant authorities/regulators: the Securities and Futures Commission in Hong Kong, Financial Supervisory Service in Korea, Securities Commission in Malaysia, Monetary Authority of Singapore, Financial Supervisory Commission in Taiwan, and the Securities and Exchange Commission of Thailand. Due to mergers and change of names, nine brokerage houses could not be categorised, specifically three brokerage houses in each of the following countries: Hong Kong, Malaysia and Singapore.

across at least two of these sources. In order to test our hypotheses, we generate two dummy variables, such as local and expatriate dummy variables. Local is a dummy variable which equals one if an analyst is local, and zero if it is expatriate or global. Expatriate equals one if the analyst is expatriate, and zero for local and global analysts. The impact of the global analysts is captured in the respective intercepts of the regressions.

3.3. Models

The H_0^1 hypothesis focuses on the unconditional difference in the relative forecast accuracy of analyst types and it is tested using an ordinary least squares (OLS) regression. The dependent variable in the OLS regression is the proportional mean absolute forecast error ($PMAFE_{ijt}$). The model includes the dummy variables for local and expatriate analysts and the control variables described in Appendix II; specifically:

$$PMAFE_{ijt} = \gamma_0 + \gamma_1 Local_i + \gamma_2 Expatriate_i + \sum \theta_n Z_{ijt}^{(n)} + \varepsilon_{ijt} \tag{5}$$

where $Z_{ijt}^{(n)}$ is the nth control variable, and ϵ_{ijt} is a suitably defined error term. In Equation (5), γ_1 (γ_2) is the difference in $PMAFE_{ijt}$ between local (expatriate) and global analysts, and $\gamma_1 - \gamma_2$ is the difference in $PMAFE_{ijt}$ between local and expatriate analysts.

In line with the prior approach in the field (e.g., Clement, 1999; Malloy, 2005; Bradley *et al.*, 2017), all the independent variables, except firm size, which is a firm-specific characteristic, are demeaned by the firm-year values. The standard errors are heteroscedasticity-consistent and double-clustered at the firm and analyst levels.

The H_0^2 hypothesis is then tested by augmenting Equation (5) such that our herding measure and the interaction terms between the herding measure and analyst types are added. Specifically, the augmented model takes the following form:

$$\begin{aligned} PMAFE_{ijt} = {} & \gamma_0 + \gamma_1 Local_i + \gamma_2 Expatriate_i + \gamma_3 DBOLD_{ijt} + \gamma_4 Local_i \\ & \times DBOLD_{ijt} + \gamma_5 Expatriate_i \times DBOLD_{ijt} + \sum \theta_n Z_{ijt}^{(n)} + \varepsilon_{ijt} \end{aligned} \tag{6}$$

An indicator variable *DBOLD* is used in Equation (6) rather than the continuous variable *BOLD* as our aim is to examine the differential effect of herding versus non-herding forecasts on forecast accuracy.[22] Using *DBOLD* also alleviates the possible noise in the measurement of *BOLD*.

[22]Our results are qualitatively similar if the continuous variable, *BOLD*, is used to measure boldness.

We are able to test H_0^2 via examination of the coefficient restrictions in Equation (6). Our focus is on the difference in *PMAFE* between *bold* forecasts of different analyst types. Hence, testing H_0: $\gamma_1 + \gamma_4 = \gamma_2 + \gamma_5$, H_0: $\gamma_1 + \gamma_4 = 0$ and H_0: $\gamma_2 + \gamma_5 = 0$, respectively, compares the accuracy of bold forecasts for local versus expatriate, local versus global, and expatriate versus global analysts. In the same vein, in order to compare the accuracy of *herding* forecasts between two groups of analysts, we test H_0: $\gamma_1 = \gamma_2$ (local versus expatriate), H_0: $\gamma_1 = 0$ (local versus global) and H_0: $\gamma_2 = 0$ (expatriate versus global). Finally, the accuracy of bold versus non-bold forecasts for each analyst type is tested with H_0: $\gamma_3 + \gamma_4 = 0$ (for local), H_0: $\gamma_3 + \gamma_5 = 0$ (for expatriate) and H_0: $\gamma_3 = 0$ (for global).

4. Empirical results

4.1. Sample composition

Table 1 reports the distribution of the sample across countries (Panel A) and time (Panel B). Panel A shows that Hong Kong is the most represented country in the sample with 160,492 out of a total of 722,272 forecasts (22.2 percent). This is followed by India (16.2 percent) and Korea (15.4 percent). The least represented country in the sample is Thailand with a total of 69,259 forecasts (9.6 percent). The 722,272 forecasts are made by 12,317 individual analysts employed by 279 brokerage houses producing forecasts for 4,430 firms across seven Asian countries. Expatriate analysts are the most representative in the sample with a total of 7,645 analysts being classified as expatriates (50.4 percent), 5,833 analysts as local (38.5 percent) and the remaining 1,690 analysts as global (11.4 percent).

4.2. Main results

Table 2 presents the results from the univariate analysis and provides the mean and median values of all variables used, and investigates whether there is any significant difference across analyst types in terms of forecast accuracy and their herding behaviour. The results reported in Table 2 show that expatriate analysts are significantly more accurate than local and global analysts, albeit the mean difference in the forecast accuracy between local and expatriate analysts is insignificant. The mean results support previous evidence in Bae *et al.*, (2008b) that resident (i.e., local and expatriate) analysts are more

Table 1
Sample details

	Forecasts (#)	Firms (#)	Houses (#)	Analyst			
				Local (#)	Expatriate (#)	Global (#)	Total (#)
Panel A: Distribution of sample by country							
Hong Kong	160,492	603	122	972	3,329	154	3,929
India	117,104	696	61	1,250	1,042	143	2,142
Korea	110,826	1,063	64	1,538	1,023	159	2,461
Malaysia	106,493	543	79	756	1,104	703	1,963
Singapore	80,995	446	78	631	1,434	359	2,016
Taiwan	76,428	688	54	610	1,121	256	1,764
Thailand	69,259	391	60	251	961	235	1,254
Total	722,272	4,430	279	5,833	7,645	1,690	12,317
Panel B: Distribution of sample by year							
1994	25,217	1,194	84	615	1,238	421	1,772
1995	24,088	1,115	88	621	1,397	368	1,963
1996	24,195	1,098	99	521	1,583	384	2,117
1997	28,143	967	117	794	1,787	399	2,463
1998	29,124	890	119	932	1,819	296	2,563
1999	31,290	967	109	913	1,616	230	2,445
2000	29,876	859	104	741	1,694	215	2,380
2001	33,359	818	112	825	1,658	221	2,511
2002	24,672	689	116	657	1,401	187	2,131
2003	30,030	736	126	526	1,255	182	1,853
2004	28,426	895	133	583	1,076	156	1,674
2005	21,645	863	140	700	1,008	114	1,697
2006	22,864	947	143	782	1,200	128	1,931
2007	24,637	1,038	146	863	1,289	136	2,113
2008	28,784	1,043	140	878	1,314	141	2,189

(continued)

Table 1 (continued)

				Analyst			
	Forecasts (#)	Firms (#)	Houses (#)	Local (#)	Expatriate (#)	Global (#)	Total (#)
2009	29,545	1,002	139	915	1,276	127	2,175
2010	29,449	1,068	137	1,002	1,284	141	2,302
2011	36,965	1,266	135	1,293	1,342	168	2,716
2012	43,312	1,327	125	1,390	1,322	174	2,803
2013	43,798	1,520	120	1,293	1,195	172	2,589
2014	42,793	1,572	114	1,198	1,106	197	2,412
2015	44,589	1,627	111	1,249	1,102	178	2,436
2016	45,471	1,668	106	1,192	1,045	174	2,337
Total	722,272	4,430	279	5,833	7,645	1,690	12,317

This table shows the number of forecasts, firms, brokerage houses and the number of local, expatriate and global analysts in each country (Panel A) and each year (Panel B). As a brokerage house (an analyst) can conduct research for several countries and for several years, the number of brokerage houses in the sample is different from the sum of brokerage houses (analysts) across seven countries and across sample periods.

accurate than global analysts, and local and expatriate analysts are equally accurate.[23] In terms of herding behaviour, the *BOLD* statistics show that global analysts produce forecasts with the smallest deviation from the consensus, indicating that they herd more. The median difference in boldness for local and global analysts is insignificant suggesting that both local and global analysts herd more compared to the expatriate analysts. Consequently, this evidence shows that locals are more likely to herd compared to expatriates. The Pearson correlation coefficient (not tabulated) between forecast accuracy (*PMAFE*) and boldness (*BOLD*) is negative and significant at the 1 percent level (Pearson = −0.306). This leaves open the possibility that the relative forecast accuracy of different analyst types is distorted by the existence of herding forecasts. This issue is investigated next in the context of multivariate analysis.

We test hypothesis H_0^1 using an OLS regression of forecast accuracy on analyst classification dummies and a set of forecast-, firm- and analyst-specific characteristics. Table 3 reports the OLS regression results in Panel A and the *F*-tests of the coefficient differences in Panel B. The results reported in the first column of Table 3 show that local analysts are more accurate than expatriate analysts (positive $\gamma_1 - \gamma_2$) and also global analysts (positive γ_1) at the 5 percent level of significance or better. Thus, we do not find support for our first null hypothesis that, on average, there is no difference in the forecast accuracy between local, expatriate and global analysts. By contrast, our results show that locals are the most accurate analyst type and expatriate analysts are as accurate as global analysts (γ_2 is positive but insignificant). This result suggests that the information endowment factor possessed by the local analysts is superior compared to the information endowment factor possessed by the expatriate analysts. This means that location is not the only factor determining the information endowment possessed by the local and expatriate analysts. Local analysts are unconditionally more accurate than expatriate analysts despite both analyst types operating locally. In terms of the control variables, we find that the accuracy of the forecasts improves as the forecasting horizon shortens and also for smaller firms (Clement, 1999; Bolliger, 2004; Bae *et al.*, 2008b; Hilary and Hsu, 2013). The accuracy of the forecasts increases with the number

[23] Bae *et al.*, (2008b) find that local and expatriate analysts are more accurate than global analysts. The coefficients and *t*-values reported in their study for local and expatriate analysts are very similar to each other. They use a sample of 32 countries, including the seven countries we look at, that are located across the world (Europe, Asia, Latin America and Australia). However, as discussed in the introduction, the difference between the resident and non-resident analysts seems to be influenced by the countries/geographical regions included in the sample. For example, local analysts in Europe are found to be more accurate than non-local (foreign) analysts (Orpurt, 2004). On the other hand, Bacmann and Bolligier (2003) find that local analysts are less accurate that foreign analysts in Latin American countries. Hence, it is vital to focus on a particular region (in our case Asia) to alleviate some of the behavioural inconsistencies encountered in the previous studies.

Table 2
Descriptive statistics

	Overall N = 722,272		Local (A) N = 257,321		Expatriate (B) N = 413,648		Global (C) N = 51,303		A – B (p-values)		A – C (p-values)		B – C (p-values)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
PMAFE (×100)	3.70	13.17	3.76	12.51	3.85	13.78	2.25	11.58	0.580	0.000	0.000	0.052	0.000	0.000
BOLD (×100)	−1.99	−21.73	−3.36	−22.01	−1.09	−21.44	−2.39	−22.65	0.000	0.000	0.015	0.754	0.000	0.003
$DBOLD_{md}$ (×100)	50.00	50.00	49.86		50.15		49.49		0.019		0.133		0.005	
Horizon	197.30	197.00	196.41	195.00	197.60	200.00	199.25	196.00	0.000	0.000	0.000	0.000	0.000	0.018
Ln (MV)	7.54	7.53	7.39	7.35	7.64	7.64	7.50	7.45	0.000	0.000	0.000	0.000	0.000	0.000
Frequency	4.87	4.00	4.87	4.00	4.87	4.00	4.84	4.00	0.562	0.000	0.039	0.001	0.070	0.924
NoIndustry	3.38	3.00	3.32	3.00	3.39	3.00	3.58	3.00	0.000	0.000	0.000	0.000	0.000	0.010
NoCompany	15.10	11.00	15.34	11.00	14.82	11.00	16.21	10.00	0.000	0.004	0.000	0.000	0.000	0.000
NoCountry	1.90	1.00	1.46	1.00	2.15	1.00	2.07	1.00	0.000	0.000	0.000	0.000	0.000	0.000
FirmExperience	2.52	1.00	2.24	1.00	2.67	1.00	2.63	2.00	0.000	0.000	0.000	0.000	0.001	0.000
GenExperience	7.36	6.00	6.44	5.00	7.91	7.00	7.58	6.00	0.000	0.000	0.000	0.000	0.000	0.000
BrkSize	60.32	47.00	32.26	25.00	76.66	77.00	69.30	75.00	0.000	0.000	0.000	0.000	0.000	0.000
PrLocalAnalysts (×100)	35.89	30.77	50.89	50.00	27.13	23.53	31.28	29.63	0.000	0.000	0.000	0.000	0.000	0.000
CS-Reg FD Dummy(×100)	37.04		45.62		31.70		37.02		0.000		0.000		0.000	
Past Underwriter > *5years* (×100)	1.75		1.40		1.96		1.76		0.000		0.000		0.002	

(continued)

Table 2 (continued)

	Overall $N = 722{,}272$		Local (A) $N = 257{,}321$		Expatriate (B) $N = 413{,}648$		Global (C) $N = 51{,}303$		A – B (*p*-values)		A – C (*p*-values)		B – C (*p*-values)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Future Underwriter $>5\,years(\times 100)$	1.14		0.83		1.36		0.94		0.000		0.013		0.000	
ADR Dummy$(\times 100)$	2.35		1.27		3.12		1.56		0.000		0.000		0.000	
Country Specialist Dummy$(\times 100)$	59.54		67.10		55.52		54.00		0.000		0.000		0.000	
Sector Specialist Dummy$(\times 100)$	5.19		0.64		7.33		10.83		0.000		0.000		0.000	
Absolute Specialist Dummy$(\times 100)$	22.44		27.64		19.79		17.74		0.000		0.000		0.000	

This table contains the mean and median values of the variables used in the study, and test results for mean and median differences between different analyst types, such as Local, Expatriate and Global. The significance of the differences in the mean and median values (across the analyst types) is represented with *p*-values, by using Cochran t-test statistics and Wilcoxon rank sum test statistics (approximated z-statistics), respectively. See Appendix II for the definition of variables.

of companies followed by an analyst and the size of the brokerage house that employs the analyst (Clement, 1999). However, analysts revising their forecasts more frequently and following firms in more countries are less accurate.

Next, although it is not formally hypothesised, we also test whether the herding behaviour varies across analyst type. Specifically, we estimate an OLS regression with a continuous dependent variable *BOLD* and three logistic regressions with binary dependent variables such as $DBOLD_{md}$, $DBOLD_{t1t3}$ or $DBOLD_{q1q4}$. Using $DBOLD_{md}$ ($DBOLD_{t1t3}$ and $DBOLD_{q1q4}$) the sample is partitioned according to the value of the boldness measure so that half (one third and one quarter) of observations with higher *BOLD* values are coded as bold forecasts and the remaining half (one third below the first tertile and one quarter below the fourth quartile) of observations are coded as herding forecasts, respectively. All four models include the dummy variables for local and expatriate analysts and the control variables used in Equation (5). Similar to the regression results reported in column (1) of Table 3, all the independent variables, except firm size which is a firm-specific characteristic, are demeaned by the firm-year values. The standard errors are heteroscedasticity-consistent and double-clustered at the firm and analyst levels.[24] The results reported in columns (2)–(5) of Table 3 show that local (negative $\gamma_1 - \gamma_2$) and global (positive γ_2) analysts are more likely to herd compared to the expatriate analysts and the results are qualitatively similar across the four measures of herding. In line with the univariate results, the coefficient γ_1 is insignificant showing that the herding tendency of local analysts is not significantly different compared to global analysts. Local and global analysts are as likely to herd and both of them are more likely to herd compared to the expatriate analysts. These results suggest that the lack of resource (information) endowment factors forces local (global) analysts to mimic other forecasts more than expatriate analysts. The lower propensity of expatriate analysts to herd is not surprising as they possess both information and resource endowment factors. In terms of the control variables, the coefficients on the forecast horizon, the number of countries followed by an analyst, analyst's general experience and also the size of the brokerage house employing the analyst are consistently positive and significant across all four models, indicating that analysts at the early stage of the forecasting horizon, employed by a large brokerage house, with more general experience and covering more countries produce bolder forecasts. However, analysts following larger firms and more companies produce less bold forecasts.

Hypothesis H_0^2 is tested by running OLS regressions of forecast accuracy on analyst classification dummies, the interaction terms between the latter and our herding measure and a set of forecast-, firm- and analyst-specific

[24]We perform a robustness check by including firm and year fixed effects or country, industry and year fixed effects in the regression; untabulated results show that our main findings are qualitatively similar for different sets of fixed effects.

Table 3
Regression results testing H_0^1

	OLS		Logit		
	$Y = PMAFE$ (1)	$Y = DBOLD$ (2)	$Y = DBOLD_{md}$ (3)	$Y = DBOLD_{t1t3}$ (4)	$Y = DBOLD_{q1q4}$ (5)
Panel A: OLS and Logit regression results					
Local (γ_1)	0.018***	−0.007	0.004	0.005	−0.002
	(2.82)	(−0.71)	(0.32)	(0.30)	(−0.08)
Expatriate (γ_2)	0.004	0.019**	0.042***	0.057***	0.056***
	(0.76)	(2.18)	(3.27)	(3.53)	(3.00)
Horizon	−0.002***	0.001***	0.001***	0.002***	0.002***
	(−60.07)	(20.84)	(49.93)	(53.94)	(53.45)
Ln (MV)	−0.003***	−0.003***	−0.020***	−0.021***	−0.021***
	(−4.62)	(−3.53)	(−10.45)	(−8.35)	(−7.30)
Frequency	−0.002**	0.000	0.004***	0.005***	0.005***
	(−2.19)	(0.07)	(3.39)	(3.41)	(2.77)
NoIndustry	0.001	−0.002	−0.004*	−0.006**	−0.003
	(1.42)	(−1.38)	(−1.87)	(−2.31)	(−1.26)
NoCompany	0.000*	−0.000**	−0.000**	−0.001**	−0.001***
	(1.77)	(−2.47)	(−2.42)	(−2.25)	(−2.80)
NoCountry	−0.003**	0.006***	0.007***	0.009***	0.013***
	(−2.04)	(3.64)	(3.16)	(3.40)	(4.11)
FirmExperience	0.001	0.001**	0.001	0.002	0.003*
	(0.87)	(2.01)	(0.81)	(1.34)	(1.73)
GenExperience	−0.000	0.002***	0.004***	0.004***	0.005***
	(−0.02)	(4.03)	(5.91)	(5.43)	(5.10)
BrkSize	0.000***	0.000***	0.000***	0.001***	0.001***
	(3.69)	(2.77)	(5.36)	(5.85)	(5.64)
Intercept	0.063***	0.002	0.154***	0.152***	0.148***

(continued)

Table 3 (continued)

	OLS		Logit		
	$Y = PMAFE$ (1)	$Y = DBOLD$ (2)	$Y = DBOLD_{md}$ (3)	$Y = DBOLD_{t1t3}$ (4)	$Y = DBOLD_{q1q4}$ (5)
	(11.53)	(0.42)	(10.61)	(8.31)	(7.09)
N	722,272	722,272	722,272	481,034	361,136
Adj R^2/Pseudo R^2	0.117	0.008	0.004	0.007	0.009
F-test/Chi^2	342.1***	50.8***	2756.3***	3154.1***	3083.5***
Panel B: Regression-based hypothesis test results					
H_0: $\gamma_1 = \gamma_2$	0.014***	−0.026***	−0.038***	−0.052***	−0.058***
	[0.003]	[0.000]	[0.000]	[0.000]	[0.000]

The first column of this table reports the OLS regression results (with the respective t-values in parentheses) of the analyst forecast accuracy ($PMAFE$) on dummy variables signifying the local and expatriate analysts and a set of firm-, forecast- and analyst-specific characteristics. Hence, in column (1) we test the first null hypothesis that, on average, there is no difference in forecast accuracy between local, expatriate and global analysts. Column (2) reports the OLS regression results using the continuous measure of boldness ($BOLD$) as a dependent variable on a set of dummy variables signifying the local and expatriate analysts and a set of firm-, forecast- and analyst-specific characteristics. Columns (3)–(5) report the logistic regression results using $DBOLD_{md}$, $DBOLD_{t1t3}$ and $DBOLD_{q1q4}$ as dependent variables (with z-values in parentheses). $DBOLD_{md}$ ($DBOLD_{t1t3}$ and $DBOLD_{q1q4}$) is a firm-year-forecast-specific indicator, which equals one if $BOLD$, the proportional mean deviation from the consensus of a forecast, is greater than its median (the third tertile and fourth quartile respectively), and zero if smaller than its median (first tertile and first quartile respectively). All the variables, except $Ln\ (MV)$, are demeaned by the firm-year values. See Appendix II for variable definitions. The t-values presented in parentheses are heteroscedasticity consistent and the standard errors are clustered by firm and analyst. H_0: $\gamma_1 = \gamma_2$ provides the coefficient difference between γ_1 and γ_2 and the corresponding $F(\chi^2)$-test results, with p-values in brackets. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively (two-tailed test).

characteristics. Table 4 reports the OLS regression results and the *F*-tests of the coefficients (and coefficient differences) obtained from these regressions using $DBOLD_{md}$, $DBOLD_{t1t3}$ and $DBOLD_{q1q4}$ as alternative measures of boldness.

The results reported in Panels A and B of Table 4 test the conditional difference in the relative forecast accuracy of analyst types. Now that the interaction terms are added in the regressions, a clear picture emerges. The results show that local analysts are the most accurate analyst type when focusing on the bold forecasts across all three measures of performance. Specifically, H_0: $\gamma_1 + \gamma_4 = \gamma_2 + \gamma_5$ (bold local versus bold expatriate) and H_0: $\gamma_1 + \gamma_4 = 0$ (bold local versus bold global) are rejected at the 1 percent level in Panel B of Table 4. We cannot reject H_0: $\gamma_2 + \gamma_5 = 0$ at the 10 percent level of significance which suggests that expatriate bold forecasts are as accurate as global bold forecasts. The potential sources of the greater informational advantage of bold locals are discussed later in this section. In line with our expectations, we also note that the coefficients on the interaction terms between *BOLD* and *Local* reported in column (1) of Table 4 are smaller compared to the respective coefficients reported in columns (2) and (3). This is because we focus on the top and bottom of the *BOLD* distribution in columns (2) and (3). Hence, *DBOLD* appears to accurately capture bold and herding forecasts. It also shows that forecast accuracy is explained by the categorisation of forecasts into bold and non-bold and also by the actual *magnitude* of boldness. Overall, we show that despite the fact that both local and expatriate analysts work locally, the information advantage of bold local analysts is still bigger compared to that of bold expatriate analysts and bold global analysts when controlling for the behavioural factors. Nevertheless, our results also show that controlling for the herding behaviour yields different results when comparing the unconditional and conditional differences in the relative forecast accuracy of expatriate and global forecasts. Specifically, we find that unconditionally expatriates are more accurate than globals but this difference disappears in the conditional setting (i.e., bold expatriates are as accurate as bold globals). Hence, we reject H_0^2 that analysts' herding behaviour does not condition the relative accuracy of the earnings forecasts of local, expatriate and global analysts.[25]

Although, given the aim of this study, we focus on the relative accuracy of bold forecasts, the relative forecast accuracy of *herding* forecasts between analyst types shows that expatriate analysts produce the most accurate herding forecasts. Specifically, H_0: $\gamma_1 = \gamma_2$, H_0: $\gamma_1 = 0$ and H_0: $\gamma_2 = 0$ in Table 4 report

[25]We also estimate separate regressions for the crisis period (i.e., 1997–1998 and 2008) and non-crisis period; untabulated results show that the evidence in the non-crisis period is largely consistent with our main findings. However, the results in the crisis period show that bold global forecasts are the most accurate, suggesting that the resource endowment factor may dominate the information endowment factor when capital markets are unstable.

Table 4
Regression results testing H_0^2

	$X = DBOLD_{md}$ (1)	$X = DBOLD_{t1t3}$ (2)	$X = DBOLD_{q1q4}$ (3)
Panel A: OLS regression results			
Local (γ_1)	−0.003	−0.009	−0.008
	(−0.56)	(−1.31)	(−0.96)
Expatriate (γ_2)	0.012**	0.012*	0.015*
	(2.21)	(1.75)	(1.90)
DBOLD (γ_3)	−0.216***	−0.317***	−0.394***
	(−19.63)	(−21.47)	(−22.57)
DBOLD × *Local* (γ_4)	0.042***	0.061***	0.070***
	(3.79)	(4.13)	(3.99)
DBOLD × *Expatriate* (γ_5)	−0.010	−0.009	−0.008
	(−0.88)	(−0.60)	(−0.43)
Horizon	−0.003***	−0.006***	−0.007***
	(−4.68)	(−5.60)	(−5.24)
Ln (MV)	−0.002***	−0.002***	−0.002***
	(−59.61)	(−56.43)	(−52.74)
Frequency	−0.001*	−0.001	−0.001*
	(−1.91)	(−1.48)	(−1.66)
NoIndustry	0.001	0.001	0.001
	(1.32)	(0.85)	(0.61)
NoCompany	0.000	0.000*	0.000
	(1.63)	(1.70)	(1.56)
NoCountry	−0.002*	−0.003**	−0.003**
	(−1.82)	(−2.10)	(−1.98)
FirmExperience	0.001	0.000	0.000
	(0.98)	(0.51)	(0.46)
GenExperience	0.000	0.001	0.001
	(0.57)	(1.24)	(1.49)
BrkSize	0.000***	0.000***	0.000***
	(4.35)	(4.61)	(4.96)
Intercept	0.063***	0.044***	0.025**
	(11.63)	(5.97)	(2.50)
N	722,272	481,034	361,136
Adj. R^2	0.138	0.139	0.142
F-test	836.7***	857.6***	851.2***
Panel B: Regression-based hypothesis test results			
H_0: $\gamma_1 = \gamma_2$	−0.015***	−0.021***	−0.023***
	[0.000]	[0.000]	[0.000]
H_0: $\gamma_1 + \gamma_4 = \gamma_2 + \gamma_5$	0.037***	0.049***	0.055***
	[0.000]	[0.000]	[0.000]
H_0: $\gamma_1 + \gamma_4 = 0$	0.039***	0.052***	0.062***
	[0.000]	[0.000]	[0.000]
H_0: $\gamma_2 + \gamma_5 = 0$	0.002	0.003	0.007
	[0.875]	[0.842]	[0.642]
H_0: $\gamma_3 + \gamma_4 = 0$	−0.174***	−0.256***	−0.324***

(continued)

Table 4 (continued)

	$X = DBOLD_{md}$ (1)	$X = DBOLD_{t1t3}$ (2)	$X = DBOLD_{q1q4}$ (3)
	[0.000]	[0.000]	[0.000]
H_0: $\gamma_3 + \gamma_5 = 0$	-0.226^{***}	-0.326^{***}	-0.402^{***}
	[0.000]	[0.000]	[0.000]

Panel A provides OLS parameter estimates (with *t*-values in parentheses) of the analyst forecast accuracy (*PMAFE*) on dummy variables signifying the local and expatriate analysts, boldness indicator (*DBOLD*), and a set of firm-, forecast- and analyst-specific characteristics. Panel B reports results testing the coefficient restrictions based on *F*-tests, with *p*-values in brackets. All the variables, except *Ln (MV)*, are demeaned by the firm-year values. See Appendix II for variable definitions. The *t*-values presented in round parentheses are heteroscedasticity consistent and the standard errors are clustered by firm and analyst. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively (two-tailed test).

the coefficient difference and significance of herding forecasts between local and expatriate, local and global, and expatriate and global, respectively. From these we can conclude that the herding forecasts produced by the expatriate analysts are the most accurate, whereas the herding forecasts produced by the local analysts are as accurate as the herding forecasts of global analysts. This is somewhat surprising as mimicking other forecasts randomly should make no difference between analyst types. One possible explanation is that different analyst types refer to different sets of prior forecasts when producing earnings forecasts. Anecdotal evidence, for example, indicates that local analysts usually refer to databases containing forecasts made only by the local brokerage houses. Thus, the relative accuracy advantage of herding expatriate forecasts compared to other herding forecasts may stem from the fact that forecasts produced by the herding expatriates are based on a full set of prior forecasts whereas the herding locals may have access to a sub-set of prior forecasts produced by the local analysts only. As a result, the herding expatriate forecasts are the most accurate herding forecasts. This finding also shows that the prior documented advantage of local analysts in terms of forecasting accuracy may be understated as herding locals are diluting this effect.

Finally, H_0: $\gamma_3 + \gamma_4 = 0$, H_0: $\gamma_3 + \gamma_5 = 0$ and H_0: $\gamma_3 = 0$ in Table 4 report the coefficient difference and significance between the bold forecasts and herding forecasts of local, expatriate and global, respectively. As expected, they are all negative and significant, indicating that bold forecasts are significantly less accurate than herding forecasts on average (Salamouris and Muradoglu, 2010; Mira and Taylor, 2011).

4.3. What drives the information advantage of bold local forecasts?

In this section we explore four potential explanations for the reported accuracy advantage of bold locals.

4.3.1. Business group affiliations

Our expectation here is that the difference between the accuracy of bold forecasts and other bold forecasts is greater in the case of business group affiliations. To test this explanation, we use the implementation of the country-specific version of Regulation Fair Disclosure (CS-Reg FD) as a shock.[26] In broad terms, this regulation requires firms to release material information that may affect their share prices to all investors simultaneously. The aim is to prohibit 'selective disclosure' of market sensitive information to certain groups of analysts and investors who may trade on this information. If our results are driven by business group affiliations, we expect the accuracy of bold local forecasts to decrease after the implementation of the CS-Reg FD.

We create a *CS-Reg FD Dummy* variable which equals one for the post-implementation period of the respective versions of Regulation Fair Disclosure in each country, and zero otherwise. This dummy variable, its interaction term with the boldness dummy as well as its interaction terms with the boldness dummy and analyst type dummy variables are included in Equation (6). The regression results tabulated in columns (1) and (2) of Table 5 show that the coefficients on the *CS-Reg FD Dummy*, the *DBOLD* × *Local* × *CS-Reg FD Dummy* and the *DBOLD* × *Expatriate* × *CS-Reg FD Dummy* are insignificant. However, the coefficient on the interaction term *DBOLD* × *CS-Reg FD Dummy* is positive and significant at the 5 percent level. These results show that on average all bold forecasts became more accurate after the implementation of the CS-Reg FD. Importantly, our main results are qualitatively similar if we control for the business group affiliation effect. Bold locals are still more accurate compared to other bold forecasts before as well as after the implementation of the CS-Reg FD. This conclusion is further supported by the sub-sample analysis reported in the last two columns in Panel A of Table 5

[26]The information on the implementation of the country-specific Fair Disclosure requirements has been collected by contacting the respective authorities in each country. We refer to these country-specific versions of Regulation Fair Disclosure as 'CS-Reg FD' to avoid confusion. In detail, Thailand implemented the Disclosure Guidelines for Listed Company Management in December 2005; Hong Kong, Part XIVA of the Security and Futures Ordinance in January 2013; Singapore, SGX Listing Rules 703, Appendix 7.1 in January 2003; Taiwan, Article 3 of the Procedures for Verification of Material information of companies listed Securities in July 2002; India, Regulation 8 of the SEBI Prohibition of Insider Training Regulations in January 2015; South Korea, Korean version Regulation Fair Disclosure in November 2002; Malaysia, Corporate Disclosure Guide in September 2011.

and further tests of coefficients in Panel B. The accuracy of all bold forecasts has increased after the implementation of the CS-Reg FD ($\gamma_{3\text{before}} - \gamma_{3\text{after}}$ is negative and significant at the 5 percent level of significance) but we still find that bold locals are more accurate than other bold forecasts with no significant differences across the two periods ($((\gamma_1+\gamma_4)_{\text{before}} - (\gamma_1+\gamma_4)_{\text{after}}$ is insignificant). Hence, business group affiliations do not explain our results.

4.3.2. Investment banking relationships

Next, we test whether the greater accuracy reported for bold locals compared to other bold forecasts stems from investment banking relationships. For this purpose we re-estimate Equation (6) augmented by including past underwriter and future underwriter dummy variables and using $DBOLD_{md}$ and $DBOLD_{q1q4}$ as measures of herding.[27] We create two types of underwriter dummies: five-year and more than five-year underwriter dummies.[28] The five-year (greater than five year) past underwriter dummy equals one if the analyst belongs to the lead or co-lead underwriter for the firm's IPO or SEO which took place no more (more) than five years ago, and zero otherwise. The respective future underwriter dummies are defined in a similar fashion.

Results reported in Table 6 show that the regression coefficients on the future underwriter dummy variables are positive and significant at the 10 percent level or better across both horizons and measures of boldness, except the greater than five years pre-IPO/SEO when using $DBOLD_{q1q4}$ as a measure of boldness. At the same time, the past underwriter dummy variables are insignificant across all horizons and measures of boldness. All the interaction terms between the affiliation dummies and our test variables are insignificant suggesting that underwriter affiliation does not explain the relative difference in the accuracy of forecasts by analyst type. Despite the explanatory power of the underwriter dummies, the regression coefficient on the bold local is still positive and significant at the 5 percent level across all the regressions reported in Table 6. A comparison of the respective coefficients on the bold local dummy variable reported in Tables 4 and 6 shows that future and past underwriter dummies do not have an impact on the difference between the bold forecasts. Hence, the difference between the accuracy of bold locals compared to other bold forecasts is not explained by investment banking relationships.

[27]Our analysis is based only on firms for which we have the underwriter information from January 1989 to June 2020. As a consequence, the number of forecasts used in the regression results reported in Table 6 drops to about 33 percent compared to the results reported in Table 4.

[28]Qualitatively similar results are obtained if we capture the underwriting affiliation for shorter periods, such as one and two years.

Table 5
OLS regression results: forecast accuracy controlling for business group affiliations

	Entire sample		Sub-sample analysis	
			Before CS-Reg FD	After CS-Reg FD
	(1)	(2)	(3)	(4)
Panel A: OLS regression results				
Local (γ_1)	−0.003	−0.000	0.001	0.002
	(−0.56)	(−0.07)	(0.18)	(0.18)
Expatriate (γ_2)	0.012**	0.011**	0.011*	0.013
	(2.21)	(2.20)	(1.75)	(1.34)
DBOLD (γ_3)	−0.216***	−0.234***	−0.234***	−0.183***
	(−19.63)	(−16.38)	(−16.15)	(−9.95)
DBOLD × *Local* (γ_4)	0.042***	0.032**	0.030**	0.049**
	(3.79)	(2.25)	(2.06)	(2.57)
DBOLD × *Expatriate* (γ_5)	−0.010	0.003	0.004	−0.032
	(−0.88)	(0.25)	(0.26)	(−1.62)
CS-Reg FD Dummy	0.002	0.002		
	(0.67)	(0.53)		
DBOLD × *Local* × *CS-Reg FD Dummy*		0.014		
		(0.60)		
DBOLD × *Expatriate* × *CS-Reg FD Dummy*		−0.035		
		(−1.58)		
DBOLD × *CS-Reg FD Dummy*		0.048**		
		(2.11)		
Control variables	Yes	Yes	Yes	Yes
Intercept	0.063***	0.063***	0.057***	0.081***
	(11.48)	(11.48)	(9.27)	(6.84)
N	722,272	722,272	454,749	267,523
Adj. R^2	0.138	0.138	0.130	0.155
F-test	792.4***	642.2***	616.1***	367.0***
Panel B: Regression-based hypothesis test results comparing models (3) and (4)				
H_0: $\gamma_1 = \gamma_1$				−0.001**
				[−0.043]
H_0: $\gamma_2 = \gamma_2$				−0.002
				[−0.604]
H_0: $\gamma_3 = \gamma_3$				−0.051**
				[0.049]

(continued)

4.3.3. Demand for local analysts' services

To test this explanation, we generate a dummy variable which takes a value of one for the ADR stocks in our sample and zero otherwise.[29] This dummy

[29]We consider firms which report their actual earning in USD to be ADR firms.

Table 5 (continued)

	Entire sample		Sub-sample analysis	
			Before CS-Reg FD	After CS-Reg FD
	(1)	(2)	(3)	(4)
H_0: $\gamma_1 + \gamma_4 = \gamma_1 + \gamma_4$				−0.020*
				[−0.080]
H_0: $\gamma_2 + \gamma_5 = \gamma_2 + \gamma_5$				0.034
				[0.181]

This table replicates our main regression model in the presence of a dummy variable controlling for the implementation of the country-specific Regulation Fair Disclosure (*CS-Reg FD*). *CS-Reg FD* is a dummy variable which equals one for the post-implementation period of the respective versions of Regulation Fair Disclosure in each country and zero otherwise. The dependent variable in all the regressions is the analyst forecast accuracy (*PMAFE*), with*DBOLDmd* used to measure boldness. The regression results reported in the first two columns are based on the entire sample of 722,272 observations, whereas the last two columns report the robustness results using a sub-sample analysis. All the variables, except *Ln (MV)*, are demeaned by the firm-year values. See Appendix II for variable definitions. The *t*-values presented in parentheses are heteroscedasticity consistent and the standard errors are clustered by firm and analyst. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively (two-tailed test).

variable is then included in Equation (6) and also used to divide the sample into ADR and non-ADR firms, enabling a sub-sample analysis. The results reported in column (1) of Table 7 show that the ADR dummy is positive and significant which indicates that earnings forecasts made for ADR firms are more accurate compared to other forecasts. Further sub-sample analysis reported in columns (2) and (3) of Panel A as well as tests of coefficients (and their differences) in Panel B provide support for the findings that local analysts lose their advantage for ADR firms but they are still more accurate compared to other bold forecasts for the non-ADR firms.

To further test the argument that the advantage of bold locals is driven by the level of interest in local firms, we capture the latter using the proportion of analysts following a firm in a particular year who are local (*PrLocalAnalysts*). A higher percentage indicates higher interest in local firms. The regression results reported in column (4) of Table 7 show that the regression coefficient on the proportion of local analysts is negative and insignificant, and the *DBOLD* × *Local* coefficient is still positive and significant. When interacted with our variable of interest in column (5), we find that all the coefficients on the interaction terms are insignificant with the exception of the *DBOLD* × *PrLocalAnalysts* coefficient which is positive and significant at the 1 percent level. This shows that bold forecasts made for firms with a higher

Table 6
OLS regression results: forecast accuracy controlling for underwriter affiliations

	X = $DBOLD_{md}$				X = $DBOLD_{q1q4}$			
	Affiliation ≤ *5 years*		*Affiliation* > *5 years*		*Affiliation* ≤ *5 years*		*Affiliation* > *5 years*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local (γ_1)	0.009	0.009	0.009	0.009	−0.000	0.000	−0.001	−0.000
	(0.88)	(0.89)	(0.87)	(0.87)	(−0.02)	(0.00)	(−0.03)	(−0.02)
Expatriate (γ_2)	0.021**	0.021**	0.021**	0.021**	0.022	0.022	0.021	0.022
	(2.24)	(2.25)	(2.25)	(2.24)	(1.54)	(1.56)	(1.53)	(1.55)
DBOLD (γ_3)	−0.204***	−0.204***	−0.206***	−0.204***	−0.371***	−0.373***	−0.375***	−0.371***
	(−11.35)	(−11.28)	(−11.53)	(−11.16)	(−12.22)	(−12.08)	(−12.44)	(−11.96)
DBOLD × *Local* (γ_4)	0.046**	0.045**	0.047**	0.044**	0.069**	0.070**	0.073**	0.069**
	(2.41)	(2.39)	(2.51)	(2.33)	(2.18)	(2.20)	(2.32)	(2.14)
DBOLD × *Expatriate* (γ_5)	−0.009	−0.007	−0.009	−0.008	−0.007	−0.004	−0.004	−0.006
	(−0.49)	(−0.37)	(−0.44)	(−0.42)	(−0.21)	(−0.12)	(−0.11)	(−0.20)
Past Underwriter	−0.001		−0.004		0.015		0.017	
	(−0.09)		(−0.43)		(1.09)		(1.39)	
Future Underwriter		0.026**		0.023**		0.029*		0.022
		(2.12)		(2.20)		(1.66)		(1.62)
DBOLD × *Local* × *Past Underwriter*	−0.010		−0.032		0.026		−0.042	
	(−0.15)		(−0.65)		(0.27)		(−0.56)	
DBOLD × *Expatriate* × *Past Underwriter*	0.045		0.014		0.066		−0.002	
	(0.70)		(0.33)		(0.69)		(−0.03)	
DBOLD × *Local* × *Future Underwriter*		−0.016		0.018		−0.002		0.051
		(−0.15)		(0.20)		(−0.01)		(0.32)
DBOLD × *Expatriate* × *Future Underwriter*		−0.029		−0.001		−0.018		0.046
		(−0.30)		(−0.01)		(−0.12)		(0.32)
DBOLD× *Past Underwriter*	0.004		0.034		−0.009		0.053	

(continued)

Table 6 (continued)

	X = $DBOLD_{md}$				X = $DBOLD_{q1q4}$			
	Affiliation ≤ *5 years*		*Affiliation* > *5 years*		*Affiliation* ≤ *5 years*		*Affiliation* > *5 years*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0.07)		(0.85)		(−0.10)		(0.85)	
DBOLD× *Future Underwriter*		0.035		0.006		0.048		−0.001
		(0.37)		(0.07)		(0.33)		(−0.01)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	0.068***	0.069***	0.068***	0.069***	0.019	0.020	0.020	0.019
	(6.88)	(6.92)	(6.90)	(6.89)	(1.04)	(1.05)	(1.09)	(1.03)
N	237,563	237,563	237,563	237,563	119,571	119,571	119,571	119,571
Adj. R^2	0.154	0.154	0.154	0.154	0.154	0.154	0.155	0.154
F-test	256.4***	255.6***	260.7***	254.1***	277.2***	273.3***	286.7***	272.1***

This table replicates our main regression model in the presence of dummy variables controlling for the past and future investment affiliations with the firm. As a consequence, these regressions are based on 928 firms for which we have the underwriter information from January 1989 to June 2020. The dependent variable in all the regressions is the analyst forecast accuracy (*PMAFE*). Boldness is measured using *DBOLDmd* in columns (1)–(4) and $DBOLD_{q1q4}$ in columns (5)–(8). The affiliation of the underwriter with the firm is measured up to five years as well as more than five years pre- or post-IPOs. The five years past affiliation dummy equals one if the analyst belongs to the lead or co-lead underwriter for the firm's IPO or SEO which took place no more than five years ago, and zero otherwise. The greater than five years past affiliation dummy equals one if the analyst belongs to the lead or co-lead underwriter for the firm's IPO or SEO which took place more than five years ago, and zero otherwise. All the variables, except *Ln (MV)*, are demeaned by the firm-year values. See Appendix II for variable definitions. The *t*-values presented in parentheses are heteroscedasticity consistent and the standard errors are clustered by firm and analyst. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively (two-tailed test).

proportion of local analysts are more accurate compared to herding forecasts and this is the case for both local and expatriate analysts. A similar conclusion is drawn when partitioning the sample based on the median value of the proportion of locals in columns (6) and (7) of Table 7.[30] These results show that the accuracy advantage of bold locals is not explained by the level of interest in local firms.

4.3.4. Specialisation of analysts vis-à-vis countries or sectors

To test for this potential effect, we generate three dummy variables which capture the specialisation of the financial analysts, such as country, sector or absolute specialists.[31] Untabulated results show that sector specialisation is rare in local brokerage houses, whereas this is a more frequent occurrence in the case of global brokerage houses.[32] Next, we include the firm-year demeaned country, sector and absolute specialisation dummy variables in Equation (6). The results tabulated in column (1) of Panel A in Table 8 show that the regression coefficients on the country, sector and absolute specialisation dummy variables are all insignificant and the regression coefficient on *DBOLD* × *Local* is still positive and significant at the 1 percent level. We further re-run our main regression model by partitioning the sample into sub-samples based on the specialisation of analysts. The results reported in columns (2)–(7) of Panel A and also the three columns in Panel B show that we still find support for our results across all the sub-samples and there is no difference in the coefficients on the *DBOLD* × *Local* across the sub-samples $((\gamma_{1+}\gamma_4)_{\text{yes}} -$

[30]In the spirit of Comiran and Siriviriyakul (2019), we also partition the sample into quartiles based on the proportion of analysts following a firm in a year. Untabulated results show that the regression coefficients on *DBOLD* × *Local* are insignificant for each quartile. We also use firm size and the number of analysts following as alternative measures to capture the interest in local firms.

[31]Following Sonney (2009), we classify analysts as country (sector) specialists if their country (sector) Herfindahl Index (HI) is larger than 0.90 and their sector (country) HI is smaller than 0.90. Analysts with country and sector HIs above 0.90 are classified as absolute specialists. See section 3.1 in Sonney (2009) for further details on the calculation of HIs.

[32]Untabulated results show that 59.5 percent of the forecasts in our sample are produced by country specialists, 5.2 percent by the sector specialists and 22.4 percent by absolute specialists. The percentage of country specialists' forecasts varies between 67.1 percent for locals, 55.5 percent for expatriates and 54.0 percent for globals. The difference in the percentage across analyst types is more striking – less than 1 percent of local forecasts are made by the sector analysts whereas 7.3 percent of expatriate and 10.8 percent of global forecasts are made by the sector specialists. Furthermore, the Pearson correlation coefficient between the bold dummy variable and country specialism is 0.07, with the sector specialism is −0.10 and with the absolute specialists is 0.06. Hence, bold forecasts are less likely to be produced by the sector specialists.

Table 7
OLS regression results: forecast accuracy controlling for the demand for local analyst services

		Sub-sample analysis				Sub-sample analysis	
	Entire sample (1)	ADR firms (2)	Non-ADR firms (3)	Entire sample (4)	Entire sample (5)	Below median prop. local analysts (6)	Above median prop. local analysts (7)
Panel A: OLS regression results							
Local (γ_1)	−0.003	0.006	−0.003	−0.003	0.014***	0.011	0.004
	(−0.56)	(0.18)	(−0.58)	(−0.53)	(2.59)	(1.25)	(0.60)
Expatriate (γ_2)	0.012**	−0.011	0.012**	0.012**	0.009*	0.008	0.008
	(2.21)	(−0.35)	(2.27)	(2.24)	(1.65)	(0.94)	(1.22)
DBOLD (γ_3)	−0.216***	−0.282**	−0.215***	−0.218***	−0.297***	−0.260***	−0.174***
	(−19.62)	(−2.57)	(−19.55)	(−19.65)	(−12.36)	(−16.09)	(−11.02)
DBOLD × *Local* (γ_4)	0.042***	0.073	0.042***	0.044***	0.026	0.017	0.023
	(3.79)	(0.74)	(3.73)	(3.93)	(1.05)	(1.03)	(1.50)
DBOLD × *Expatriate* ($\gamma 5$)	−0.010	0.055	−0.011	−0.009	0.026	0.010	−0.010
	(−0.88)	(0.66)	(−0.98)	(−0.77)	(1.05)	(0.58)	(−0.70)
ADR Dummy	0.042***						
	(3.40)						
PrLocalAnalysts				−0.008	−0.008		
				(−1.47)	(−1.47)		
DBOLD × *Local* × *PrlocalAnalysts*					−0.051		
					(−0.77)		
DBOLD × *Expatriate* × *PrLocalAnalysts*					−0.085		
					(−1.28)		
DBOLD× *PrLocalAnalysts*					0.245***		
					(3.77)		
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	0.064***	0.056	0.065***	0.068***	0.068***	0.043***	0.081***

(continued)

Table 7 (continued)

		Sub-sample analysis				Sub-sample analysis	
	Entire sample (1)	ADR firms (2)	Non-ADR firms (3)	Entire sample (4)	Entire sample (5)	Below median prop. local analysts (6)	Above median prop. local analysts (7)
	(11.73)	(0.88)	(11.88)	(10.41)	(10.41)	(5.04)	(12.50)
N	722,272	16,984	705,288	702,929	702,929	337,081	365,848
Adj. R^2	0.138	0.102	0.139	0.139	0.139	0.137	0.142
F-test	784.1***	361.9***	828.7***	761.3***	628.1***	492.9***	436.4***
Panel B: Regression-based hypothesis test results comparing models (2) and (3) as well as models (6) and (7)							
H_0: $\gamma_1 = \gamma_1$			0.009				0.007
			[0.603]				[0.750]
H_0: $\gamma_2 = \gamma_2$			−0.023				0.000
			[−0.403]				[0.963]
H_0: $\gamma_3 = \gamma_3$			−0.067				−0.086***
			[−0.496]				[−0.000]
H_0: $\gamma_1 + \gamma_4 = \gamma_1 + \gamma_4$			0.040				0.001
			[0.531]				[0.920]
H_0: $\gamma_2 + \gamma_5 = \gamma_2 + \gamma_5$			0.043				0.020
			[0.516]				[0.298]

This table replicates our main regression model when controlling for the demand for local analyst services. *ADR Dummy* takes a value of one if I/B/E/S forecasted earnings are reported in US dollars and zero otherwise. *PrLocalAnalysts* is the proportion of analysts following a firm in a particular year who are local. The dependent variable in all the regressions is the analyst forecast accuracy (*PMAFE*). Boldness is measured using *DBOLDmd* in all the regressions. The regression results reported in the first column are based on the entire sample of 722,272 observations. The sample is then partitioned into ADR and non-ADR firms in columns (2) and (3). The regression results reported in columns (4)–(7) are estimated on our sample after excluding firm-years with zero local analysts following the firm. The last two columns report the robustness results using a sub-sample analysis. All the variables, except *Ln (MV)*, are demeaned by the firm-year values. See Appendix II for variable definitions. The *t*-values presented in parentheses are heteroscedasticity consistent and the standard errors are clustered by firm and analyst. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively (two-tailed test).

$(\gamma_{1+}\gamma_4)_{no}$ are insignificant). Overall, our results are robust when controlling for the specialism of local, expatriate and global analysts.

4.3.5. Other potential explanations

Prior studies in the field identify other potential sources of the accuracy advantage of local analysts. First, Tan et al. (2001) show that mandatory IFRS adoption improved foreign analyst forecast accuracy. Hence, bold locals may be more accurate compared to other bold forecasts because they are better at understanding the national accounting standards. To test this argument, we re-run Equation (6) restricted to the post-2008 period, when firms in our sample are not required to report their financial statements using the national accounting standards. Untabulated results show that the regression coefficient on the bold locals is 0.038 and significant at the 5 percent level, which is comparable to the coefficient reported in column (2) of Table 4. This suggests that the advantage of bold locals is not driven by better understanding of the national accounting standards.

Second, bold local forecasts may be more accurate as they are produced closer to the announcement day. Although we control for the forecasting horizon in our main regression, to tease out this effect we interact forecasting horizon with the bold dummy, bold local and bold expatriate dummy variables and include these interaction terms in Equation (6). Untabulated regression results show that our findings are not explained by the forecasting horizon.[33]

Third, Mayew (2008), using the transcripts from earnings conference calls, shows that managers discriminate among analysts by allowing more management access to more favourable analysts. In our case, it is possible that managers favour local analysts because they produce more favourable/optimistic forecasts. Untabulated results, however, show that bold locals are less optimistic compared to other bold forecasts. These results are not in line with the discrimination of certain analyst types.

Finally, the accuracy advantage of bold locals may stem from the fact that local analysts are better than expatriate or global analysts. By design, analysts in our sample can produce bold as well as herding forecasts. Hence, if locals are consistently better than expatriates or globals, the herding local forecasts should also be more accurate than other herding forecasts. However, the results reported in Table 4 indicate that this is not the case: herding locals are as accurate as herding globals. Thus, our results cannot be explained by consistently better-quality forecasts produced by the local analysts.

[33]Untabulated regression results show that on average bold forecasts are more accurate for longer horizons but there is no difference between the local and expatriate bolds in this regard.

Table 8
OLS regression results: forecast accuracy controlling for specialisation of analysts

		Country specialists		Sector specialists		Absolute specialists	
	Entire sample (1)	Yes (2)	No (3)	Yes (4)	No (5)	Yes (6)	No (7)
Panel A: OLS regression results							
Local (γ_1)	−0.003	−0.005	0.001	−0.045	−0.003	−0.012	−0.001
	(−0.64)	(−0.70)	(0.07)	(−1.64)	(−0.53)	(−1.02)	(−0.22)
Expatriate (γ_2)	0.011**	0.008	0.016**	0.034**	0.010*	0.009	0.012**
	(2.13)	(1.11)	(2.21)	(2.41)	(1.74)	(0.79)	(2.02)
DBOLD (γ_3)	−0.216***	−0.217***	−0.215***	−0.231***	−0.214***	−0.218***	−0.215***
	(−19.64)	(−15.15)	(−14.17)	(−6.99)	(−19.08)	(−11.08)	(−17.87)
DBOLD × *Local* (γ_4)	0.042***	0.046***	0.035**	0.181***	0.039***	0.035*	0.046***
	(3.80)	(3.12)	(2.09)	(3.28)	(3.43)	(1.69)	(3.67)
DBOLD × *Expatriate* (γ_5)	−0.010	−0.004	−0.017	−0.007	−0.011	−0.015	−0.009
	(−0.88)	(−0.28)	(−1.08)	(−0.20)	(−0.97)	(−0.69)	(−0.71)
Country Specialist Dummy	0.002						
	(0.37)						
Sector Specialist Dummy	−0.012						
	(−1.41)						
Absolute Specialist Dummy	−0.008						
	(−1.23)						
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	0.063***	0.064***	0.063***	0.116***	0.063***	0.057***	0.065***
	(11.62)	(9.42)	(6.13)	(3.49)	(11.42)	(3.54)	(11.03)
N	722,272	430,019	292,253	37,521	684,751	162,081	560,191
Adj. R^2	0.138	0.137	0.139	0.142	0.138	0.141	0.137
F-test	690.8***	767.4***	416.9***	103.2***	853.1***	250.4***	850.6***

(continued)

Table 8 (continued)

	Entire sample (1)	Country specialists: Yes (2)	Country specialists: No (3)	Sector specialists: Yes (4)	Sector specialists: No (5)	Absolute specialists: Yes (6)	Absolute specialists: No (7)
Panel B: Regression-based hypothesis test results for the sub-samples							
H_0: $\gamma_1 = \gamma_1$			−0.006		−0.042		−0.011
			[−0.507]		[−0.136]		[−0.407]
H_0: $\gamma_2 = \gamma_2$			−0.007		0.024		−0.003
			[−0.692]		[0.257]		[−0.809]
H_0: $\gamma_3 = \gamma_3$			−0.001		−0.017		−0.003
			[−0.053]		[−0.514]		[−0.864]
H_0: $\gamma_1 + \gamma_4 = \gamma_1 + \gamma_4$			0.012		0.100**		−0.022
			[0.528]		[0.018]		[−0.328]
H_0: $\gamma_2 + \gamma_5 = \gamma_2 + \gamma_5$			0.013		0.028		−0.009
			[0.599]		[0.461]		[−0.696]

This table replicates our main regression model when controlling for the specialisation of analysts as country, sector and absolute specialists. Analysts' specialisation is captured via three dummy variables which take a value of one if the analyst is classified as a country, sector or absolute specialist, and zero otherwise. We classify analysts as country (sector) specialists if their country (sector) Herfindahl Index (HI) is larger than 0.90 and their sector (country) HI is smaller than 0.90. Analysts with country and sector HIs above 0.90 are classified as absolute specialists. The dependent variable in all the regressions is the analyst forecast accuracy (*PMAFE*). Boldness is measured using *DBOLDmd* in all the regressions. The regression results reported in column (1) are based on the entire sample of 722,272 observations. The remaining columns report the regression results for the sub-sample analysis for the three categories of analysts. For example, the regression results reported in column (2) are based on the sub-sample of forecasts made by country specialists whereas the results in column (3) are based on the forecasts made by the non-country specialists. All the variables, except *Ln (MV)*, are demeaned by the firm-year values. See Appendix II for variable definitions. The *t*-values presented in parentheses are heteroscedasticity consistent and the standard errors are clustered by firm and analyst. ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively (two-tailed test).

5. Discussion and conclusion

This paper examines whether analysts' herding behaviour has a significant impact on their forecasting accuracy. To start, we test our first null hypothesis by re-examining the relative forecast accuracy of local, expatriate and global analysts using a sample of seven Asian countries. Then, we briefly explore whether the propensity of analysts to herd varies by analyst type. In this paper we argue that in order to compare the relative forecasting accuracy of different analyst types, one should control for the herding behaviour of analysts and ultimately use the bold earnings forecasts as a barometer to evaluate the segregated forecasting ability of analysts. This is because herding forecasts are produced by simply mimicking other forecasts and do not reflect the true endowments possessed by different analyst types. Consequently, we finally test our second null hypothesis by examining the relative forecast accuracy of bold forecasts by analyst type. To the best of our knowledge this is the first study to investigate the relative forecast accuracy of local, expatriate and global analysts by taking into account analysts' herding behaviour.

Our results suggest that local analysts are the most accurate analyst type when accounting for their herding behaviour. Bold forecasts produced by the local analysts are more accurate compared to other bold forecasts. These results are consistent across different measures of boldness, samples and periods of time. This suggests that the information advantage of bold local analysts is bigger than that of bold expatriate analysts despite the fact that local and expatriate analysts are both resident analysts. We test four competing explanations aimed at identifying the source of the accuracy advantage of bold locals, such as business group affiliations, investment banking relationships, demand for local analysts' services and specialisation of analysts vis-à-vis countries or sectors. The results show that none of these hypotheses explain the accuracy advantage of bold local forecasts.

These results echo the conclusion drawn by Conroy *et al.*, (1997) that local analysts in Japan, *for whatever reason*, have a better gauge of the information announced by the firm they forecast. Brown *et al.*, (2015, p. 3) show that 'private communication with management is a more important input to analysts' earnings forecasts and stock recommendations than (their own) primary research, recent earnings performance, and recent 10-K and 10-Q reports'. It is possible that the four sources of information advantage considered in this paper do not capture this 'private communication channels' with the management of the firm. Future research potentially could explore the role of gender in producing bolder forecasts[34] (Kumar, 2010) and explore

[34]Kumar (2010) shows, in the context of US firms, that female analysts issue bolder and more accurate forecasts and their accuracy increases with the market segments with lower female concentration. The author concludes that female analysts have better than average skill due to self-selection and financial markets recognise their superior abilities.

further the exact source of information used by the analyst types. For example, Hu *et al*., (2008) show that information sources have a significant impact on analysts' information comprehension, analysing abilities and job quality in China. Specifically, analysts tend to exhibit greater information comprehension and better job quality when they conduct more company-level surveys. In addition, anecdotal evidence indicates that local brokerage houses may use different databases compared to foreign analysts when forecasting earnings. This type of analysis is beyond the scope of this paper. Importantly though, we show for the first time that herding behaviour of analysts is present in the Asian markets and this behaviour affects the accuracy of earnings forecasts. Therefore, it is vital for investors, regulators and academics to be cognisant of these potential biases, especially given the growing relevance and appeal of Asian emerging markets. It also offers useful evidence to brokerage houses when deciding about their location and the role of behavioural factors in the earnings forecasting of financial analysts. Our evidence shows that location matters but this needs to be considered in conjunction with behavioural factors.

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Appendix I
Sample formation

Description	Obs. lost	Obs. left
One-year ahead forecasts for seven Asian counties (Jan. 1994–Dec. 2016)		1,040,416
Non-missing for all control variables (i.e., horizon, firm size, frequency of forecasts, number of analysts, industries, companies, countries, general and firm experience and brokerage size)	59,265	981,151
$0 \leq$ Horizon ≤ 400	10,931	970,220
Non-missing for *PMAFE* (i.e., non-missing actual EPS and/or forecasted EPS, non-zero mean accuracy forecast error)	11,443	958,777
Non-missing for *BOLD* and *BOLDSCORE*	120,560	838,217
Year 1994–2006		353,189
Year 2007–2016		485,028
Identification of brokerage house into *Local*, *Expatriate* or *Global*	115,945	722,272
Year 1994–2006	260	352,929
Year 2007–2016	155,685	369,343

This table provides details regarding the construction of the sample. All the variables used in the study and referred to in this paper are defined in Appendix II. The control variables are measured using all available data in I/B/E/S international and US files up to the fiscal year end 2016. We require non-missing analysts' one-year ahead earnings forecasts and actual earnings in order to calculate *PMAFE*. In addition, we need at least two forecasts made by different analysts 90 days prior to a specific forecast to calculate *BOLD* and *BOLDSCORE*. Finally, only observations in which a brokerage house is identified as local, expatriate or global are used in the study. As mentioned in Section 3.1, we classify the brokerage houses into *Local*, *Expatriate* or *Global* using the sample of forecasts between 1994 and 2006 and then extrapolate this classification post-2006 as I/B/E/S ceased to provide the translation code for the brokerage houses post-2006. The subsequent analysis is based on the winsorised values of three continuous variables (*PMAFE*, *BOLD* and *MV*) at one percent each in the bottom and top tails.

Appendix II
Definitions of the variables

Variable	Description
Panel A: Main variables	
Local$_i$	*Local*$_i$ equals unity if analyst i is regarded as a local analyst, and zero otherwise, adjusted by firm-year averages. A local analyst is defined as an analyst employed in a local brokerage house located inside a particular country in which the covered firm's equity is traded
Expatriate$_i$	*Expatriate*$_i$ equals unity if analyst i is regarded as an expatriate analyst, and zero otherwise, adjusted by firm-year averages. An expatriate analyst is one working for a foreign brokerage house operating in a country where the covered firm's equity is traded
Global$_i$	*Global*$_i$ equals unity if analyst i is regarded as a global analyst, and zero otherwise, adjusted by firm-year averages. A global analyst is defined as an analyst who is working outside the country in which the firm's equity is traded and forecasts earnings for local firms
$BOLD_{ijt}$	$BOLD_{ijt}$ is the proportional mean deviation from the consensus, defined as the ratio of the difference between the deviation of a forecast made by analyst i for firm j at time t from the consensus forecast calculated using forecasts within 90 days before the forecast (DC_{ijt}) and the mean deviation of all forecasts for firm j in the fiscal year T (MDC_{jT}), to the mean deviation
$PMAFE_{ijt}$	$PMAFE_{ijt}$ is the proportional mean absolute forecast error, defined as the ratio of the difference between the absolute forecast error made by analyst i for firm j at time t (AFE_{ijt}) and the mean absolute forecast error of all forecasts for firm j in the fiscal year T ($MAFE_{jT}$), to the mean absolute forecast error. Following Bae *et al.*, (2008b), in order to facilitate the interpretation of the calculated variable, we multiply it by minus one. Thus, it measures accuracy rather than inaccuracy
Panel B: Control variables	
Horizon$_{ijt}$	Forecast horizon is the time period (in days) between the date of a forecast made by an individual analyst and the reported date of the actual earnings, adjusted by firm-year averages
$Ln\ (MV)_{jt}$	Logarithm of a firm's market value as a proxy of firm size
Frequency$_{it}$	Number of forecasts produced by an individual analyst for a particular company in each year, adjusted by firm-year averages
NoIndustry$_{it}$	Number of industries (using I/B/E/S classification) followed by an analyst each year, adjusted by firm-year averages
NoCompany$_{it}$	Number of companies followed by an individual analyst in each year, adjusted by firm-year averages
NoCountry$_{it}$	Number of countries followed by an individual analyst in each year, adjusted by firm-year averages
FirmExperience$_{it}$	Number of years of experience in following a particular company by an individual analyst in each year, adjusted by firm-year averages
GenExperience$_{it}$	Number of years of experience for an individual analyst in each year, adjusted by firm-year averages

(continued)

Appendix II (continued)

Variable	Description
$BrkSize_{it}$	Number of analysts employed by the brokerage house in each year, adjusted by firm-year averages
CS-Reg FD Dummy	A dummy variable which equals one for the post-implementation period of the respective versions of Regulation Fair Disclosure in each country and zero otherwise.
Past Underwriter	A dummy variable which equals one if the analyst belongs to the lead or co-lead underwriter for the firm's past IPO or SEO, and zero otherwise. This dummy variable is calculated for two periods: for IPO or SEO which took place no more than five years ago and more than 5 year ago
Future Underwriter	A dummy variable which equals one if the analyst belongs to the lead or co-lead underwriter for the firm's future IPO or SEO, and zero otherwise. This dummy variable is calculated for two periods: for IPO or SEO which took place no more than five years and more than five year ago after the issue of the forecast by the analyst
ADR Dummy	A dummy variable which takes a value of one if I/B/E/S forecasted earnings are reported in US dollars and zero otherwise
PrLocal Analysts	The proportion of analysts following a firm in a particular year who are local
Country/Sector/Absolute Specialist Dummy	Analysts' specialisation is captured via three dummy variables which take a value of one if the analyst is classified as a country, sector or absolute specialist, and zero otherwise, adjusted by firm-year averages. We classify analysts as country (sector) specialists if their country (sector) Herfindahl Index (HI) is larger than 0.90 and their sector (country) HI is smaller than 0.90. Analysts with country and sector HIs above 0.90 are classified as absolute specialists. See section 3.1 in Sonney (2009) for further details on the calculation of HIs